Impact of Pay Transparency on Gender Wage Inequality: Evidence from Job Postings Regulation in Taiwan

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Abstract

Mandatory wage reveal on job postings is a popular pay transparency policy recently. However, the evaluation of the policy's effectiveness is still rare. Using online job posting data and representative survey data, I examine Taiwan's wage reveal policy enacted in 2018. With a difference-in-differences model, I find that while the earnings of workers with stronger policy exposure increase, the policy does not close the gender wage gap in general. The following robustness check excludes the potential bias due to annual minimum wage increases. My paper shows that external/cross-firm pay transparency can raise the wage for low-paying jobs, but no evidence supports that the policy can reduce gender inequality. The finding implies that the government can apply a wage reveal policy to help workers in low-wage jobs.

Keywords: pay transparency, wage reveal, job postings, gender wage gaps, difference-in-differences

JEL Codes: J31, J78

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1 Introduction

Wage inequality and discrimination are long-standing issues in labor economics (Cain 1986). One important cause is that wage information is not transparent in labor markets. Non-transparent wages allow employers to secretly exercise discrimination based on gender, race, or other characteristics unrelated to labor productivity. Moreover, employers can charge a markup on the wages because workers lack knowledge about the value of their labor and tend to underestimate it. In response to this problem, pay transparency policies have been introduced in several European countries and some US localities in recent decades (Cullen 2024). Since the history of pay transparency policies is not long, the influence of these policies is yet to be fully evaluated.

This paper examines a pay transparency policy implemented in 2018 that requires recruiters in Taiwan to reveal the expected wage range in job postings. The policy mandates wage disclosure for all positions paying less than 40,000 Taiwan Dollars (NTD) monthly (equivalent to $1,328 in 2018). The cutoff differentiates the policy exposure across various jobs based on their wage distribution before the law was enacted. Using differences in time and policy exposure, I apply a difference-in-difference model to estimate the effects of the wage reveal policy on wages. Since females may benefit more from pay transparency (Chen, Fung, and LaViers 2023), I further test the gender differentials of the policy impacts, which is the primary focus of this paper.

I use two different types of data from 2016 to 2021 for the estimation. First, I use job posting data from one of the leading employment websites to examine whether firms react to the policy. The data includes the posting date, the industry, the occupation, and the location of the position. It also includes information on whether the wage is revealed in the posting. If the wage is revealed, the data records the wage range or the minimum expected wage of the position. Second, I use the Manpower Utilization Survey for wage information in the labor market. This dataset is similar to the Current Population Survey's Annual Social and Economic Supplement (the March CPS survey). The survey records the employment status of each person in the sample. If one is labeled as currently employed, the data provides the industry, the occupation, the location, and the wage information. Individual characteristic variables are also included in the data.

The empirical evidence shows that firms adapted to the policy. More job postings included wage ranges after the policy took effect, with larger changes in jobs more exposed to the policy. The findings lead us to evaluate the wage reveal effect on wages and gender wage gaps. The estimation shows that people working in job categories more exposed to the policy now have higher wages than those in less affected positions. However, the policy does not create significant differences in gender wage gaps between the more affected job categories and the less affected ones. Since the minimum wage level increases annually during the observed years, it is possible that the wage reveal policy interacts with these increases. Therefore, I excluded the job categories most influenced by the minimum wage from the sample. The reestimation demonstrates results similar to the primary findings of the full sample. The robustness check shows that the effect of the wage reveal policy is independent of the minimum wage increases.

This paper contributes to two strands of literature. First, it adds to the discussion about how wage information can help workers. Previous research explicitly focused on how wage information helps workers in the wage (re)negotiation process. For instance, Jäger et al. (2024) found that wage information can change workers' intentions regarding job search and wage negotiation. Roussille (2024) showed that statistics of expected wages can reduce the gender ask gap in the job matching process and result in a smaller offer gap. Chen, Fung, and LaViers (2023) used an experiment to find that wage range information can encourage females to negotiate for higher wages. My findings aim to add evidence to how information affects gender differentials in the labor market.

Second, my paper joins the recent investigation into the effectiveness of pay transparency policies. Governments worldwide use various policies to achieve different types of pay transparency. Cullen (2024) sorted them into three categories: pay transparency among workers in the same firm and at the same level (horizontal transparency), among workers in the same firm but at different levels (vertical transparency), and among workers in competing firms (cross-firm transparency). Previous literature focuses on the effect of horizontal transparency policies. It is not only because they were adopted earlier[1] but also because such policies directly target discrimination in wages. Cullen (2024) summarizes the findings in the related literature and points out that horizontal transparency policies drag down wages when closing the gender wage gap. In contrast, revealing wage ranges in job

1. See Table 1 in Cullen (2024)

postings is a less discussed strand of pay transparency policy. Job postings are open to the public, so they provide information not only to potential employees but also to other firms in the market. Therefore, it is considered a cross-firm transparency policy. Since the history of wage reveal policies is much shorter, the discussion of policy effects is rare in the literature. Arnold, Quach, and Taska (2022) use an online job posting dataset to show that the policy in Colorado increases the posting wage. Frimmel et al. (2023) use an Austrian vacancy-worker dataset and find that the wage reveal policy can help reduce the gender wage gap by correcting women's misperception of wages when they need to decide whether to accept an offer in a short time. My research provides additional evidence of the wage reveal effect on gender wage gaps. Additionally, I propose an identification strategy that does not require a link between the job posting and the position winner. The strategy also allows the examination of the effects on incumbent workers.

The rest of the paper is organized as follows. Section 2 describes the policy settings, the data sources, and the definition of treatment differentials. Section 3 explains the identification strategy. Section 4 demonstrates the empirical findings. Finally, Section 5 concludes the paper.

2 Background and Data

2.1 Wage Reveal Policy in Taiwan

This paper examines the effect of the 2018 reform of Taiwan's Employment Service Act. The new law requires all recruiters in Taiwan to reveal the wage range on job postings if the minimum monthly pay for the position is less than 40,000 Taiwan dollars (NTD), which equals $1,328 in 2018. Violation can cause a fine of at least 60,000 NTD and no more than 360,000 NTD (approximately $2,000-$10,000). In 2019, the Ministry of Labor (MOL) advised that the posted wage range be no larger than 5,000 NTD in response to critiques on the unrestrictedly wide wage ranges.

The law reform process was initiated in March 2017, and the Legislative Yuan (Taiwan's congress) approved it in November 2018. The new regulation has been enforced since November 30, 2018.[2] However, in observance of the upcoming law change, MOL asked employment websites to encourage

2. Table A.1 shows the timeline of the legislative process.

their firm clients to reveal the wage range on the job postings starting from October 2017.[3] Therefore, I consider the time between October 2017 and November 2018 to be the transitional period. Figure 1 shows the share of the job postings with the wage range revealed in the job posting data. It is clear that the reveal rate steadily increases during the transitional period.

2.2 Data

I use two different datasets in this research to estimate the effect of the wage reveal policy. First, I use the job posting data from a leading employment website to examine whether firms react to the policy. Second, I use an official survey on labor outcomes in Taiwan to analyze the effect of wage reveals on wages and gender wage gaps.

2.2.1 Job Posting Data

The job posting data is from the 1111 Job Bank. Established in 1999, 1111 Job Bank is now the second-largest employment website in Taiwan. 1111 provides the records of all active postings on the 1111 Job Bank website between 2016 and 2021. The data includes the wage range (if revealed), the industry code, the occupation code, and the location for each posting. Both industry and occupation codes can correspond to Taiwan's standard classifications down to 4 digits, and the location is recorded at the township level. Table 1 Panel A reports the summary statistics of the job posting data.

2.2.2 Wage Data

I use the Manpower Utilization Survey (MUS) for my analyses of wages and gender wage gaps. The MUS is conducted by Taiwan's Directorate General of Budget, Accounting and Statistics. It is commonly conducted every May[4] together with the monthly Manpower Survey. MUS is a nationally representative survey that provides information on employment and labor conditions. For the people working in the survey year, the survey reports their earnings and the industry, occupation, and location of their positions. The data also includes individual characteristics such as gender,

3. According to the email message from the 1111 Job Bank to author.

4. 2021's MUS is conducted in October due to the COVID-19 pandemic breakout in Taiwan during the usual survey time.

education attainment, tenure in the current position, marital status, and number of children. Table 1 Panel B reports the summary statistics of the MUS within the selected sample.

The data of job postings and individuals' wages can be linked to each other by industry, occupation, and location of the posting/individual, which is related to the definition of the treatment group described in the next section.

2.3 Sample Selection, Difference in Treatment, and Data Compatability

I select the sample using the following criteria to fit the research design. To test the compliance of the policy, I use all job postings between 2016 and 2021 with no missing values.[5] To estimate the effects on wages and the gender wage gap, I restrict the sample to full-time, private-sector employees paid monthly. There are two reasons for the sample restriction. First, a policy on job postings should only affect employed workers, so individuals who are employers and self-employed workers are excluded. Moreover, the wage structure of public-sector workers is publicly available, and the wage reveal policy should not affect the corresponding labor market. Second, the minimum wage level increases yearly during the observation period, and it can affect part-time and hourly-paid workers specifically. Excluding them could prevent minimum wage changes from affecting the estimation. Furthermore, most postings for part-time or not monthly-paid positions have revealed wage information, so the policy should barely affect these workers.

Unlike the statewide policy in Colorado described in Arnold, Quach, and Taska (2022), the wage reveal policy in Taiwan is a nationwide policy. Therefore, a treatment group based on geography is infeasible for this research. Since job matching in Taiwan demonstrates strong seasonality,[6] and the wage data is reported yearly, a treatment group based on the within-year time difference (such as the definition used in Frimmel et al. (2023)) is also inappropriate for this paper.

Instead, I use the level of policy exposure to differentiate the treatment. As it is impossible

5. Some active postings between 2016 and 2021 were posted before 2016. These *old* postings are excluded from the sample to ensure that I observe all wage reveal decisions in a specific year.

6. The postings' posted dates are concentrated within three months before Lunar New Year, and the peak of removed date is within two months after Lunar New Year. See Figures A.1.

to evaluate the policy exposure to each individual, I group the positions/individuals in the same industry, occupation, and county into a job category. Next, I evaluate the level of exposure with the share of workers earning less than 40,000 NTD monthly in 2017 (the year before the transition). Intuitively, as the higher the share of workers earning under 40,000 NTD, it is more likely that a new position in the category needs to have the wage range revealed. Hence, I consider the categories with the higher share to be the more exposed group of workers. Finally, I define the categories with the share above the weighted median as the more affected group; the rest are in the less-exposed (comparison) group. The analyses of wages and gender wage gaps focus on the years between 2016 and 2021 to be consistent with the estimation of the effects on job postings.

Since the job posting data is from a private employment service provider, one may wonder whether the job posting data can be comparable to the wage data. As the level of policy exposure differentiates the treatment, I need the policy exposure distribution of the datasets to be close to each other. Figure A.2 shows the distribution of the policy exposure (the share of 2017 wages less than 40,000 NTD within the job category) for each dataset in the base year (2017). The distributions do not look very different from each other. Figure A.3 provides more straightforward evidence that both datasets have shares of high-exposure cells similar to each other. The descriptive evidence supports that the job posting data is comparable to MUS in the treatment assignment, which allows the estimation of the policy effects on job postings to be an eligible first-stage result for discussing gender wage gaps. Table A.2 lists the job categories the most and the least exposed to the policy.

3 Identification Strategy

3.1 How Does Pay Transparency Affect Gender Wage Inequality?

As documented by Cullen (2024), pay transparency policies provide necessary information for workers, especially those at the bottom of the wage distribution, to fight against discrimination and inequality in earnings. The wage information can help reduce wage gaps in three ways. Firstly, employers may change their behaviors for two reasons. The first reason is the stronger competition in recruiting workers. Employers compete to recruit workers, and wage information can strengthen competition and thus give employers smaller chances to underpay employees. The second reason is unsustainable discrimination. Taste-based discrimination is rarely detectable when the outcome is not disclosed to the public or at least all stakeholders. When wages are revealed in the labor market, discrimination becomes costly for employers due to pressure from discriminated workers and public opinion. As a result, firms need to abandon their preferences for characteristics unrelated to productivity, reducing taste-based wage gaps through pay transparency.

Secondly, wage information can correct job seekers' expected earnings. Theoretically, the wage is decided by the marginal product of labor in a perfectly competitive market with complete information. In many cases, however, employers have richer information about their employees' actual productivity, given their knowledge of the production process and the output market. This asymmetric information allows employers to retain markups from the wages they pay. Pay transparency policies, which aim to reduce the information gaps in productivity, weaken firms' ability to underpay their workers. Moreover, earners with less knowledge about their own productivity particularly benefit from pay transparency (Jäger et al. 2024).

Female workers especially gain from correcting wage expectations, as empirical evidence shows that they systematically underestimate their productivity and the value of outside options. Roussille (2024) found that by providing information on the wage that recruiters bid, the gender gap in pay candidates ask for can be reduced. Furthermore, the gender gaps in bid wages and dealt wages are also eliminated.

Lastly, additional information from pay transparency can increase women's willingness to bargain for their earnings. Chen, Fung, and LaViers (2023) show that a narrow (and thus meaningful) wage range in a job posting can encourage female workers to negotiate their salary. Women's stronger tendency toward wage negotiations from pay transparency could potentially increase their earnings. This can apply to any current employees. Both men and women can renegotiate their wages and result in a wage increase for staying workers.

In conclusion, pay transparency is expected to reduce gender wage gaps by affecting employers' behaviors, correcting job seekers' wage expectations, and encouraging job seekers and current workers to bargain for their wages. While I cannot separate the effects from each channel, I estimate the total effect of the wage reveal policy with the identification strategies specified in the next section.

3.2 Estimation of the Effects on Job Posting

Since firms may have already revealed the wage information in the affected postings before the reform of the law, it is essential to evaluate how largely the policy changes the job postings on the market before testing the effects on labor market outcomes. Therefore, I adopt the difference-in-difference method to understand how the wage reveal policy affects job postings. The first difference is the time difference. The pre-period of the policy is before October 2017. The transition period is between October 2017 and November 2018. Finally, the after-period of the policy starts in December 2018. The second difference is the exposure difference, which defines the control and treatment groups by the share of workers earning less than 40,000 NTD in a job category in 2017. The model is described as the following equation:

$$
\begin{aligned}
revealed_{jt} = \alpha + \sum_{p \in \{trans, after\}} & \left\{ \beta_{1p} \cdot \mathbf{1}(t \in p) \cdot highexposed_{c(j)} + \beta_{2p} \cdot \mathbf{1}(t \in p) \right\} \\
& + \phi_{f(j)} + \theta_{c(j)} + \mu_{m(t)} + \varepsilon_{jt},
\end{aligned}
\tag{1}
$$

where

$$
trans = [2017m10, 2018m11], \; after = [2018m12, 2021m12].
$$

In Equation 1, $revealed_{jt}$ indicates whether the wage range is revealed on the posting j which is posted at time t. $highexposed_{c(j)}$ expresses whether a posting in industry-occupation-county category c is highly exposed to the policy. $trans$ and $after$ represent the transition period (October 2017 to November 2018) and the after period (since December 2018) of the policy. Therefore, β_{1p} is the coefficient of interest. It shows the additionally increased probability of wages being revealed in high-exposed job categories compared to low-exposed job categories.

$\phi_{f(j)}$ and $\theta_{c(j)}$ are the firm fixed effect and the job category fixed effect, respectively. The two sets of fixed effects capture unobservable factors that can affect wage-revealing decisions from industries, occupations, locations, and firms.[7] $\mu_{m(t)}$ is the month fixed effect of posting time, which controls the within-year seasonality. Lastly, ε_{jt} is the error term, and the standard errors are clustered at the industry-occupation-county level, following the suggestion in Abadie et al. (2023).

The following equation performs a *yearly* event study of the difference in wage reveal between the job categories more and less affected by the policy:

$$\begin{aligned} revealed_{jt} = \alpha + \sum_{p \in [2016,2021], p \neq 2017} \Big\{ & \beta_{1p} \cdot \mathbf{1}(t = p) \cdot highexposed_{c(j)} \\ & + \beta_{2p} \cdot \mathbf{1}(t = p) \Big\} + \phi_{f(j)} + \theta_{c(j)} + \mu_{m(t)} + \varepsilon_{jt}. \end{aligned} \tag{2}$$

I perform the event study at the year level to filter out the noise from seasonality. β_{1p} estimates the difference in reveal rate compared to 2017. Assuming that it is the policy to make changes in wage reveal rate on job postings, β_{1p} should be significantly larger than zero only when p is after 2017. Other terms in Equation 2 have the same definition as in Equation 1 except that t indicates years.

3.3 Effects on Labor Market Outcomes

3.3.1 Employment

The wage reveal effects on individual employment cannot be directly measured because the policy exposure on the non-working population is unobservable. Instead, I examine the effects on employment by testing how the policy changes the proportion of workers in high-exposed job categories compared to that of low-exposed job categories with the difference-in-difference model as follows:

$$\begin{aligned} workersper100k_{klt} = \alpha + \sum_{p \in \{trans, after\}} \Big\{ & \beta_{1p} \cdot \mathbf{1}(t \in p) \cdot highexposed_{kl} \\ & + \beta_{2p} \cdot \mathbf{1}(t \in p) \Big\} + \theta_{kl} + \tau_t + \varepsilon_{klt}, \end{aligned} \tag{3}$$

7. Note that a firm can hire in different industries, occupations, and places. Thus, the two sets of fixed effects are not inclusive of each other.

where

$$trans = \{2018\},\ after = [2019, 2021].$$

In Equation 3, $workersper100k_{klt}$ is the number of full-time, monthly paid, and private sector workers in industry-occupation pair k per 100,000 labor force population in county l in year t. $highexposed_{kl}$ is an indicator for whether industry-occupation pair k in county l is highly exposed to the policy. $trans$ and $after$ represent the years in the transition period (2018) and the after period (2019-2021) of the policy.[8] Consequently, the coefficient of the difference-in-differences term, β_{1p}, is the coefficient of interest in the model. It represents the additional change in employment in the high-exposed job categories compared to low-exposed job categories under the influence of the new law. θ_{kl} is the industry-occupation-county fixed effect, and τ_t is the survey year fixed effect. ε_{klt} is the error term, and the standard errors are clustered at the industry-occupation-county level.

I further do an event study to estimate the pattern of wage reveal policy effect on employment with the following equation:

$$\begin{aligned} workersper100k_{klt} = \alpha + \sum_{p \in [2016, 2021], p \neq 2017} \Big\{ & \beta_{1p} \cdot \mathbf{1}(t \in p) \cdot highexposed_{kl} \\ & + \beta_{2p} \cdot \mathbf{1}(t \in p) \Big\} + \theta_{kl} + \varepsilon_{klt}, \end{aligned} \tag{4}$$

Here β_{1p} tells us the employment differential between the job categories affected more and less by the policy compared with the employment difference in 2017. I expected β_{1p} to be significantly larger than zero only when p is after 2017 if it is the wage reveal policy making the employment of more exposed job categories grow faster than the wage of less exposed positions. Other terms in Equation 4 have the same definition as in Equation 3.

In addition, I use the following model to distinguish the employment effect on female workers

8. The transition of the wage reveal policy is between October 2017 and November 2018, and the policy is enforced since December 2018. Since the MUS is conducted every year in May, the 2018 survey falls into the transition period, and the surveys in 2019 and after are in the after-period.

from that on male workers. The regression equation is described as follows:

$$
\begin{aligned}
workersper100k_{klgt} = \alpha + \sum_{(p \in trans, after)} \Big\{ & \beta_{1p} \cdot \mathbf{1}(t \in p) \cdot female_g \cdot highexposed_{kl} \\
& + \beta_{2p} \cdot \mathbf{1}(t \in p) \cdot female_g + \beta_{3p} \cdot \mathbf{1}(t \in p) \cdot highexposed_{kl} \Big\} \\
& + \beta_4 \cdot female_g \cdot highexposed_{kl} + \beta_5 \cdot female_g \\
& + \theta_{kl} + \tau_t + \varepsilon_{klgt},
\end{aligned}
\tag{5}
$$

where

$$trans = \{2018\},\ after = [2019, 2021].$$

In Equation 5, the dependent variable is split by gender. $workersper100k_{klgt}$ is the number of full-time, monthly paid, and private sector workers in industry-occupation pair k per 100,000 gender g labor force population in county l in year t. $female_g$ is the dummy variable indicating whether gender g is female. It interacts with the period dummies, the high-exposed job category dummy, and the interaction term. Consequently, the coefficient of the triple-difference term, β_{1p}, is the coefficient of interest in the model. It represents the additional change in gender employment differentials for the high-exposed jobs compared to low-exposed jobs under the influence of the new law. In other words, the coefficient measures the effect of the wage reveal policy on gender employment gaps. Other terms have the same definition as in Equation 3.

3.3.2 Wages

To understand how the wage reveal policy influences wages in Taiwan, I apply a difference-in-difference model as follows:

$$
\begin{aligned}
\log(wage_{it}) = \alpha + \sum_{p \in \{trans, after\}} & \Big\{ \beta_{1p} \cdot \mathbf{1}(t \in p) \cdot highexposed_{c(j)} + \beta_{2p} \cdot \mathbf{1}(t \in p) \Big\} \\
& + X_i \Gamma + \theta_{c(i)} + \tau_t + \varepsilon_{ict},
\end{aligned}
\tag{6}
$$

where

$$trans = \{2018\},\ after = [2019, 2021].$$

In Equation 6, $wage_{it}$ is individual i's monthly wage in year t. $highexposed_{c(i)}$ is an indicator for whether industry-occupation-county category c, where individual i works, is highly exposed to the policy. $trans$ and $after$ represent the years in the transition period (2018) and the after period (2019-2021) of the policy. Consequently, the coefficient of the difference-in-differences term, β_{1p}, is the coefficient of interest in the model. It represents the additional change in wages for the high-exposed workers compared to low-exposed workers under the influence of the new law.

X_i is a vector of individual characteristics, including gender, education attainment, age, marital status, having children or not, and working tenure in the current position.[9] $\theta_{c(i)}$ is the industry-occupation-county fixed effect, and τ_t is the survey year fixed effect. ε_{it} is the error term, and the standard errors are clustered at the industry-occupation-county level.

I further do an event study to estimate the pattern of wage reveal policy effect on wages with the following equation:

$$\begin{aligned}\log(wage_{it}) = \alpha + \sum_{p\in[2016,2021], p\neq 2017} \Big\{ & \beta_{1p} \cdot \mathbf{1}(t \in p) \cdot highexposed_{c(j)} \\ & + \beta_{2p} \cdot \mathbf{1}(t \in p) \Big\} + X_i\Gamma + \theta_{c(i)} + \varepsilon_{ict},\end{aligned} \tag{7}$$

Here β_{1p} tells us the wage differential between the workers affected more and less by the policy compared with the wage difference in 2017. I expected β_{1p} to be significantly larger than zero only when p is after 2017 if it is the wage reveal policy making the wage of more exposed positions grow faster than the wage of less exposed positions. Other terms in Equation 7 have the same definition as in Equation 6.

9. The data is cross-sectional, so only one age value and one working tenure value can be observed for each individual in the data.

3.3.3 Gender Wage Gaps

To investigate how the wage reveal policy influences the gender wage gap in Taiwan, I apply a triple-differences model that distinguishes the wage effect on female workers from that on male workers. The regression equation is described as follows:

$$
\begin{aligned}
\log(wage_{it}) = \alpha + \sum_{(p \in trans, after)} & \Big\{ \beta_{1p} \cdot \mathbf{1}(t \in p) \cdot female_i \cdot highexposed_{c(i)} \\
& + \beta_{2p} \cdot \mathbf{1}(t \in p) \cdot female_i + \beta_{3p} \cdot \mathbf{1}(t \in p) \cdot highexposed_{c(i)} \Big\} \\
& + \beta_4 \cdot female_i \cdot highexposed_{c(i)} + \beta_5 \cdot female_i \\
& + X_i \Gamma + \theta_{c(i)} + \tau_t + \varepsilon_{ict},
\end{aligned}
\tag{8}
$$

where

$$trans = \{2018\},\ after = [2019, 2021].$$

In Equation 8, $female_i$ is the dummy variable indicating whether individual i is female. It interacts with the period dummies, the high-exposed category dummy, and the interaction term. Consequently, the coefficient of the triple-difference term, β_{1p}, is the coefficient of interest in the model. It represents the additional change in female-to-male relative wage for the high-exposed workers compared to low-exposed workers under the influence of the new law. In other words, the coefficient measures the effect of the wage reveal policy on gender wage gaps. Other terms have the same definition as in Equation 6, except that X_i does not contain the gender dummy now.

Similar to the previous estimation of the effect on wages, I use the event-study method to capture the trend of the wage reveal effect on gender wage gaps with the following equation:

$$\begin{aligned}\log(wage_{it}) = \alpha + \sum_{p\in[2016,2021],p\neq 2017} \Big\{ & \beta_{1p} \cdot \mathbf{1}(t \in p) \cdot female_i \cdot highexposed_{c(i)} \\ & + \beta_{2p} \cdot \mathbf{1}(t \in p) \cdot female_i + \beta_{3p} \cdot \mathbf{1}(t \in p) \cdot highexposed_{c(i)} \Big\} \\ & + \beta_4 \cdot female_i \cdot highexposed_{c(i)} + \beta_5 \cdot female_i \\ & + X_i\Gamma + \theta_{c(i)} + \varepsilon_{ict},\end{aligned} \tag{9}$$

β_{1p} is the coefficient of interest, which evaluates the difference in gender wage gaps between the high-exposed and the low-exposed positions in comparison with the 2017 level. Other terms in Equation 9 are defined the same as in Equation 6 and 8.

4 Empirical Results

4.1 Effects on Job Postings

Table 2 presents the estimation results of the effects on job postings. During the transition period, job categories highly exposed to the policy show a 2.16 percentage point increase (22.0%) in wage reveal rates compared to low-exposed categories, which experience a 9.81 percentage point increase. The difference in wage reveal rates diminishes but remains positive in the post-policy period, although it is no longer statistically significant.

The event study results corroborate these findings. Figure 2 illustrates that the disparity in wage reveal rates between highly exposed and low-exposed job categories widens during the transition period, decreases post-policy implementation, yet remains higher than pre-policy levels.

Empirical results indicate that firms react to the policy, with more affected industry-occupation-county categories exhibiting stronger reactions. This differential response to the policy persists partially after its enforcement. These findings validate the use of the share of 2017 earnings below 40,000 NTD as an intensity measure for treatment, facilitating the evaluation of causal effects on wages in the subsequent section.

4.2 Effects on Labor Market Outcomes

4.2.1 Effects on Employment

Table 3 shows the estimation of the wage reveal policy effect on employment. The point estimates are positive in both the transition period and the after-period, but the estimated effects are not statistically significant. Figure 3 plots out the estimation results of the event study. While the estimated coefficients are increasing after the policy comes into effect, the effect size remains statistically insignificant. The results suggest that wage revealing might not be a dominating factor in employment.

Although the wage reveal policy does not significantly influence employment, the policy might have different impacts on male and female workers. Figure 4 shows that the employment effects of wage reveal policy have different trends on different gender workers. However, the effects on employment are not significantly different from zero in any year for both genders. Table 4 demonstrates similar findings. I find that the wage reveal policy might encourage females to have a job more exposed to the policy than males, but the difference is not significant for the 90% level of confidence. The results again show that the wage reveal policy does not have strong effects on employment regardless of gender, and Figure A.4 supports my finding above.

4.2.2 Effects on Wage

Table 5 presents the estimated effects of the policy on wages. On average, workers in positions highly exposed to the policy experience an additional wage increase of 1.31% in the transitional year compared to those in low-exposed positions. This difference slightly expands to 1.61% after the policy is enforced.

The event study depicted in Figure 5 provides a clearer insight into the policy's effect on wages. It indicates that job categories with higher exposure to the policy exhibit greater wage increases between 2018 and 2020. The wage gap widens in 2021, coinciding with the onset of the COVID-19 pandemic in Taiwan. It remains uncertain whether COVID-19 affected the effectiveness of the wage reveal policy. Nonetheless, the results suggest that the policy benefits workers in fields where low-wage jobs are prevalent.

With the results in the previous section, I find that the wage reveal policy increases workers' wages. However, one may wonder if the policy has different effects by gender. To discuss the heterogeneous wage effects on different genders, I perform the event study of wage effects by gender. Figure 6 shows that the policy effects have similar patterns on male and female workers except for the year 2020. Additionally, Table 6 presents the estimation results of the policy's impact on the gender wage gap. The differences in relative wage changes are less than 1 percentage point and are not statistically significant at the 90% confidence level in both periods. The event study results depicted in Figure A.5 do not provide evidence of any policy effects on gender wage gaps. In other words, the findings do not support the notion that the wage reveal policy helps in closing overall gender wage gaps.

While no general effects were identified, the policy may affect specific populations differently. Given that the policy uses monthly wages to determine whether a posting should reveal the wage range, it is anticipated that the policy could have a more pronounced impact on workers earning around the cutoff. Table 7 displays the estimated policy effects within specific wage ranges. The first two columns restrict the sample by nominal wages centered at the policy cutoff (40,000 NTD), while the remaining three columns report estimation results based on wage percentiles each year. Similar to the full sample, no significant effects are observed in the restricted samples after the policy is enacted. Interestingly, a negative effect on the gender wage gap is observed among workers earning between the first and third quartiles during the transition period. Since this negative effect is not evident in the post-policy period, it may reflect a temporary phenomenon during the transition. Further investigation using more detailed data, such as monthly data, is warranted.

The policy's effect could also vary by individuals' characteristics. Therefore, I disaggregate the sample by age, tenure, educational attainment, marital status, and parental status. Table 8 shows the estimation of the policy effects by age or working tenure. I find that workers aged 40 or above and workers with a tenure longer than 12 months benefit from the wage reveal policy. This result suggests that the policy can increase wages for staying workers and older workers. This is surprising because the policy aims to help young workers with little experience in the labor market (Parliamentary Library 2018). Moreover, the effects are stronger on old/senior male workers, while the gender gaps are not statistically significant. On the other hand, I find significant negative effects on the gender wage gap among individuals with children or without a bachelor's degree, while other characteristics do not appear to determine the policy's effect on gender wage gaps. Detailed estimation results are provided in Appendix Tables A.5, and A.6.

4.3 Impacts of Minimum Wage Increases

Taiwan's minimum wage increases annually during the years observed (2016-2021).[10] In 2016, the minimum monthly wage was 20,008 NTD, rising to 24,000 NTD by 2021, the final year of observation. Each year between, the minimum wage increased by 200-1,100 NTD.[11] Although the minimum wage level remains below the policy cutoff after increases, these changes could potentially impact the same demographic affected by wage reveal policies.

To assess whether minimum wage adjustments introduce bias into my estimation of wage reveal effects, I conducted two robustness checks. First, I examined changes in the gender wage gap in the years preceding the policy transition (2016-2017). Table 9 presents the estimation results, indicating no significant difference in wages and in gender wage gap changes between individuals in highly exposed and less exposed positions during these pre-policy years. This suggests that the 2017 minimum wage increase did not differentially affect gender wage gaps among workers more or less exposed to wage reveal policies. Therefore, there is no evidence to suggest that subsequent years with wage reveal policies in effect would be influenced differently by minimum wage increases.

However, previous research suggests that minimum wage adjustments can impact gender wage gaps, particularly at the lower end of the wage distribution Li and Ma (2015) in urban China, Hallward-Driemeier, Rijkers, and Waxman (2017) in Indonesia, Majchrowska and Strawiński (2018) in Poland, and Caliendo and Wittbrodt (2022) in Germany). Concerns may arise that these effects could confound findings on wage reveal effects. As an additional robustness check, I excluded positions most affected by minimum wage changes from the sample.

Tables 10 and 11 present estimations from the sample excluding industry-occupation-county

10. There are two minimum wage levels in Taiwan. One is for hourly wages, and the other is for monthly wages. The minimum hourly wage primarily affects part-time workers, which is not in the universe of my sample. Therefore, I consider only the minimum monthly wage changes in this paper.

11. Table A.7 lists all minimum monthly wage increases between 2016 and 2022.

categories most influenced by minimum wage changes. In Column (1) of each table, I excluded job categories where more than 5% of workers earned no more than 21,009 NTD in 2017. Since for many job categories, the share of workers earning less than 21,009 NTD in 2017 is close to zero, the 5% threshold conveniently excludes a sufficient number of minimum wage jobs without significantly reducing observations. In Column (2) of each table, I further restricted the sample by excluding job categories where more than 5% of workers earned no more than 22,000 NTD in 2017, aiming to narrow down the unaffected groups (by minimum wage changes).[12] The estimation results are generally consistent with the primary findings after excluding the job categories most affected by the minimum wage increases. I still find the wage reveal can affect wages without gender differences. This exercise reinforces the conclusion that minimum wage changes do not compromise the estimation of wage reveal policy effects on wages and gender wage gaps.

5 Conclusion

In this paper, I examine how mandatory wage disclosure in job postings affects labor market outcomes, using a recent legislative reform in Taiwan as a case study. Given empirical evidence supporting firms' reactions to such policies, I employ a difference-in-differences model to estimate the impact of wage disclosure on employment and wages. I assess treatment exposure using the proportion of workers earning below the policy cutoff (40,000 NTD) within specific job categories and locations prior to the reform. I divide the sample into high- and low-exposure groups to capture the primary difference in the model.

My findings suggest that the wage reveal policy does not have significant effects on employment. Regression results indicate that the policy increases earnings among highly exposed workers, and the effects seem to focus on male workers. However, the gender wage gaps due to the policy are statistically insignificant. Upon further segmenting the sample to explore heterogeneity in the wage disclosure effect, I discover that the policy specifically benefits staying workers who tend to be

12. 21,009 NTD is the minimum monthly wage level in 2017, and 22,000 NTD is the minimum wage level in 2018. Therefore, Column (1) excludes the workers whose wages are likely to be bounded by minimum wage, and Column (2) excludes the workers whose wages are *going to be bounded* in the following year.

older and have longer tenure. Besides, I observe that the policy may widen gender wage gaps among workers with children or without bachelor's degrees. To address concerns about annual minimum wage increases during the observation period, I conduct a robustness check by excluding job categories with high proportions of minimum wage earners. The results remain consistent with the original estimation, suggesting that the findings are robust to variations in minimum wage levels.

This study contributes to the ongoing discourse on pay transparency, emphasizing its impact on wage differentials. While wage disclosure policies may help mitigate wage inequality within the distribution, they do not appear to significantly influence gender wage gaps as anticipated and may even have adverse effects on specific groups of workers. Therefore, policymakers may need to explore alternative strategies to combat gender inequality. Implementing policies that encourage wage renegotiations among incumbent workers could be a promising approach, leveraging improved pay transparency to empower workers with better information.

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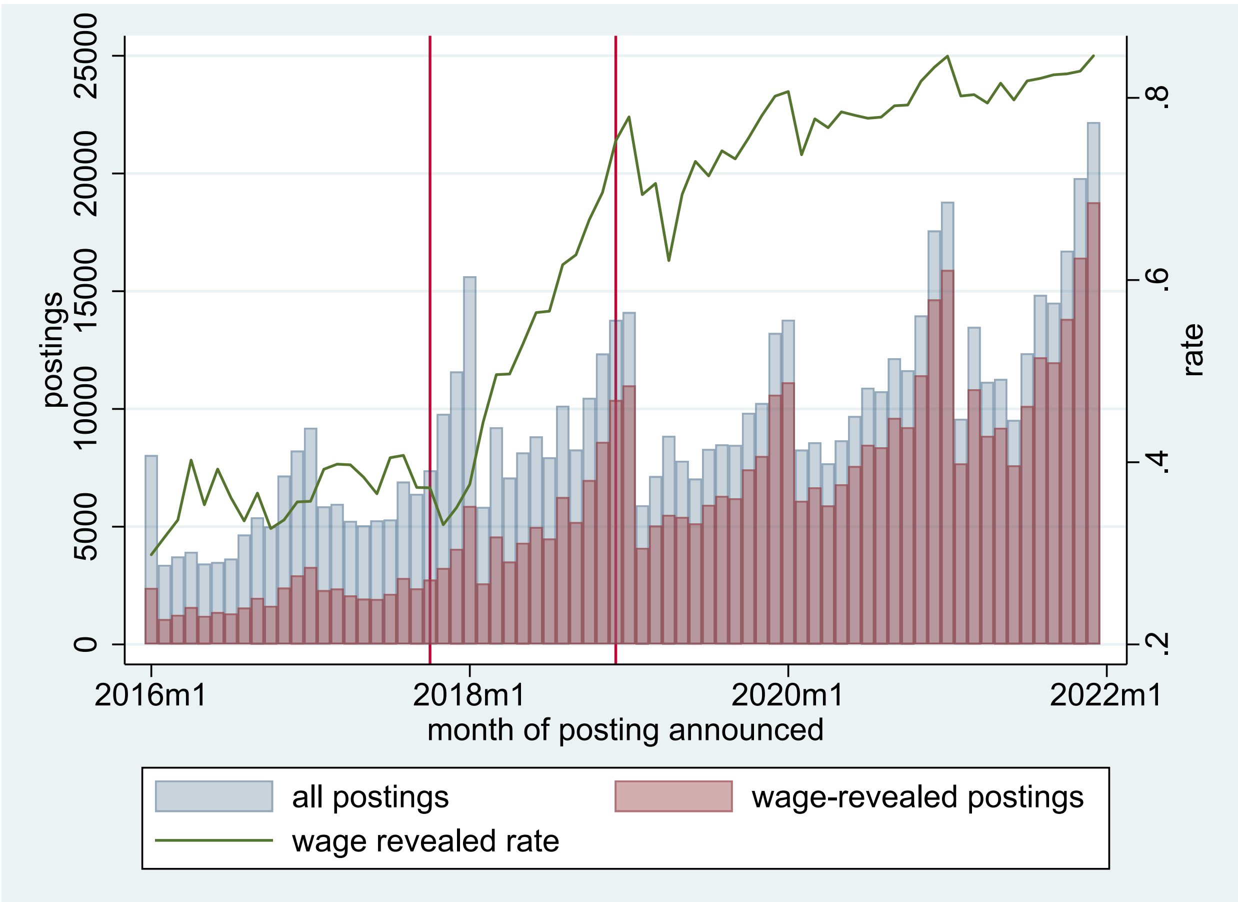
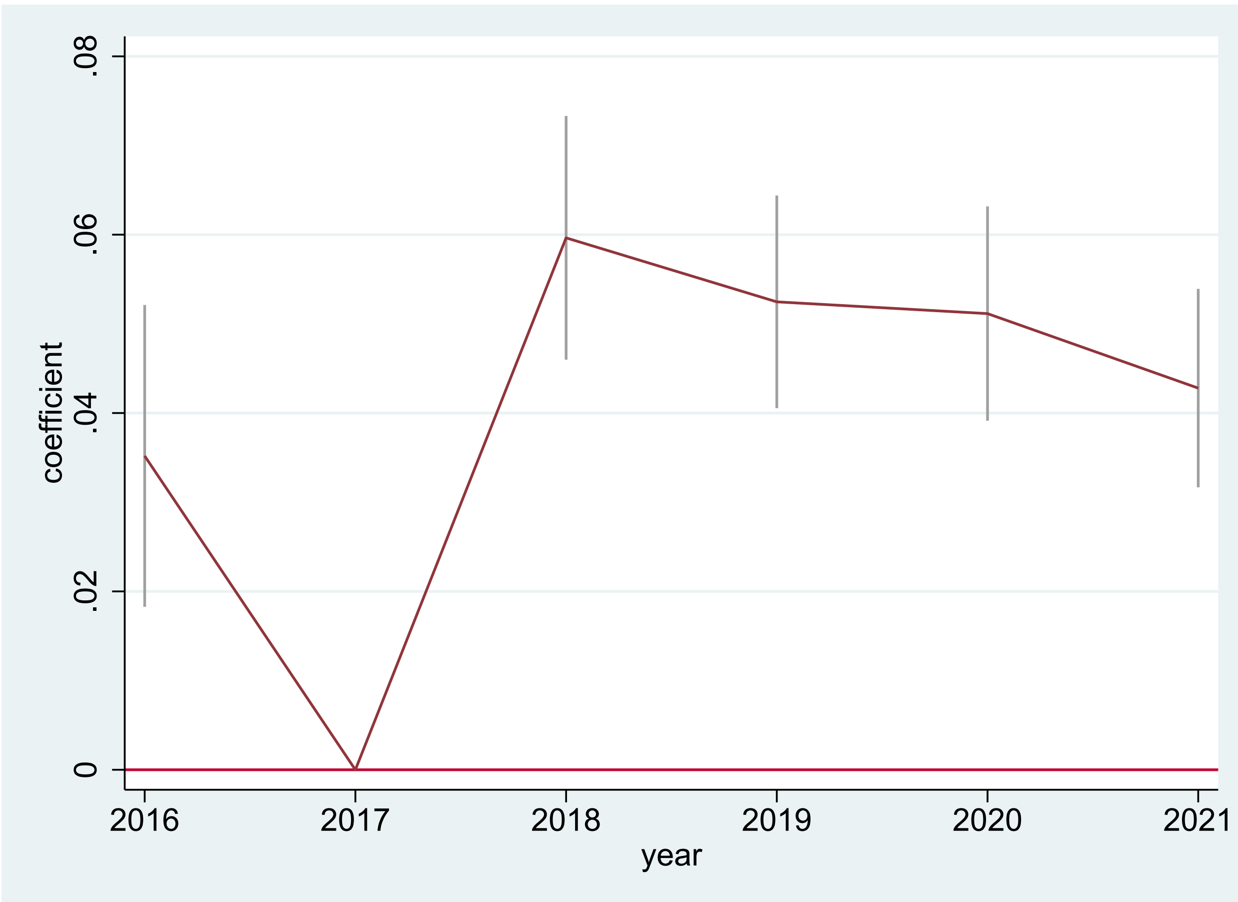
Figures and Tables

Figure 1: Number of Job Postings and Share of Wage Range Revealed



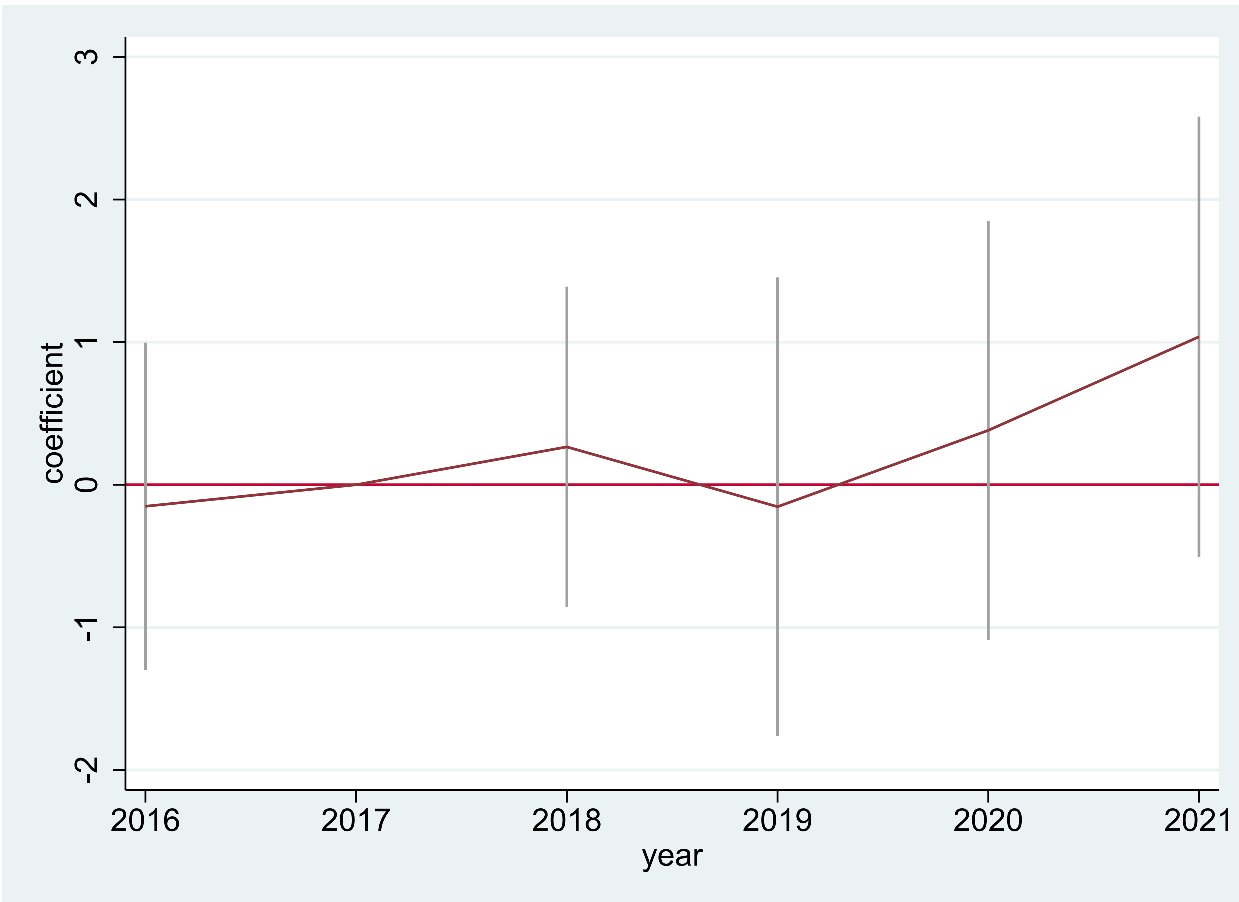
Source: Made by author with the 1111 Job Posting Data.

Figure 2: The Policy Effect on Job Postings' Wage Range Reveal: Event Study



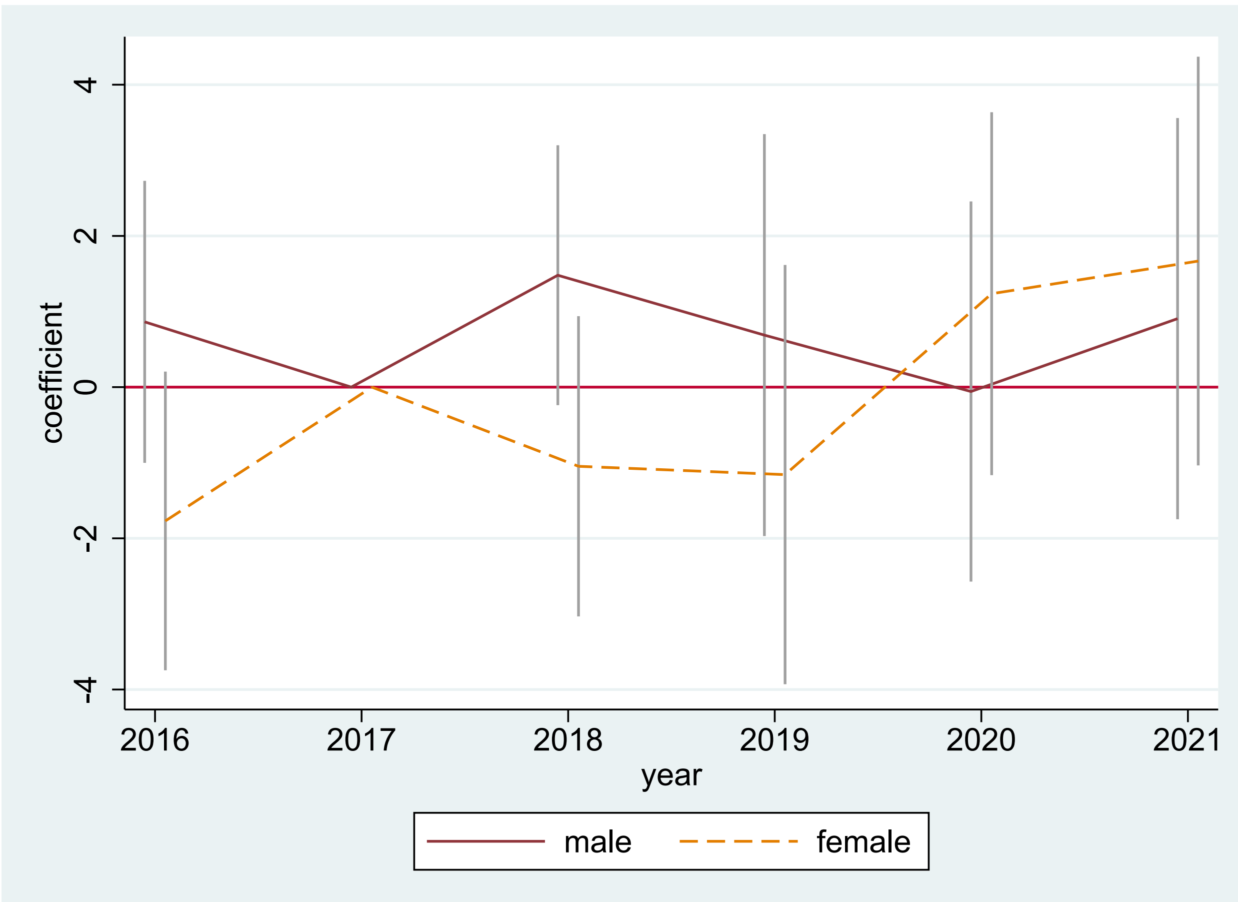
Note: The figure shows the event-study extension of the estimation of the policy effect on job postings' wage reveal by Equation 1. The dependent variable is whether a posting includes the wage range information. The line represents the coefficients of the relative difference in reveal rates between high-exposed and low-exposed positions compared to 2017. Each spike shows the 95% confidence interval of the coefficients in the regarding month. The industry-occupation-county fixed effects and the firm fixed effects are controlled. Robust standard errors clustered at the industry-occupation-county level.

Figure 3: The Policy Effect on Employment: Event Study



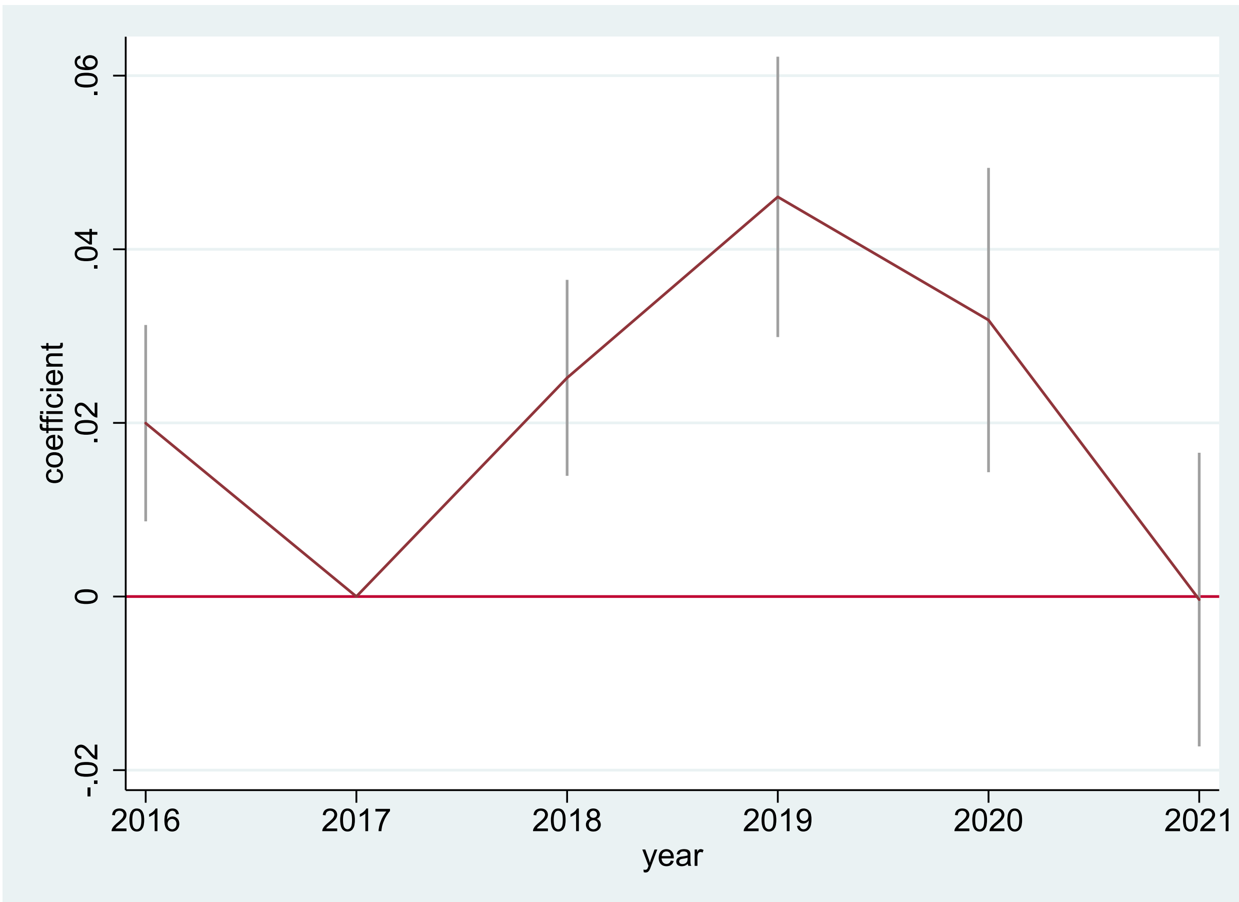
Note: The figure shows the event-study extension of the estimation of wage reveal policy effect on employment. The sample is the population of ages 15 or older, which is defined as the labor force. The dependent variable is the number of full-time, monthly paid, and private sector workers in a particular industry-occupation pair per 100,000 labor force population in a county. The line represents the coefficients of the relative difference in number of workers between high-exposed and low-exposed job categories compared to 2017. Each spike shows the 95% confidence interval of the coefficients in the regarding year. The estimations are controlled for the industry-occupation-county fixed effects and the year fixed effects. The robust standard errors are clustered at the industry-occupation-county level.

Figure 4: The Policy Effect on Employment: Event Study, by Gender



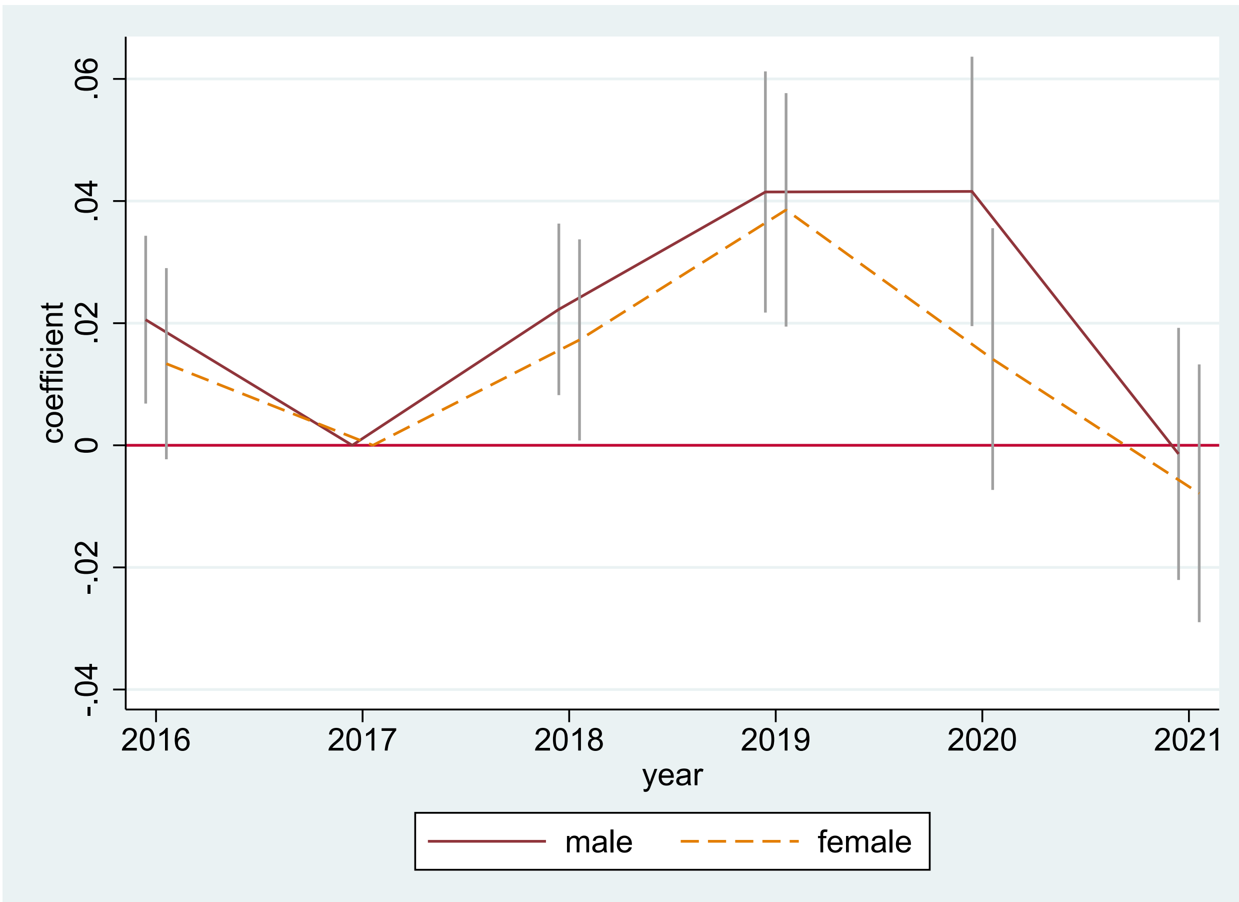
Note: The figure shows the event-study extension of the estimation of wage reveal policy effect on male and female employment. The sample is the population of ages 15 or older, which is defined as the labor force. The dependent variable is the number of full-time, monthly paid, and private sector workers in a particular industry-occupation pair per 100,000 specific gender labor force population in a county. The line represents the coefficients of the relative difference in number of workers between high-exposed and low-exposed job categories compared to 2017. Each spike shows the 95% confidence interval of the coefficients in the regarding year. The estimations are controlled for the industry-occupation-county fixed effects and the year fixed effects. The robust standard errors are clustered at the industry-occupation-county level.

Figure 5: The Policy Effect on Monthly Wage: Event Study



Note: The figure shows the event-study extension of the estimation of wage reveal policy effect on monthly wage. The sample is restricted to full-time, private-sector workers who are paid monthly. The dependent variable is the logarithmic monthly wage in 2017 Taiwan dollars. The line represents the coefficients of the relative difference in wage between high-exposed and low-exposed positions compared to 2017. Each spike shows the 95% confidence interval of the coefficients in the regarding year. The estimations are controlled for gender, age (in quadratic), education attainment, marital status, parental status, and working tenure in the current position (in quadratic), the industry-occupation-county fixed effects, and the firm fixed effects. The robust standard errors are clustered at the industry-occupation-county level.

Figure 6: The Policy Effect on Wages: Event Study, by Gender



Note: The figure shows the event-study extension of the estimation of the estimation of wage reveal effect on male's and female's wage by Equation 8. The sample is restricted to full-time, private-sector workers who are paid monthly. The dependent variable is the logarithmic monthly wage in 2017 Taiwan dollars. The line represents the coefficients of the relative difference in wage between high-exposed and low-exposed positions compared to 2017. Each spike shows the 95% confidence interval of the coefficients in the regarding year. The estimations are controlled for age (in quadratic), education attainment, marital status, parental status, and working tenure in the current position (in quadratic), the industry-occupation-county fixed effects, and the firm fixed effects. The robust standard errors are clustered at the industry-occupation-county level.

Table 1: Summary Statistics

Variable	N	Mean	high-exposed	low-exposed	difference
Panel A: 1111 Job Posting Data					
high-exposed	679,336	0.42	1.00	0.00	—-
reveal rate	679,336	0.66	0.74	0.60	0.14***
until Sept. 2017	115,367	0.36	0.44	0.31	0.13***
Oct. 2017-Nov. 2018	132,742	0.51	0.59	0.45	0.14***
since Dec. 2018	431,227	0.79	0.86	0.73	0.13***
Panel B: Manpower Utilization Survey (MUS)					
high-exposed	94,373	0.50	1.00	0.00	—-
wage (in 2017 NTD)	94,373	39,209.62	32,038.82	46,364.01	-14,325.19***
female	94,373	0.47	0.52	0.42	0.10***
age (years)	94,373	38.93	38.48	39.38	-0.90***
tenure (months)	94,373	94.84	85.48	104.17	-18.69***
high school degree & above	94,373	0.88	0.84	0.93	-0.09***
bachelor & above	94,373	0.29	0.17	0.40	-0.23***
married	94,373	0.48	0.45	0.52	-0.07***
have children	94,373	0.49	0.47	0.50	-0.03***

Source: 1111 Job Posting Data and MUS, 2016-2021.

Note: The MUS sample is restricted to full-time, private-sector workers who are paid monthly. High-exposed represents the indicators of the industry-occupation-county categories which are highly exposed to the policy. Wages are deflated by CPI and reported in 2017 NTD. The age is measured in years, and the working tenure is measured in months. The high school degree include vocational high school degrees.

Table 2: The Policy Effect on Job Postings' Wage Range Reveal

	(1) revealed	(2) revealed	(3) revealed
trans × high-exposed	0.0055	0.0077	0.0216***
	(0.0083)	(0.0081)	(0.0067)
after × high-exposed	-0.0077	0.0032	0.0127
	(0.0131)	(0.0135)	(0.0096)
trans	0.1434***	0.1360***	0.0981***
	(0.0055)	(0.0054)	(0.0048)
after	0.4251***	0.4081***	0.3328***
	(0.0077)	(0.0078)	(0.0075)
high-exposed	0.1354***		
	(0.0168)		
Constant	0.3093***	0.3775***	0.4273***
	(0.0094)	(0.0047)	(0.0046)
Observations	650,679	650,460	623,860
Adjusted R^2	0.153	0.203	0.406
IND-OCCU-CTY FE		V	V
Firm FE			V
Month FE			V

Data Source: 1111 Job Bank Posting Data.

Note: This table shows the estimation of the policy effect on job postings' wage reveals by Equation 1. The dependent variable is whether a posting includes the wage range information. Trans and after represent the indicators of the transition period (between October 2017 and November 2018) and the after period (since December 2018), respectively. High-exposed represents the indicators of the industry-occupation-county categories which are highly exposed to the policy. IND-OCCU-CTY FE means the industry-occupation-county fixed effects are controlled in the column. Month FE and Firm FE means the month fixed effects and the firms fixed effects are controlled in the column, respectively. Robust standard errors clustered at the industry-occupation-county level are in parentheses. ***: $p<0.01$; **: $p<0.05$; *: $p<0.1$.

Table 3: The Policy Effect on Employment

	(1) workers per 100K labor force	(2) workers per 100K labor force	(3) workers per 100K labor force
trans $\times$ high-exposed	0.3946	0.3380	0.3395
	(0.7440)	(0.6149)	(0.6149)
after $\times$ high-exposed	0.5282	0.4901	0.4910
	(0.7532)	(0.5906)	(0.5911)
trans	1.3053**	0.1595	
	(0.5891)	(0.5071)	
after	2.3806***	0.1503	
	(0.5748)	(0.4882)	
high-exposed	-4.8076		
	(3.0021)		
Observations	8,069	8,054	8,054
Adjusted R^2	0.001	0.975	0.975
IND-OCCU-CTY FE		V	V
Year FE			V

Data Source: Manpower Utilization Survey, 2016-2021.

Note: This table shows the estimation of wage reveal policy effect on employment. The sample is the population of ages 15 or older, which is defined as the labor force. The dependent variable is the number of full-time, monthly paid, and private sector workers in a particular industry-occupation-county category per 100,000 labor force population. Trans and after represent the indicators of the transition period (2018) and the after period (since 2019), respectively. High-exposed represents the indicators of the industry-occupation-county categories that are highly exposed to the policy. IND-OCCU-CTY FE means the industry-occupation-county fixed effects are controlled in the column. Year FE means the year fixed effects are controlled in the column. Robust standard errors clustered at the industry-occupation-county level are in parentheses. ***: $p<0.01$; **: $p<0.05$; *: $p<0.1$.

Table 4: The Policy Effect on Gender Employment Gaps

	(1) workers per 100K labor force	(2) workers per 100K labor force	(3) workers per 100K labor force
female × trans × high-exposed	-0.2402	-0.8602	-0.8650
	(1.5526)	(1.2606)	(1.2610)
female × after × high-exposed	3.5170**	1.9736	1.9709
	(1.6137)	(1.3332)	(1.3345)
female × trans	-0.6280	0.5284	0.5340
	(1.1981)	(0.9911)	(0.9914)
female × after	-3.4195***	-1.1331	-1.1274
	(1.3006)	(1.0666)	(1.0680)
female × high-exposed	4.7282	10.8404***	10.8426***
	(3.2813)	(3.7527)	(3.7526)
trans × high-exposed	1.1075	0.8520	0.8498
	(1.1452)	(0.9405)	(0.9406)
after × high-exposed	-0.6821	-0.4514	-0.4539
	(1.2173)	(0.9841)	(0.9840)
female	-1.7915	-9.1679***	-9.1741***
	(2.3186)	(2.6422)	(2.6424)
trans	1.2053	-0.0734	
	(0.8574)	(0.7378)	
after	3.6168***	0.8542	
	(0.9972)	(0.8347)	
high-exposed	-7.8385*		
	(4.1371)		
Observations	13,321	13,308	13,308
Adjusted R^2	0.001	0.781	0.781
IND-OCCU-CTY FE		V	V
Year FE			V

Data Source: Manpower Utilization Survey, 2016-2021.
Note: This table shows the estimation of the wage reveal effect on gender employment gaps. The sample is the population of ages 15 or older, which is defined as the labor force. The dependent variable is the number of full-time, monthly paid, and private sector workers in a particular industry-occupation-county category per 100,000 male/female labor force population. Trans and after represent the indicators of the transition period (2018) and the after period (since 2019), respectively. High-exposed represents the indicators of the industry-occupation-county categories that are highly exposed to the policy. For each column, the estimations are controlled for age (in quadratic), education attainment, marital status, parental status, and working tenure in the current position (in quadratic). Table A.4 shows the coefficients of the controlled variables. IND-OCCU-CTY FE means the industry-occupation-county fixed effects are controlled in the column. Year FE means the year fixed effects are controlled in the column. Robust standard errors clustered at the industry-occupation-county level are in parentheses. ***: $p<0.01$; **: $p<0.05$; *: $p<0.1$.

Table 5: The Policy Effect on Monthly Wage

	(1)	(2)	(3)
	log(wage)	log(wage)	log(wage)
trans × high-exposed	0.0088	0.0131**	0.0131**
	(0.0059)	(0.0053)	(0.0053)
after × high-exposed	0.0089	0.0176***	0.0161**
	(0.0076)	(0.0067)	(0.0067)
trans	0.0378***	0.0343***	
	(0.0050)	(0.0043)	
after	0.1121***	0.0923***	
	(0.0064)	(0.0054)	
high-exposed	-0.2247***		
	(0.0121)		
Observations	94,373	94,344	94,344
Adjusted R^2	0.415	0.547	0.551
IND-OCCU-CTY FE		V	V
Year FE			V

Data Source: Manpower Utilization Survey, 2016-2021.

Note: This table shows the estimation of wage reveal policy effect on monthly wage. The sample is restricted to the full-time, private-sector workers who are paid monthly. The dependent variable is the logarithmic monthly wage in 2017 Taiwan dollars. Trans and after represent the indicators of the transition period (2018) and the after period (since 2019), respectively. High-exposed represents the indicators of the industry-occupation-county categories which are highly exposed to the policy. For each column, the estimations are controlled for gender, age (in quadratic), education attainment, marital status, parental status, and working tenure in the current position (in quadratic). Table A.3 shows the coefficients of the controlled variables. IND-OCCU-CTY FE means the industry-occupation-county fixed effects are controlled in the column. Year FE means the year fixed effects are controlled in the column. Robust standard errors clustered at the industry-occupation-county level are in parentheses. ***: p<0.01; **: p<0.05; *: p<0.1.

Table 6: The Policy Effect on Gender Wage Gaps

	(1) log(wage)	(2) log(wage)	(3) log(wage)
female × trans × high-exposed	-0.0011	-0.0035	-0.0025
	(0.0121)	(0.0104)	(0.0104)
female × after × high-exposed	-0.0195	-0.0075	-0.0080
	(0.0120)	(0.0099)	(0.0099)
female × trans	0.0035	0.0052	0.0047
	(0.0103)	(0.0085)	(0.0086)
female × after	0.0423***	0.0295***	0.0304***
	(0.0108)	(0.0084)	(0.0085)
female × high-exposed	0.0210	0.0328***	0.0321***
	(0.0130)	(0.0115)	(0.0114)
trans × high-exposed	0.0088	0.0142*	0.0137*
	(0.0081)	(0.0073)	(0.0073)
after × high-exposed	0.0145	0.0183**	0.0170**
	(0.0100)	(0.0085)	(0.0085)
female	-0.1805***	-0.1926***	-0.1925***
	(0.0108)	(0.0089)	(0.0088)
trans	0.0366***	0.0323***	
	(0.0069)	(0.0060)	
after	0.0947***	0.0802***	
	(0.0085)	(0.0069)	
high-exposed	-0.2325***		
	(0.0137)		
Observations	94,373	94,344	94,344
Adjusted R^2	0.415	0.548	0.552
IND-OCCU-CTY FE		V	V
Year FE			V

Data Source: Manpower Utilization Survey, 2016-2021.

Note: This table shows the estimation of the wage reveal effect on gender wage gaps by Equation 8. The sample is restricted to the full-time, private-sector workers who are paid monthly. The dependent variable is the logarithmic monthly wage in 2017 Taiwan dollars. Trans and after represent the indicators of the transition period (2018) and the after period (since 2019), respectively. High-exposed represents the indicators of the industry-occupation-county categories which are highly exposed to the policy. For each column, the estimations are controlled for age (in quadratic), education attainment, marital status, parental status, and working tenure in the current position (in quadratic). Table A.4 shows the coefficients of the controlled variables. IND-OCCU-CTY FE means the industry-occupation-county fixed effects are controlled in the column. Year FE means the year fixed effects are controlled in the column. Robust standard errors clustered at the industry-occupation-county level are in parentheses. ***: p<0.01; **: p<0.05; *: p<0.1.

Table 7: The Policy Effect on Gender Wage Gaps within Specific Wage Intervals

Wage Interval	[25K, 55K]	[30K, 50K]	[p(5), p(95)]	[p(10), p(90)]	[p(25), p(75)]
	(1)	(2)	(3)	(4)	(5)
	log(wage)	log(wage)	log(wage)	log(wage)	log(wage)
female × trans × high-exposed	-0.0005	-0.0002	0.0083	0.0102	-0.0225***
	(0.0088)	(0.0070)	(0.0093)	(0.0084)	(0.0067)
female × after × high-exposed	-0.0067	0.0021	-0.0018	0.0018	0.0069
	(0.0086)	(0.0080)	(0.0090)	(0.0081)	(0.0062)
female × trans	0.0060	-0.0056	0.0080	0.0047	0.0084
	(0.0066)	(0.0051)	(0.0074)	(0.0063)	(0.0053)
female × after	0.0190***	0.0089	0.0312***	0.0173***	0.0146***
	(0.0068)	(0.0056)	(0.0075)	(0.0063)	(0.0043)
female × high-exposed	-0.0082	-0.0097	-0.0033	-0.0094	-0.0102
	(0.0095)	(0.0075)	(0.0104)	(0.0097)	(0.0066)
trans × high-exposed	0.0113*	0.0104*	0.0110	0.0076	0.0250***
	(0.0064)	(0.0053)	(0.0067)	(0.0063)	(0.0051)
after × high-exposed	0.0160**	0.0089	0.0199***	0.0135**	0.0085*
	(0.0067)	(0.0057)	(0.0076)	(0.0066)	(0.0047)
female	-0.1114***	-0.0566***	-0.1435***	-0.1103***	-0.0523***
	(0.0069)	(0.0049)	(0.0078)	(0.0071)	(0.0044)
Observations	76,200	48,819	85,025	75,028	46,388
Adjusted R^2	0.396	0.227	0.483	0.419	0.284

Data Source: Manpower Utilization Survey, 2016-2021.

Note: This table shows the estimation of the wage reveal effect on gender wage gaps within the wage interval specified. For the wage interval, K represent thousands NTD, and p(x) represents the x-th percentiles in the observed year. The sample is restricted to the full-time, private-sector workers who are paid monthly in addition to the wage interval specified in each column. The dependent variable is the logarithmic monthly wage in 2017 Taiwan dollars. Trans and after represent the indicators of the transition period (2018) and the after period (since 2019), respectively. High-exposed represents the indicators of the industry-occupation-county categories which are highly exposed to the policy. For each column, the estimations are controlled for age (in quadratic), education attainment, marital status, parental status, and working tenure in the current position (in quadratic), the industry-occupation-county fixed effects, and the year fixed effects. Robust standard errors clustered at the industry-occupation-county level are in parentheses. ***: $p<0.01$; **: $p<0.05$; *: $p<0.1$.

Table 8: The Policy Effect on Gender Wage Gaps, by Age or Working Tenure

Sample	age<40	age≥ 40	tenure<12 mo.	tenure≥ 12 mo.
	(1)	(2)	(3)	(4)
	log(wage)	log(wage)	log(wage)	log(wage)
female $\times$ trans $\times$ high-exposed	-0.0004	-0.0046	-0.0083	-0.0038
	(0.0118)	(0.0181)	(0.0398)	(0.0111)
female $\times$ after $\times$ high-exposed	0.0060	-0.0202	-0.0231	-0.0090
	(0.0120)	(0.0150)	(0.0285)	(0.0102)
female $\times$ trans	-0.0010	0.0101	-0.0036	0.0074
	(0.0098)	(0.0149)	(0.0354)	(0.0091)
female $\times$ after	0.0187*	0.0424***	0.0335	0.0312***
	(0.0101)	(0.0127)	(0.0243)	(0.0088)
female $\times$ high-exposed	0.0186	0.0380**	0.0328	0.0314***
	(0.0120)	(0.0164)	(0.0249)	(0.0120)
trans $\times$ high-exposed	0.0088	0.0208*	0.0228	0.0139*
	(0.0091)	(0.0116)	(0.0276)	(0.0076)
after $\times$ high-exposed	0.0051	0.0272**	0.0174	0.0176**
	(0.0103)	(0.0111)	(0.0203)	(0.0088)
female	-0.1469***	-0.2397***	-0.1348***	-0.1982***
	(0.0095)	(0.0126)	(0.0210)	(0.0090)
Observations	49,385	44,829	7,516	86,558
Adjusted R^2	0.489	0.595	0.506	0.549

Data Source: Manpower Utilization Survey, 2016-2021.

Note: This table shows the estimation of the wage reveal effect on gender wage gaps within the criteria specified. The age is measured in years, and the working tenure is measured in months. The sample is restricted to full-time, private-sector workers who are paid monthly in addition to the criterion specified in each column. The dependent variable is the logarithmic monthly wage in 2017 Taiwan dollars. Trans and after represent the indicators of the transition period (2018) and the after period (since 2019), respectively. High-exposed represents the indicators of the industry-occupation-county categories which are highly exposed to the policy. For each column, the estimations are controlled for age (in quadratic), education attainment, marital status, parental status, and working tenure in the current position (in quadratic), the industry-occupation-county fixed effects, and the year fixed effects. Robust standard errors clustered at the industry-occupation-county level are in parentheses. ***: $p<0.01$; **: $p<0.05$; *: $p<0.1$.

Table 9: Differences in Wages and Gender Wage Gaps before the Policy

	(1) log(wage)	(2) log(wage)
female × Year 2017 × high-exposed		0.0065
		(0.0099)
female × Year 2017		0.0019
		(0.0083)
female × high-exposed		0.0313**
		(0.0135)
Year 2017 × high-exposed	-0.0158***	-0.0193***
	(0.0056)	(0.0069)
Year 2017	0.0297***	0.0286***
	(0.0049)	(0.0054)
female	-0.1719***	-0.1901***
	(0.0060)	(0.0103)
Observations	31,267	31,267
Adjusted R^2	0.576	0.576

Data Source: Manpower Utilization Survey, 2016-2021.

Note: This table shows the estimation of differences in wages and gender wage gaps between high-exposed and low-exposed groups before the wage reveal policy (*i.e.* 2016-2017). Column (1) reports the difference in wages, and Column (2) reports the difference in gender wage gaps. The sample is restricted to the full-time, private-sector workers who are paid monthly. The dependent variable is the logarithmic monthly wage in 2017 Taiwan dollar. High-exposed represents the indicators of the industry-occupation-county categories which are highly exposed to the policy. For each column, the estimations are controlled for age (in quadratic), education attainment, marital status, parental status, and working tenure in the current position (in quadratic), and the industry-occupation-county fixed effects. Robust standard errors clustered at the industry-occupation-county level are in parentheses. ***: p<0.01; **: p<0.05; *: p<0.1.

Table 10: The Policy Effect on Monthly Wages, Excluding the Influence from Minimum Wage Increases

	(1) log(wage)	(2) log(wage)
trans × high-exposed	0.0113**	0.0133**
	(0.0054)	(0.0060)
after × high-exposed	0.0131*	0.0127
	(0.0070)	(0.0085)
Observations	85,657	65,167
Adjusted R^2	0.544	0.527

Data Source: Manpower Utilization Survey, 2016-2021.

Note: This table shows the estimation of the wage reveal effect on monthly wages, excluding the positions which are most influenced by minimum wage increases. Column (1) includes the industry-occupation-county categories with less than 5% workers earning no more than 21,009 NTD in 2017, and Column (2) includes the groups with less than 5% workers earning no more than 22,000 NTD in 2017. The sample is restricted to the full-time, private-sector workers who are paid monthly in addition to the exclusion specified in each column. The dependent variable is the logarithmic monthly wage in 2017 Taiwan dollars. Trans and after represent the indicators of the transition period (2018) and the after period (since 2019), respectively. High-exposed represents the indicators of the industry-occupation-county categories which are highly exposed to the policy. For each column, the estimations are controlled for age (in quadratic), education attainment, marital status, parental status, and working tenure in the current position (in quadratic), the industry-occupation-county fixed effects, and the year fixed effects. Robust standard errors clustered at the industry-occupation-county level are in parentheses. ***: $p<0.01$; **: $p<0.05$; *: $p<0.1$.

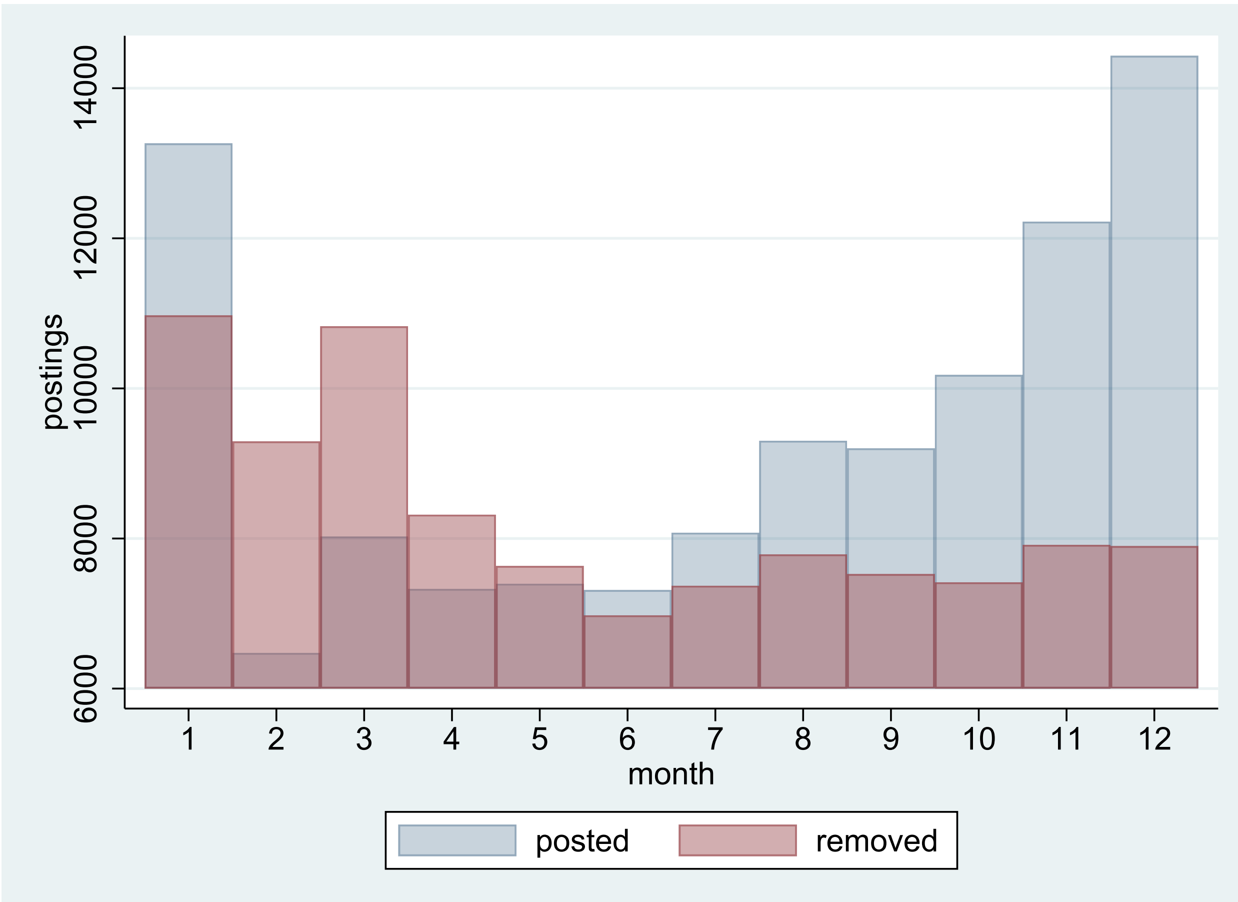
Table 11: The Policy Effect on Gender Wage Gaps, Excluding the Influence from Minimum Wage Increases

	(1) log(wage)	(2) log(wage)
female $\times$ trans $\times$ high-exposed	-0.0033	-0.0078
	(0.0108)	(0.0119)
female $\times$ after $\times$ high-exposed	-0.0081	-0.0112
	(0.0101)	(0.0120)
female $\times$ trans	0.0050	0.0032
	(0.0087)	(0.0091)
female $\times$ after	0.0307***	0.0314***
	(0.0086)	(0.0089)
female $\times$ high-exposed	0.0271**	0.0399***
	(0.0117)	(0.0131)
trans $\times$ high-exposed	0.0124*	0.0169*
	(0.0075)	(0.0086)
after $\times$ high-exposed	0.0143	0.0152
	(0.0087)	(0.0105)
female	-0.1917***	-0.1896***
	(0.0089)	(0.0091)
Observations	85,657	65,167
Adjusted R^2	0.544	0.528

Data Source: Manpower Utilization Survey, 2016-2021.
Note: This table shows the estimation of the wage reveal effect on gender wage gaps, excluding the positions which are most influenced by minimum wage increases. Column (1) includes the industry-occupation-county categories with less than 5% workers earning no more than 21,009 NTD in 2017, and Column (2) includes the groups with less than 5% workers earning no more than 22,000 NTD in 2017. The sample is restricted to the full-time, private-sector workers who are paid monthly in addition to the exclusion specified in each column. The dependent variable is the logarithmic monthly wage in 2017 Taiwan dollars. Trans and after represent the indicators of the transition period (2018) and the after period (since 2019), respectively. High-exposed represents the indicators of the industry-occupation-county categories which are highly exposed to the policy. For each column, the estimations are controlled for age (in quadratic), education attainment, marital status, parental status, and working tenure in the current position (in quadratic), the industry-occupation-county fixed effects, and the year fixed effects. Robust standard errors clustered at the industry-occupation-county level are in parentheses. ***: $p<0.01$; **: $p<0.05$; *: $p<0.1$.

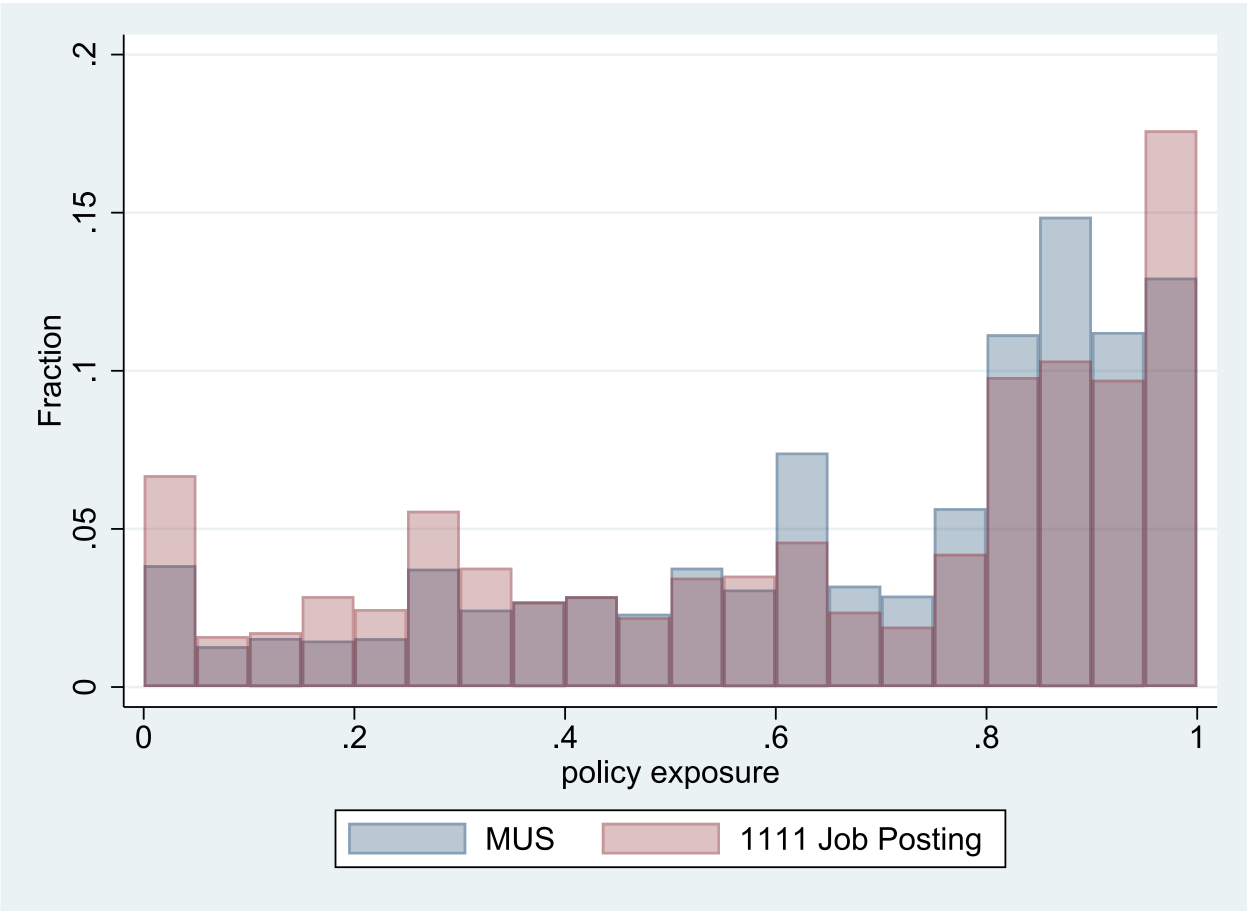
A Appendix Figures and Tables

Figure A.1: Number of Job Postings and Share of Wage Range Revealed



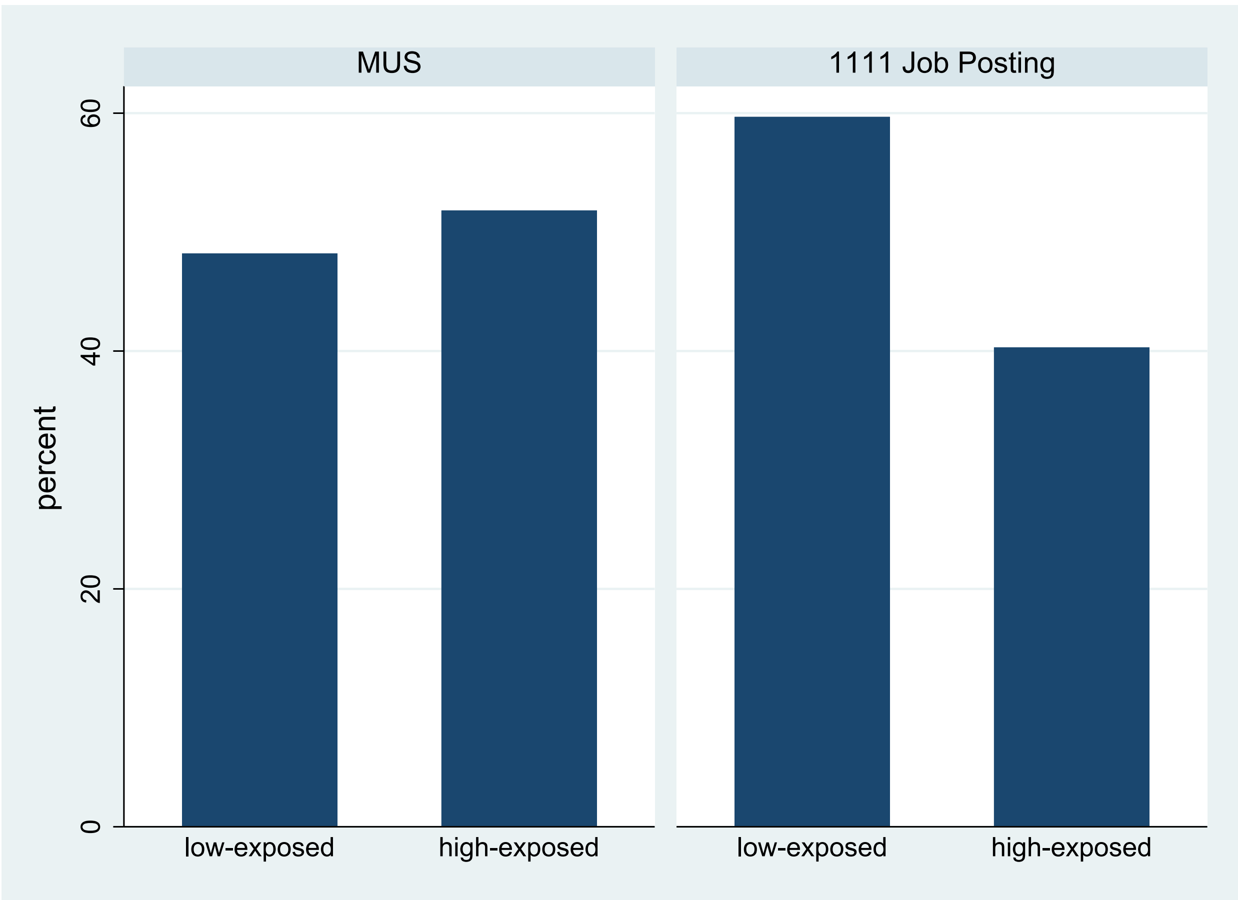
Note: The figure shows the average number of postings posted and removed between 2016 and 2021.

Figure A.2: Policy Exposure Distribution



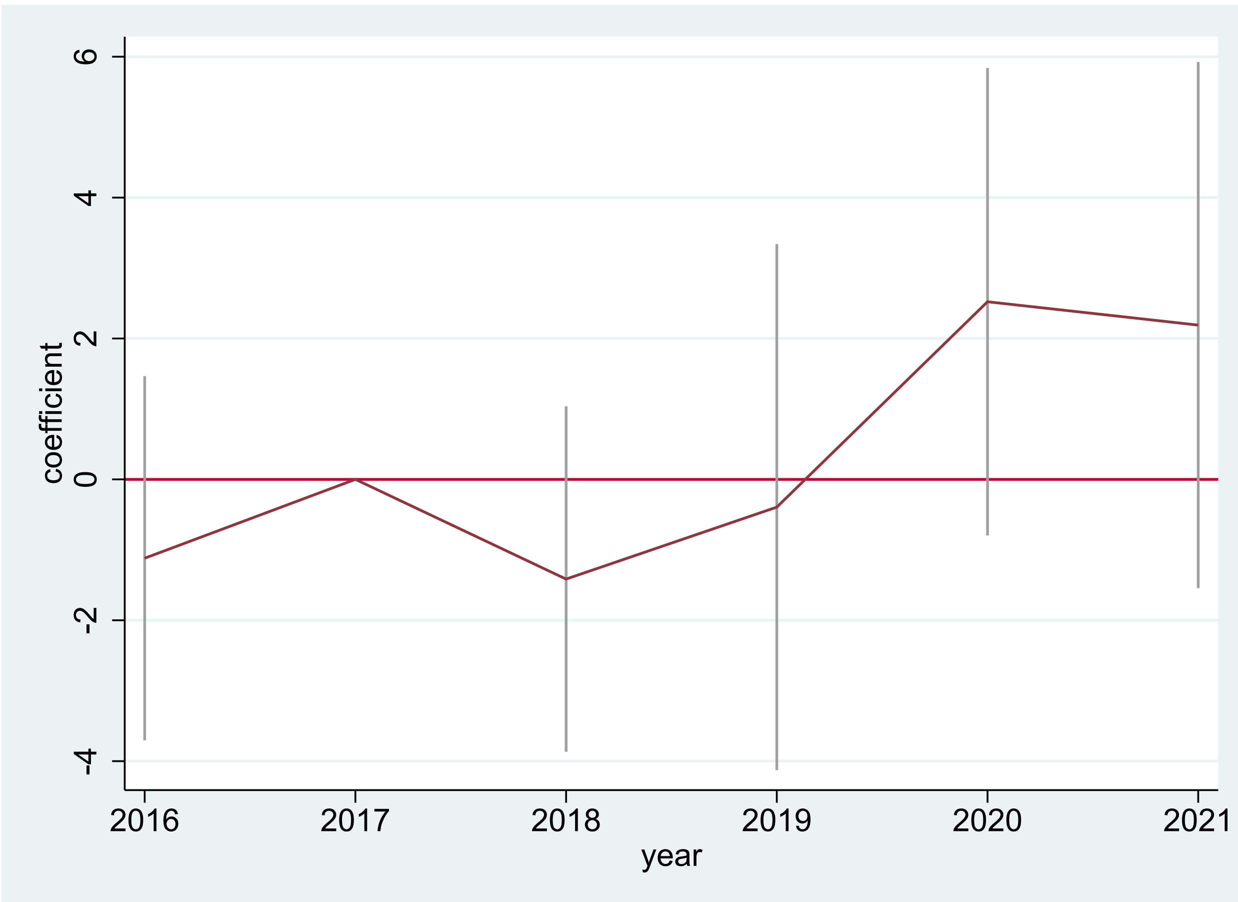
Note: The figure shows the policy exposure in the base year. The base year in MUS is 2017, and the base year in the 1111 Job posting data is October 2016 through September 2017.

Figure A.3: Policy Exposure Group



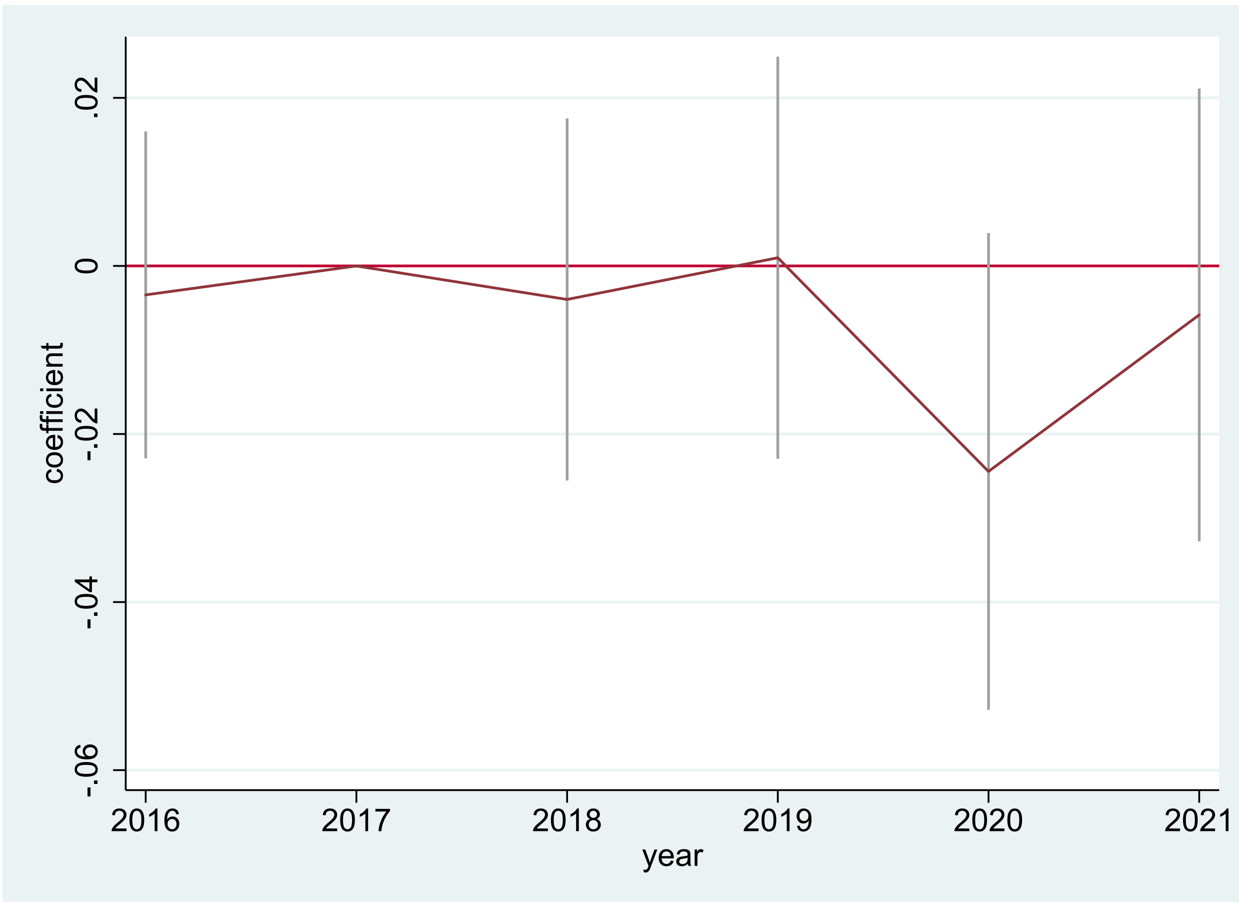
Note: The figure shows the policy exposure in the base year. The base year in MUS is 2017, and the base year in the 1111 Job posting data is October 2016 through September 2017.

Figure A.4: The Policy Effect on Gender Employment Gaps: Event Study



Note: The figure shows the event-study extension of the estimation of the estimation of wage reveal effect on gender wage gaps by Equation 5. The sample is the population of ages 15 or older, which is defined as the labor force. The dependent variable is the number of full-time, monthly paid, and private sector workers in a particular industry-occupation-county category per 100,000 male/female labor force population. The line represents the coefficients of the relative difference in the gender employment gap between high-exposed and low-exposed positions compared to 2017. Each spike shows the 95% confidence interval of the coefficients in the regarding year. The estimations are controlled for the industry-occupation-county fixed effects and the firm fixed effects. The robust standard errors are clustered at the industry-occupation-county level.

Figure A.5: The Policy Effect on Gender Wage Gaps: Event Study



Note: The figure shows the event-study extension of the estimation of the estimation of wage reveal effect on gender wage gaps by Equation 8. The sample is restricted to the full-time, private-sector workers who are paid monthly. The dependent variable is the logarithmic monthly wage in 2017 Taiwan dollars. The line represents the coefficients of the relative difference in gender wage gap between high-exposed and low-exposed positions compared to 2017. Each spike shows the 95% confidence interval of the coefficients in the regarding year. The estimations are controlled for age (in quadratic), education attainment, marital status, parental status, and working tenure in the current position (in quadratic), the industry-occupation-county fixed effects, and the firm fixed effects. The robust standard errors are clustered at the industry-occupation-county level.

Table A.1: Legislation Timeline of Taiwan's Wage Reveal Policy

Date	Legislation Process
November 25, 2016 March 17, 2017	First reading[1]
May 8, 2017	Committee discussion (1)
October, 2017	Ministry of Labor suggesting job websites to reveal wages
April 19, 2018	Committee discussion (2, conclusion)
October 22, 2018	Caucus discussion
November 9, 2018	Second and third readings
November 30, 2018	Enactment[2]

Note: **1.** Two bills aiming wage reveal are proposed in the two different date. They were merged into one bills later in the committee discussions and all following processes. **2.** The 2018 reform of the Employment Service Act is signed and announced at November 28, but the new law is actually enacted at November 30.

Table A.2: The Most and the Least Exposed Job Categories

	Industry	Occupation	Location	% workers earning ≤40k NTD	# of workers
Most exposed					
1.	Other service activities	Craft and Related Trades Workers	New Taipei	100.00	12,878
2.	Wholesale and retail trade	Service and Sales Workers	Pingtung	100.00	13,155
3.	Transportation and storage	Clerical Support Workers	New Taipei	97.46	12,072
4.	Administrative and support service activities	Elementary Occupations	New Taipei	97.04	12,853
5.	Manufacturing	Plant and Machine Operators and Assemblers	Nantou	95.97	18,527
Least exposed					
1.	Financial and insurance activities	Managers	Taipei	0.00	13,549
2.	Manufacturing	Managers	Taichung	0.00	12,520
3.	Financial and insurance activities	Managers	New Taipei	0.00	10,294
4.	Manufacturing	Managers	New Taipei	1.47	27,486
5.	Manufacturing	Managers	Taipei	3.25	22,575

Data Source: Manpower Utilization Survey, 2017.

Note: The policy exposure is measured by the share of workers earning less than 40,000 NTD in 2017. The number of workers is recovered to population size with the survey weights. The job categories with less than 10,000 workers are excluded from the ranking as outliers.

Table A.3: The Policy Effect on Monthly Wage, Extended Table

	(1) log(wage)	(2) log(wage)	(3) log(wage)
trans × high-exposed	0.0088	0.0131**	0.0131**
	(0.0059)	(0.0053)	(0.0053)
after × high-exposed	0.0089	0.0176***	0.0161**
	(0.0076)	(0.0067)	(0.0067)
trans	0.0378***	0.0343***	
	(0.0050)	(0.0043)	
after	0.1121***	0.0923***	
	(0.0064)	(0.0054)	
high-exposed	-0.2247***		
	(0.0121)		
female	-0.1532***	-0.1627***	-0.1626***
	(0.0057)	(0.0049)	(0.0049)
high school	0.1287***	0.0688***	0.0664***
	(0.0084)	(0.0048)	(0.0048)
bachelor	0.1849***	0.1019***	0.1135***
	(0.0097)	(0.0054)	(0.0059)
age	0.0194***	0.0186***	0.0187***
	(0.0013)	(0.0009)	(0.0009)
age^2	-0.0002***	-0.0002***	-0.0002***
	(0.0000)	(0.0000)	(0.0000)
married	0.0613***	0.0407***	0.0406***
	(0.0046)	(0.0039)	(0.0039)
have children	-0.0097**	-0.0022	-0.0003
	(0.0049)	(0.0040)	(0.0040)
tenure	0.0011***	0.0010***	0.0010***
	(0.0001)	(0.0001)	(0.0001)
$tenure^2$	-0.0000***	-0.0000***	-0.0000***
	(0.0000)	(0.0000)	(0.0000)
Observations	94,373	94,344	94,344
Adjusted R^2	0.415	0.547	0.551
IND-OCCU-CTY FE		V	V
Year FE			V

Data Source: Manpower Utilization Survey, 2016-2021.

Note: This table shows the estimation of wage reveal policy effect on monthly wage with all coefficents of controlled variables reported. See the notes of Table 5.

Table A.4: The Policy Effect on Gender Wage Gaps, Extended Table

	(1) log(wage)	(2) log(wage)	(3) log(wage)
female $\times$ trans $\times$ high-exposed	-0.0011	-0.0035	-0.0025
	(0.0121)	(0.0104)	(0.0104)
female $\times$ after $\times$ high-exposed	-0.0195	-0.0075	-0.0080
	(0.0120)	(0.0099)	(0.0099)
female	-0.1805***	-0.1926***	-0.1925***
	(0.0108)	(0.0089)	(0.0088)
high school	0.1284***	0.0687***	0.0664***
	(0.0084)	(0.0047)	(0.0047)
bachelor	0.1858***	0.1026***	0.1142***
	(0.0098)	(0.0053)	(0.0058)
age	0.0194***	0.0185***	0.0186***
	(0.0013)	(0.0009)	(0.0009)
age^2	-0.0002***	-0.0002***	-0.0002***
	(0.0000)	(0.0000)	(0.0000)
married	0.0612***	0.0405***	0.0404***
	(0.0046)	(0.0039)	(0.0039)
have children	-0.0100**	-0.0030	-0.0011
	(0.0049)	(0.0040)	(0.0040)
tenure	0.0011***	0.0010***	0.0010***
	(0.0001)	(0.0001)	(0.0001)
tenure^2	-0.0000***	-0.0000***	-0.0000***
	(0.0000)	(0.0000)	(0.0000)
Observations	94,373	94,344	94,344
Adjusted R^2	0.415	0.548	0.552
IND-OCCU-CTY FE		V	V
Year FE			V

Data Source: Manpower Utilization Survey, 2016-2021.
Note: This table shows part of Table 6 with all coefficents of controlled variables reported. See the notes of Table 5.

Table A.5: The Policy Effect on Gender Wage Gaps, by Education Attainment

Sample	below high school	high school and above	no bachelor	bachelor and above
	(1)	(2)	(3)	(4)
	log(wage)	log(wage)	log(wage)	log(wage)
female $\times$ trans $\times$ high-exposed	-0.0185	-0.0004	-0.0146	0.0036
	(0.0370)	(0.0108)	(0.0131)	(0.0174)
female $\times$ after $\times$ high-exposed	-0.0174	-0.0039	-0.0363***	0.0135
	(0.0369)	(0.0103)	(0.0115)	(0.0180)
female $\times$ trans	0.0205	0.0001	0.0155	-0.0100
	(0.0342)	(0.0089)	(0.0114)	(0.0132)
female $\times$ after	0.0246	0.0271***	0.0633***	0.0130
	(0.0349)	(0.0086)	(0.0101)	(0.0133)
female $\times$ high-exposed	0.0574*	0.0338***	0.0488***	0.0575***
	(0.0344)	(0.0112)	(0.0133)	(0.0156)
trans $\times$ high-exposed	0.0381**	0.0106	0.0241***	0.0181
	(0.0186)	(0.0077)	(0.0086)	(0.0125)
after $\times$ high-exposed	0.0469*	0.0131	0.0310***	0.0235
	(0.0246)	(0.0088)	(0.0092)	(0.0149)
female	-0.2462***	-0.1876***	-0.2182***	-0.1616***
	(0.0317)	(0.0087)	(0.0105)	(0.0123)
Observations	11,025	83,144	65,834	28,347
Adjusted R^2	0.438	0.552	0.504	0.584

Data Source: Manpower Utilization Survey, 2016-2021.

Note: This table shows the estimation of the wage reveal effect on gender wage gaps by education attainment. The age is measured in years, and the working tenure is measured in months. The sample is restricted to the full-time, private-sector workers who are paid monthly in addition to the criterion specified in each column. The dependent variable is the logarithmic monthly wage in 2017 Taiwan dollars. Trans and after represent the indicators of the transition period (2018) and the after period (since 2019), respectively. High-exposed represents the indicators of the industry-occupation-county categories which are highly exposed to the policy. For each column, the estimations are controlled for age (in quadratic), education attainment, marital status, parental status, and working tenure in the current position (in quadratic), the industry-occupation-county fixed effects, and the year fixed effects. Robust standard errors clustered at the industry-occupation-county level are in parentheses. ***: $p<0.01$; **: $p<0.05$; *: $p<0.1$.

Table A.6: The Policy Effect on Gender Wage Gaps, by Marital or Parental Status

Sample	married	not married	have children	no children
	(1)	(2)	(3)	(4)
	log(wage)	log(wage)	log(wage)	log(wage)
female $\times$ trans $\times$ high-exposed	-0.0080	0.0087	-0.0122	0.0080
	(0.0127)	(0.0155)	(0.0122)	(0.0158)
female $\times$ after $\times$ high-exposed	-0.0147	0.0057	-0.0206*	0.0092
	(0.0124)	(0.0149)	(0.0123)	(0.0153)
female $\times$ trans	0.0114	-0.0036	0.0131	-0.0015
	(0.0107)	(0.0125)	(0.0098)	(0.0131)
female $\times$ after	0.0303***	0.0273**	0.0332***	0.0241*
	(0.0105)	(0.0124)	(0.0101)	(0.0130)
female $\times$ high-exposed	0.0150	0.0249*	0.0242**	0.0308**
	(0.0127)	(0.0146)	(0.0123)	(0.0149)
trans $\times$ high-exposed	0.0119	0.0127	0.0134	0.0166
	(0.0083)	(0.0115)	(0.0085)	(0.0112)
after $\times$ high-exposed	0.0199**	0.0062	0.0138	0.0162
	(0.0091)	(0.0116)	(0.0096)	(0.0117)
female	-0.1214***	-0.2468***	-0.1243***	-0.2529***
	(0.0103)	(0.0116)	(0.0099)	(0.0120)
Observations	48,075	46,128	46,969	47,222
Adjusted R^2	0.479	0.585	0.493	0.594

Data Source: Manpower Utilization Survey, 2016-2021.
Note: This table shows the estimation of the wage reveal effect on gender wage gaps by marital or parental status. The sample is restricted to the full-time, private-sector workers who are paid monthly in addition to the criterion specified in each column. The dependent variable is the logarithmic monthly wage in 2017 Taiwan dollars. Trans and after represent the indicators of the transition period (2018) and the after period (since 2019), respectively. High-exposed represents the indicators of the industry-occupation-county categories which are highly exposed to the policy. For each column, the estimations are controlled for age (in quadratic), education attainment, marital status, parental status, and working tenure in the current position (in quadratic), the industry-occupation-county fixed effects, and the year fixed effects. Robust standard errors clustered at the industry-occupation-county level are in parentheses. ***: $p<0.01$; **: $p<0.05$; *: $p<0.1$.

Table A.7: Mimimum Monthly Wage Level in Taiwan, 2016-2021

Year	Minimum Monthly Wage (NTD)	Increase Rate (%)	CPI Increase Rate (%)
2016	20,008	—-	1.40
2017	21,009	5.00	0.62
2018	22,000	4.72	1.36
2019	23,100	5.00	0.55
2020	23,800	3.03	-0.23
2021	24,000	0.84	1.97

Note: The 2016 minimum wage level was enacted on July 1, 2015. For other years listed, the minimum wage level was enacted on January 1 in the regarding year. The minimum wage level is reported in nominal terms. The CPI increase rate is retrieved from National Statistics, Taiwan (https://www.stat.gov.tw).