The Effects of Pay Transparency on Posted and Realized Wages

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Abstract

Pay transparency laws are increasingly discussed and have been implemented in several jurisdictions in the United States as a means of improving pay equity. Pay transparency laws increase the amount of publicly available market wage information, but little is known about how employers and workers respond to this increased wage information. I examine the effects of the pay transparency law by exploiting a Colorado law that required the inclusion of wage information in job postings, using online job posting data and CPS data. Using a difference-in-differences design, I find that the pay transparency law increased the fraction of job postings with salary information by nearly 50 percentage points. The pay transparency law increased posted wages by about 5 percent. Specifically, the law increased the lower bound of posted salaries by 1.3% and the upper bound by 8.1%. I do not find significant effects on realized wages, suggesting that the increase in posted wages was driven by a disproportionate increase in the posting of wages for higher-paying jobs. The pay transparency law decreased the gender wage gap for job changers and job stayers by 8.9% and 1.1%, respectively. The narrowing of the gender wage gap was driven by an increase in female wages and a decrease in male wages.

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1 Introduction

In recent years, pay transparency laws have gained traction around the world as a way to improve labor market outcomes for workers. In the United States, several jurisdictions have recently enacted pay transparency laws requiring the disclosure of wages in job postings. Colorado is the first state to require all employers to include wage rates or ranges and benefits in every job posting, beginning January 1, 2021. New York City's wage transparency law went into effect on November 1, 2022. California and Washington implemented their transparency laws in January 2023. These pay transparency laws substantially increase the amount of publicly available information on market pay. For example, as Figure 1 shows, Colorado's pay transparency law increased the fraction of job postings with salary information from below 10% to over 60%. Despite this change, there is little research on how employers are responding to increased pay transparency because pay transparency laws are just beginning to take effect.

In this paper, I study the effect of the pay transparency law on posted wages, realized wages, and the gender wage gap using the Colorado pay transparency law. The first dataset is the online job posting data from LinkUp. LinkUp is a leading data aggregator that has assembled a database of job postings sourced directly from company websites. The second dataset is the CPS. It complements the job posting data because it is representative of the U.S. population and includes realized wages.

I use a difference-in-differences (DID) design to study the effects of pay transparency. Using the states that have state-wide salary history bans as the control group, I estimate the first-stage effect of Colorado's wage disclosure requirement on the fraction of job postings that have wage information as well as the effects on posted wages. In this design, I compare Colorado and the control states before and after the act went into effect. Under the assumption that in the absence of Colorado's pay transparency law, outcomes for job postings would have had the same trend in Colorado as in other states, the coefficient of interest identifies the causal effect of the wage disclosure requirement in job postings.

The parallel trend assumption of the DID design might be violated because of two threats. The first one is the confounding effects of the COVID-19 pandemic and the accompanying recession. If the pandemic affected the labor market in Colorado differently than in other states, in 2021 and 2022 in particular, the estimated effects are not causal.

To address the first threat, I compare the general and sector-specific trends of job postings in Colorado versus other states before and after the COVID-19 pandemic erupted and find that the COVID-19 pandemic did not affect the structure of job postings in Colorado very differently from other states.

Wage posting varied considerably among different occupations in the pre-period. Occupations such as community service, education, protection, agriculture, construction, and transportation were more likely to include wage information in their job postings than other occupations prior to 2021. This trend may be due to these occupations having a higher proportion of job postings from the public sector, which historically had greater pay transparency than the private sector. In addition, these occupations have lower pay and wage posting is more prevalent among lower-wage jobs given that low-wage workers are easily replaceable (Lachowska et al., 2022a). However, after the pay transparency law, compliance in wage posting across occupations is more similar proportionally. Noncompliance was non-negligible in every occupation, ranging from 33% to 54%.

Wage posting differs by firm size only when it is required. Using the number of job postings created by a firm each year as a proxy for firm size, I keep a balanced firm-year panel and find that in Colorado, larger firms are more likely to post wage information in the post-period. In contrast, there is no relationship between wage posting and firm size when there is no regulation at all. Larger firms are more likely to be discovered by job applicants and reported to the CDLE if they do not comply with the wage transparency law because they have more job openings. This might explain why larger firms have higher compliance in Colorado.

Pay transparency law increased the fraction of job postings with salary information by nearly 50 percentage points. In the first month of enactment, the law immediately increased the fraction of job postings with salary information by about 35 percentage points. Interestingly, the results do not suggest any anticipation effect, although the law was passed in 2019, two years before the law went into effect.

The pay transparency law increased posted wages by about 5%. Specifically, it increased the lower bound of posted salaries by 1.3% and the upper bound by 8.1%. The effects are similar in magnitude for job postings with salary ranges and job postings with salary rates. I find heterogeneous effects across occupations. The point estimates for computer and sales occupations are negative, although none of them is significant at the 5% significance level, and the magnitude is small. For occupations with positive point estimates, the effects range from below 0.25% to 20%. In sum, the effects of the pay transparency law on posted wages are generally positive across occupations, but the magnitude of the effect varies a lot.

I do not find evidence suggesting that employers posted wide salary ranges to hide true salary information. I examine the effect of the pay transparency law on the ratio of the maximum salary to the minimum salary (maximum salary/minimum salary). Although there is a moderate increase in both the total quantity and fraction of job postings with a maximum salary greater than one and a half times the minimum salary, these job postings still make up a small portion of all job postings with salary information in Colorado. In general, most salary ranges are narrow enough to be informative.

Despite a 5% increase in posted wages, the pay transparency law has no effect on realized wages. I define job changers as employed individuals who have changed their employers during the survey period of CPS and define the rest as job stayers and examine the effect for the subsamples. I do not find any significant effect on hourly wage rates for either job changers or job stayers, although job changers are likely to be directly exposed to posted wage information. Since realized wages almost did not change, the increase in posted wages might primarily result from the within-occupation compositional change. Pay transparency may also increase competition among employers and render employers to increase posted wages, but employers should not have increased wages for incumbent employees on a large scale.

The pay transparency law decreased the gender wage gap by decreasing male and increasing female wages. The narrowing in the gender wage gap is the largest for job changers - 8.9%. For job stayers, the estimated decline in the gender wage gap is about 1.1% and insignificant. The event study graph shows that a portion of the reduction in the gender wage gap is attributed to a decline in wages for males. In sum, Colorado's pay transparency law proves effective in advancing pay equity and diminishing the gender wage gap, while some of this reduction is driven by adverse effects on male wages.

Why does pay transparency reduce the gender wage gap among job changers? One possibility is that wage information in job postings changed job seekers' beliefs about the distribution of wages, more for women than for men, and consequently, changed their reservation wages. Cortés et al. (2023) find that both males and females have upward biased beliefs about future earnings, but females have less biased beliefs. In addition, females update their beliefs faster than males during the job search process. Roussille (2022) shows that although females ask for lower wages in salary negotiations than comparable males, the gender ask gap is fully eliminated if the median ask salary for that job is provided. Taking the evidence together, by making anticipated wage data accessible, the pay transparency law might render women to update their beliefs and seek higher-paying positions. This could potentially displace certain males who, in the absence of the wage transparency law, might have secured those high-earning roles, and resulted in the decrease in male wages.

Related literature - This study relates to several strands of literature.

First, this study contributes to a growing literature on the effects of pay transparency on employees and job seekers. The literature documents substantial information friction in the job search process; for example, only 23% of recent hires know exactly how much the position paid before they got hired (Hall and Krueger, 2012). Workers also have substantial misperceptions about others' wages and their outside options (Caldwell and Harmon, 2019; Caldwell and Danieli, 2022; Cullen and Perez-Truglia, 2022; Jäger et al., 2022; Roussille, 2022). Both observational studies and field experiments shed light on the effects of pay transparency on employee outcomes such as wage, satisfaction, turnover, effort, and returns to job search. For example, Mas (2017) finds that pay disclosure in the public sector leads to wage cuts among high earners. Card et al. (2012) show that revealing peer salaries affects job satisfaction and search behavior. Cullen and Perez-Truglia (2022) provide evidence that employees work harder when they find their bosses earn more than they thought. In contrast, they work less hard when they learn that their peers earn more.

Among studies of pay transparency for workers, this paper is closely related to those on the returns to job search. Using a policy reform that mandated the inclusion of wage information in job advertisements in Slovakia, Skoda (2022) finds that the realized wages of new hires increased by 3%. This was mainly due to wage increases in companies that previously did not include wage information. The job advertisements of these complying companies received more clicks and applications as a result of the reform. The wage increase was not due to an increase in the quality of applicants, but was likely due to lower wage expectations among applicants. Frimmel et al. (2022) study a similar wage disclosure mandate in job ads in Austria, but find no overall effect on realized wages. The mixed results on the impact of pay transparency on the level of wages call for more work on this topic. In addition, because the mandates in Slovakia and Austria were nationwide, there were no control groups, and any wage changes over the study periods were attributed to the wage disclosure mandates. This paper uses states with salary history bans but no wage disclosure requirements as the control group, which better isolates the causal effect of the Colorado wage disclosure mandate.

Second, this paper speaks to the effect of pay transparency on employers. Most previous studies are entirely focused on employee outcomes, with a few exceptions that investigate the employer side. One notable exception is Cullen et al. (2022), documenting that firms also face significant information frictions on wages that other employers pay. They suggest that firms compress the wages of new hires towards the market salary benchmark (which is the market median in this study) after gaining access to the salary benchmarking tool. I examine the effect of pay transparency on employers in a context where not only employers but also workers have access to posted wages of various firms. Another exception is Arnold et al. (2022). They find that posted wages increased by about 3% following Colorado's pay transparency law by comparing Colorado and all other states in the U.S. They suggest that the wage increase reflects a compositional change in job postings. There was a disproportionately larger increase in higher-paying jobs with wage information because of the wage disclosure requirement. Consistent with Arnold et al. (2022), I also find a 3% increase in posted wages as a result of the Colorado pay transparency law, but I take a step further and study the effect of the pay transparency law on realized wages and examine the mechanisms.

Finally, this paper contributes to the recent literature that examines less traditional explanations and interventions for the persistence of the gender wage gap. Cortés et al. (2023) document that women accept job offers substantially earlier than men, and consequently, have lower accepted earnings than men. They provide direct lab evidence that women are more risk-averse and have lower beliefs about future earnings, which leads to lower reservation wages. Adding on to this evidence, Roussille (2022) shows that while women tend to ask for lower salaries than their equivalent male peers, offering median salary data to candidates fully eliminates this disparity in salary negotiations. Disclosing wages (Baker et al., 2023; Lyons and Zhang, 2023) or the gender wage differential (Gamage et al., 2020) also mitigates the gender wage gap. Beyond informing the disadvantaged group, several papers posit that salary history bans also reduce the gender wage gap (Bessen et al., 2020; Frimmel et al., 2022; Sinha, 2022). Complementing these studies, my paper illuminates how the growing emphasis on pay transparency—specifically, the disclosure of wage information in job advertisements—is effective not just in reducing the gender wage gap, but possibly even overturning it.

The rest of the paper will proceed as follows. Section 2 will discuss the institutional details of the Colorado law and introduce the data. Section 3 will report the results in job postings. Sections 4 and 5 will report the results on realized wages and the gender wage gap respectively. Section 6 will discuss the assumptions and section 7 will conclude.

2 Institutional Background and Data

2.1 Colorado's Equal Pay for Equal Work Act

On January 1, 2021, Colorado's Equal Pay for Equal Work Act (EPEWA) went into effect. This act applies to all employers and employees in Colorado, both public and private. This act requires employers to (1) provide the wage rate or range and employment benefits in their job postings, (2) keep records of job descriptions and wage rate history for each employee, and (3) notify employees of promotional opportunities. It also prohibits employers from asking about or relying on a job applicant's salary history, i.e., the salary history ban. My focus will be on the first component of this act: including wage information in job postings.

Specifically, this act requires the disclosure of "the hourly or salary compensation, or a range of the hourly or salary compensation, and a general description of all the benefits and other compensation to be offered to the hired applicant" (Colorado General Assembly, 2019). The salary range must be for the particular job advertised and may extend from the lowest to the highest amount the employer genuinely believes it would pay for that position (CDLE, 2021). For example, the Colorado Department of Labor states that "an employer cannot post a $70,000 - $100,000 range for a junior accountant position just because it pays senior accountants at the higher end of that range." This act does not allow employers to post a salary range with no lower or upper bound, like $30,000 and above or below $80,000. An employer is permitted to pay more or less than the indicated range when a vacancy is eventually filled.

I focus on the effect of including wage information in job postings among all components of Colorado's pay transparency law because this is the first time wage information is required in job postings in the United States. Another component of the law, the salary history ban, has been implemented in several states and cities and has been studied in several papers. For example, both (Sinha, 2022) and (Sran et al., 2020) show that salary history bans decrease the gender wage gap. (Sran et al., 2020) also document that employers are more likely to include wage information in job postings in response to salary history bans but offer lower pay. Since the salary history ban affects wages and job posting-related outcomes, if I compare Colorado with states that neither have the wage disclosure requirement nor have salary history bans, it would be difficult to interpret the results. [1] To separate out

[1] Although salary history bans prohibit employers from asking about a job applicant's salary history, job applicants can still share past pay information on a voluntary basis.

the effect of wage posting from the Colorado law, I use a subset of states with state-wide salary history bans as the control group. Specifically, I use West Coast states - California, Oregon, and Washington - as the control group. As of December 2019, Alabama, California, Connecticut, Delaware, Illinois, Maine, Massachusetts, Oregon, Rhode Island, Vermont, and Washington had state-wide salary history bans. Among these states, West Coast states are more similar to Colorado in labor market conditions. Both Colorado and West Coast states have strong technology sectors and relatively progressive labor laws, including higher minimum wages and worker protections. Oregon was the first state in the control group to enforce a ban on salary history disclosure for all employers and agencies on October 6, 2017. Later, California and Washington followed suit and implemented their salary history bans on January 1, 2018 and July 28, 2019, respectively.

Enforcement of the law came mainly through education and rarely financial penalties. Individuals can submit compliant forms to the Colorado Department of Labor if they find an employer violates the law. After investigating a complaint, the state labor department would first issue a no-fines Warning and Order to the employer if it found a violation such that the employer had the chance to comply. Most employers complied after learning of a violation and thus avoided a fine (Chuang, 2022). According to the law, the non-compliance-related fine can range from $500 to $10,000 per violation.

2.2 LinkUp Job Posting Data

The first dataset is online job posting data from LinkUp. LinkUp is a leading data aggregator that has assembled a database of job postings sourced directly from company websites. Compared with Burning Glass Technologies (BGT), the most commonly used source of job postings data in economics literature (e.g., Arnold et al., 2022; Forsythe et al., 2020), LinkUp only scrapes data from company websites whereas BGT scrapes both job boards and company websites. This might be the reason why the sample size of job posting data from LinkUp is smaller than BGT. For example, the numbers of job postings from LinkUp are 54% and 71% of the numbers of job postings from BGT in 2020 and 2021, respectively.[2]

This dataset is at the job-posting level. For each job posting, it contains the job title, created and removed dates, company name, city, state, zipcode, ONet occupation code, and text-based job description. LinkUp does not extract salary information from raw job descriptions so I use a question answering deep learning model to extract salary rates or

[2]In 2020, there are 15,191,843 and 28,076,468 job postings from LinkUp and BGT respectively. In 2021, there are 24,975,953 and 35,147,684 job postings from LinkUp and BGT respectively.

ranges. The detailed description of the whole procedure is in the data appendix.[3] The study period is from January 2017 to November 2022. I exclude remote jobs from the sample.

Table 1 shows the summary statistics of the LinkUp job posting data from 2017 - 2020 for Colorado and the control states separately. As Panel A shows, from 2017 - 2020, only 7% of job postings in Colorado and the control states contained wage information. Panel B summarizes the subsample of job postings with wage information. I convert wages to annual rates when employers report hourly, weekly, biweekly, or monthly rates in job postings in order to make posted wages comparable to each other. Specifically, I multiply hourly rates by 2080 (52 weeks $\times$ 40 hours per week), weekly rates by 52, biweekly rates by 26, and monthly rates by 12. If the job posting includes a salary range, I record the low, high, and midpoint of the range as the minimum, maximum, and midpoint salaries, respectively. If the job posting includes a wage rate, the midpoint, minimum, and maximum salaries recorded are all equal to the wage rate. Among job postings with salary information, the average posted salary is lower in Colorado than in the control states ($45,022 vs. $54,249). In Colorado, about 29% of job postings with salary information list annual wage rates and 66% list hourly wage rates. The control states have similar job postings with annual wage rates (29%) and slightly fewer job postings with hourly wage rates (63%) in proportion.

Figure 1 shows the fraction of job postings with salary information for Colorado versus other states by month. Before 2021, the fraction of job postings with salary information was below 10% in both Colorado and other states. In January 2021, the share in Colorado increased dramatically to 40% and then continued to increase to about 65% by the end of 2022, while the share in other states increased only moderately to 20% by the end of 2022. In summary, although there was still non-negligible non-compliance at the end of 2022, the fraction of job postings with salary information increased after Colorado's pay transparency law went into effect.

Table 2 provides a comparison of the distribution of occupations of job postings in Colorado versus all other states in 2017-2020, the period before the law was enacted. The distribution is quite similar in Colorado versus all other states. Because of the large sample size, many of the differences in proportions of occupations between Colorado and other states are statistically significant at the 1% level, but the magnitude of the differences is small.

To assess the representativeness of the LinkUp data, I compare the LinkUp job posting

[3] Question answering is a task in the field of natural language processing. Question answering models can retrieve the answer to a question from a given text.

data with the CPS wage data by occupation in Figure 2. Since CPS does not contain annual wage rates, I generate annual wage rates by multiplying hourly rates by 2080. Each dot represents an occupation. The blue circles display the mean wage of the respective occupation from the LinkUp data on the x-axis and the CPS full sample on the y-axis. The orange diamonds display the mean wage of the respective occupation from the LinkUp data on the x-axis and the mean wage of the respective occupation from the CPS job changer subsample on the y-axis. Job changers are defined as workers who can be credibly identified as having changed jobs in the CPS survey period. Both axes use units of thousands to denote the x- and y coordinates of each circle.

The results show that mean wages from the CPS are similar to mean wages from LinkUp for most occupations, with the exception of the six highest-paying occupations. The difference in wages between LinkUp and CPS for higher-paying occupations is likely due to the hourly rate in CPS being topcoded at \$99.99, which is equivalent to an annual rate topcoded at \$207,979. Between 7% and 22% of wages among the six highest-paying occupations are topcoded in the CPS. Overall, with the exception of the six highest-paying occupations, most circles are close to the 45-degree line, indicating that posted wages are comparable to wages from a representative survey across occupations.

2.3 CPS Wage Data

The second dataset is the CPS. It complements the job posting data because it is representative of the U.S. population and includes realized wages. The survey lasts four consecutive months, followed by an eight-month break, and then another four consecutive months before participants leave the survey. In the monthly basic files, the survey records demographic information for each household member, such as age, sex, education, and location. It also records their labor market outcomes, such as employment status, industry, and occupation. For six of the eight months of the survey, employed participants are asked if they changed employers from the previous month. The monthly basic files do not contain data on individual earnings. The Outgoing Rotation Group supplement records earnings information in the 4th and 8th months of the survey. For those workers paid an hourly wage, CPS reports how much the respondent earned per hour in the current job, and I use the reported hourly wage rate as the outcome variable. For salaried workers, I compute the hourly rate by dividing the weekly earnings by the reported usual number of hours per week the respondent reports being at their main job. [4]

I restrict my sample to the civilian non-institutionalized population aged between 22 and 64. I focus on this particular group of individuals because they typically have enough time to graduate from college and start working by age 22 and remain in the labor force until retirement. Around 57.64% of workers in the sample are paid by the hour.

3 The Effect of Pay Transparency Law in Online Postings

3.1 Descriptive Evidence

Which employers posted wage information in job vacancies before the pay transparency law required them to do so? Panel A of Figure 4 displays the fraction of job postings with salary information by occupation in Colorado, separately for the pre- and post-period. The left panel suggests that wage posting varied considerably among different occupations in the pre-period. Occupations such as community service, education, protection, agriculture, construction, and transportation were more likely to include wage information in their job postings than other occupations prior to 2021. This trend may be due to these occupations having a higher proportion of job postings from the public sector, which historically had greater pay transparency than the private sector. In addition, these occupations have lower pay, and wage posting is more prevalent among lower-wage jobs given that low-wage workers are easily replaceable (Lachowska et al., 2022a). However, after the pay transparency law, as shown in the right panel, there were fewer disparities in wage posting across occupations. Noncompliance was non-negligible in every occupation, ranging from 33% to 54%.

Panel B of Figure 4 displays the fraction of job postings with salary information by occupation in the control states. The wage posting pattern in the pre-period is very similar to Colorado. The pattern persisted from the pre- to the post-period, with a small increase for each occupation.

Wage posting differs by firm size only when it is required. Using the number of job postings created by a firm each year as a proxy for firm size, I keep a balanced firm-year panel and illustrate the relationship between firm size and wage posting in Figure 5. Panel A of the binscatter shows that in Colorado, larger firms are more likely to post wage information in the post-period. In contrast, there is no relationship between wage posting and firm size when there is no regulation at all, as shown by the blue lines in Panel A and

[4] This method for calculating the hourly wage of salaried workers aligns with (Lachowska et al., 2022b).

Panel B. Larger firms are more likely to be discovered by job applicants and reported to the CDLE if they do not comply with the wage transparency law because they have more job openings. This might explain why larger firms have higher compliance in Colorado.

3.2 Event Study Design

To estimate the first-stage effect of Colorado's pay transparency law on salary posting, I implement an event study specification of the following form:

$$Y_{ist} = \sum_{t=-12, t\neq -1}^{23} \beta_t Treat_{ist} + \mu_{j(i)} + \theta_{c(i),t} + \epsilon_{ist}, \tag{1}$$

where Y_{ist} is the binary variable for whether job posting i in state s at month t contains wage information or not. $Treat_{ist}$ is the binary variable that indicates whether the job posting is subject to the wage disclosure requirement in Colorado. $\mu_{p(i)}$ is a job fixed effect that controls for job characteristics that at least include the employer. In my preferred specifications, the job fixed effect is an employer-occupation-zipcode interaction, where I define occupation as the six-digit Standard Occupational Classification (SOC) code. $\theta_{c(i),t}$ are month fixed effects that are functions of characteristics of job $c(i)$. For example, in the preferred specifications, I include occupation-month and sector-month fixed effects so that the treatment effects are identified only by within-occupation and within-sector variations.

The coefficient of interest in Equation 1 is β_t. It is the coefficient of the treatment status indicator $Treat_{ist}$. I normalize t in the way that $t = 0$ corresponds to January 2021, the first month Colorado's wage disclosure requirement was effective. The omitted time category is $t = -1$. β_t represents the difference in the fraction of job postings that have wage information between Colorado and the control states in month t after taking out the difference in the month before the enactment of the pay transparency law.

To examine the effect of the pay transparency law on posted wages, I also estimate Equation 1 using log posted midpoint wages, log posted minimum wages, and log posted maximum wages.

For each outcome variable estimated by Equation 1, I also estimate a compressed DID specification of the following form to summarize the results:

$$Y_{ist} = \beta Treat_{ist} + \mu_{j(i)} + \theta_{c(i),t} + \epsilon_{ist}. \tag{2}$$

3.3 Effect on Salary Posting

Figure 6 shows the event study estimates of the effect of the pay transparency law on the fraction of job postings with salary information. In the first month of enactment, the law immediately increased the fraction of job postings with salary information by about 35 percentage points.

Interestingly, the results do not suggest any anticipation effect, although the law was passed in 2019, two years before the law went into effect. This might be because employers (1) do not want to share wage information earlier than their competitors; (2) do not expect strict enforcement from the Colorado government in the first several months of the law; (3) are not aware of the law.

The effects of the pay transparency law on wage posting across occupations are moderately different. I separately estimate Equation 1 for each 2-digit SOC occupation code and display the estimates in Figure 7. The effect of the pay transparency law on wage posting is positive for all occupations, although some estimates have wide confidence intervals and are not statistically significant at the 5% level. The point estimates for different occupations range from 30 to 65 percentage points. The effects are the largest for medicine and health support occupations (65 and 59 percentage points respectively). The effect is the smallest for agriculture occupations (30 percentage points).

3.4 Effect on Posted Salaries

The pay transparency law increased posted midpoint salaries. Columns (1) - (3) of Table 1 show estimated effects on posted midpoint salaries across different specifications. All three estimates are positive and significant at the 1% significance level. In the preferred specification (Column (3)), the pay transparency law increased posted midpoint wages by 5%. Figure 8 shows the event study estimates of the effect of the pay transparency law on posted midpoint salaries. The positive effect on posted midpoint salaries starts to reveal three months after the enactment of the law, and continues to increase slowly.

The midpoint salary is the average of the minimum and maximum salaries. Is the increase in the midpoint salary driven by the increase in minimum or maximum salaries, or both? To answer this question, I separately examine the effects on the minimum and maximum salaries in job postings. Columns (4) - (6) of Table 1 report estimated effects on posted minimum salaries. I find about a 1.3% increase for the lower bound of salary ranges and is only significant on the margin. The effect on the maximum salary is much larger: I find about an 8.1% increase in the upper bound of salary ranges, as Columns (7) - (9) show. Figure 9 displays the event study estimates of the effects on posted minimum and maximum salaries. These results suggest that the increase in posted midpoint wages is mainly driven by the increase in the upper bound of posted salary ranges.

The midpoint salary is defined as the salary rate itself if a salary rate rather than a range is provided, and a salary rate does not effectively have a lower or upper bound. Do previous results suggest increases in both salary rates and salary ranges? To answer this question, I split the sample by the wage setting approach - salary range or salary rate. Columns (1) - (3) of Table 4 report treatment effects on posted midpoint salaries using the subsample of job postings with salary ranges. The estimated effect is about 2.6%. Columns (4) - (6) of Table 4 report treatment effects on posted midpoint salaries using the subsample of job postings with salary rates. The magnitude and significance of the estimate vary across specifications. In the preferred specification, where I include SOC-Month FE, Firm-SOC-Zipcode FE, and Sector-Month FE, the estimated effect is about 3.0% and is significant at the 1% significance level. In sum, the pay transparency law increased both posted salary ranges and posted rates.

The effect of the pay transparency law on posted wages also differs across occupations. I estimate Equation 1 separately for each 2-digit SOC occupation code and display the estimates in Figure 10. Because there are fewer observations within each occupation, the 95% confidence intervals are wide and most estimates are not significantly different from zero. The point estimates for computer and sales occupations are negative, although none is significant at the 5% significance level, and the magnitude is small. For occupations with positive point estimates, the effects range from below 0.25% to 20%. In sum, the effects of the pay transparency law on posted wages are generally positive across occupations, but the magnitude of the effect varies a lot.

Salary ranges are only informative to job seekers if they are narrow enough. Even under the pay transparency law, firms could hide accurate salary information by posting very broad salary ranges. For example, even though the midpoint is the same, a salary range of \$50K to \$100K is unlikely to be as useful to a job seeker as a range of \$60K to \$90K. Therefore, I examine the effect of the pay transparency law on the ratio of the maximum salary to the minimum salary (maximum salary/minimum salary). Panel A of Figure 11 shows the histogram of the frequencies of job postings across the range of max/min wage ratios in Colorado. There is an increase in the number of job postings across the entire range of ratios in the post period, which is a mechanical result of the pay transparency law. The pre-post difference is greatest where the ratio is between 1 and 1.5. Above the ratio of 1.5, the difference is smaller as the ratio goes higher. In sum, while there are some job postings with a ratio of maximum salary to minimum salary above 1.5 or even above 2, they do not constitute a large proportion of all job postings with salary information in Colorado. In contrast, in the control states, the variation across the range of ratios is small, as Panel B of figure Figure 11 shows.

I also examine whether there are proportionally more job postings with a max/min wage ratio above certain thresholds as a result of the pay transparency law. There is no formal definition of a *wide range* versus a *narrow range*, so I choose 1.5 and 2 as two ad hoc ratio thresholds. Table 5 shows the effect of the pay transparency law on the proportion of job postings with a max/min ratio above 1.5 and 1.75 among job postings with salary information. As columns (1) - (3) show, the fraction of job postings with a max/min ratio above 1.5 increases by about five percentage points, suggesting a moderate increase in wide salary ranges. As columns (4) - (6) show, the share of job postings with a max/min ratio above 1.75 increases by about one percentage point, but this is not statistically significant. Consistent with the histograms in Figure 11, there is a moderate increase in job postings with wide salary ranges, but in general, most salary ranges are narrow enough to be informative.

4 The Effect of Pay Transparency on Realized Salaries

The pay transparency law increased posted wages by 5%. A natural question then is whether higher advertised wages translate into realized wages. To answer this question, in this section, I examine the effects of the pay transparency law on realized wages using the CPS.

4.1 Diff-in-Diff Design

I use Equation 3 to estimate the dynamic effect of the pay transparency law on realized wages and test parallel pre-trends in the outcome:

$$log(Wage_{ismt}) = \sum_{t=-4, t\neq -1}^{1} \beta_t Treat_{ismt} + X_{ismt}\Gamma + \lambda_s + \lambda_t + \lambda_m + \epsilon_{ismt}, \tag{3}$$

where $log(Wage_{ismt})$ is the log of realized hourly wage of individual i in state s, year t, and calendar month m. I aggregate the data to the annual level to gain statistical power, as the sample size per month in CPS is too small. $Treat_{ismt}$ is the binary variable that indicates whether the individual i is surveyed in 2021 or 2022 and in Colorado. X_{it} is a vector of control variables: sex, age, race, education, occupation, industry, private/public sector indicator, full-time/part-time status, and whether the worker is paid hourly. λ_s, λ_t, and λ_m denote state, year, and calendar month fixed effects, respectively.

I also estimate a compressed DID specification:

$$log(Wage_{ismt}) = \beta Treat_{ismt} + X_{ismt}\Gamma + \lambda_s + \lambda_t + \lambda_m + \epsilon_{ismt}. \tag{4}$$

4.2 Effect on Realized Salaries

Figure 12 shows the effect on realized wage rates by year, using data from CPS. Before 2021, there was no discernable variation in hourly wage between Colorado and the control states. In the post-period, the effect of the pay transparency law on realized wages is insignificant in both 2021 and 2022. The pay transparency law has no effect on realized wages, despite a 5% increase in posted wages, as the previous section shows.

Table 6 shows the effects on realized wage rates using the full sample, the subsample of job changers, and the subsample of job stayers separately. I define job changers as employed individuals who have changed their employers before their earnings are recorded in the 4th and 8th months of the survey and define the rest as job stayers. Since employed participants are asked if they have changed employers from the previous month only for six of the eight months of the survey, I cannot identify those who changed employers in the other two months and they will be misclassified as job stayers. In the preferred specification, where I control for state, calendar month, occupation-year fixed effect, and industry-year fixed effect, I do not find any significant effect on hourly wage rates for either job changers or job stayers, although job changers are likely to be directly exposed to posted wage information.

4.3 Discussing Effects on Posted and Realized Wages

One major concern with the causal interpretation of the estimates in job postings is the compositional change in job postings before and after the implementation of Colorado's pay transparency law. When employers can choose between wage posting and bargaining, lower-paying jobs sort into wage posting and wage bargaining is more prevalent among higher-paying jobs (Lachowska et al., 2022a). Thus, if there was a greater increase in wage posting in higher-paying jobs than in lower-paying jobs after the wage disclosure requirement became effective, then the estimated effects would capture both compositional changes and causal effects and be biased. This potential bias is caused by non-random missing wages in job postings when wage disclosure was not in place.

Since realized wages almost did not change, the increase in posted wages might primarily result from the within-occupation compositional change. Pay transparency may also increase competition among employers and render employers to increase posted wages, but employers should not have increased wages for incumbent employees on a large scale.

5 The Effect of Pay Transparency on the Gender Wage Gap

Colorado's pay transparency law intends to promote pay equity and reduce the gender wage gap. In this section, I examine whether this law achieves its first intended goal of reducing the gender wage gap.

5.1 Diff-in-diff Design

I modify Equation 3 and estimate an event-study specification of the following form to estimate the effect of the pay transparency law on the gender wage gap:

$$\begin{aligned}\log(Wage)_{it} = &\sum_{t=-4, t\neq -1}^{1} \beta_t Treat_{it} Female_i + \alpha_1 Female_i + \alpha_2 Treat_{it} \\ &+ \alpha_3 Female_i CO_i + X_{it}\Gamma + \lambda_s + \lambda_t + \epsilon_{it}, \quad (5)\end{aligned}$$

where $Female_i$ indicates whether the individual is a female and CO_i indicates whether the individual lives in Colorado. The coefficient of interest, β_t, represents the effect of the pay transparency law on the gender wage gap.

As in the previous section, I also use a compressed triple difference specification:

$$\begin{aligned}\log(Wage)_{it} = &\beta Treat_{it} Female_i + \alpha_1 Female_i + +\alpha_2 Treat_{it} \\ &+ \alpha_3 Female_i CO_i + \alpha_4 Female_i Post_t + X_{it}\Gamma + \lambda_s + \lambda_t + \epsilon_{it}, \quad (6)\end{aligned}$$

where *Post* indicates the years (2021 and 2022) after the pay transparency law went into effect.

5.2 Effect on Gender Wage Gap

I first present the time-varying effects of Colorado's pay transparency law on the gender wage gap. As Panel A of 13 shows, before 2021, there was no systematic difference in the gender wage gap between Colorado and the control states, except for in 2019. After the pay transparency law was enacted, the effect was small in the first year and was positive and significant in the second year.

Is the decrease in the gender wage gap driven by an increase in female wages, or a decrease in male wages, or both? To answer this question, I display the effects of the pay transparency law on male and female wages respectively, in Panel B of 13. Again, there are no significant changes in either male or female wages in 2021. However, trends in male and female wages diverged in the second year. There is an increase in female wages along with a decrease in male wages, both of which contribute to the decrease in the gender wage gap.

Table 7 displays the effects of the pay transparency law on the gender wage gap estimated by Equation 6. The primary coefficient of interest is $Female \times Treat$ (row 1), representing the female wage premium. A positive value of this coefficient suggests a narrowing of the gender wage gap. The coefficient on $Female$ (row 2) is the baseline gender wage gap in the control states. The coefficient on $Treat$ (row 3) indicates the effect on male wages. Columns (1)-(3) show the estimates from the full sample. Across these specifications, I only observe a suggestive reduction in the gender wage gap of about 1% and is not significant at the 10% level. This law appears to have a minimal impact on male wages in the full sample, with a mere 0.2% decline, according to Column (3), which is not statistically significant at the 10% level.

Given that the pay transparency law is likely to have a more pronounced effect on job seekers than on those not actively pursuing new job opportunities, I show estimates using the subsamples of job changers (Columns (4)-(6)) and job stayers (Columns (7)-(9)). For job changers, the gender wage gap declines by 8.9% (Column (6)) and the estimate is significant at the 5% significance level. Conversely, for job stayers, the estimated decline in the gender wage gap is only 1.1% and insignificant (s.e. = 0.009). Additionally, the law's influence varies between male job changers and stayers. A portion of the reduction in the gender wage gap is attributed to a decline in wages for male job changers. As per my preferred specification in Column (6), male wages for this group diminished by 2.5%. For male job stayers, I still find negative estimates ranging from -0.5% to -0.2%, but none is statistically significant. In sum, Colorado's pay transparency law proves effective in advancing pay equity and diminishing the gender wage gap, while some of this reduction is driven by adverse effects on wages for male job changers.

5.3 Potential Mechanism

Why does pay transparency reduce the gender wage gap among job changers? One possibility is that wage information in job postings changed job seekers' beliefs about the distribution of wages, more for women than for men, and consequently, changed their reservation wages. Cortés et al. (2023) find that both males and females have upward biased beliefs about future earnings, but females have less biased beliefs.[5] In addition, females update their beliefs faster than males during the job search process. They use a job search model and show that the reservation wage increases with belief about the distribution of wages. Roussille (2022) shows that although females ask for lower wages in salary negotiations than comparable males, the gender ask gap is fully eliminated if the median ask salary for that job is provided. Taking the evidence together, by making anticipated wage data accessible, the pay transparency law might render women to update their beliefs and seek higher-paying positions. This could potentially displace certain males who, in the absence of the wage transparency law, might have secured those high-earning roles, and resulted in the decrease in male wages.

6 Discussion

6.1 Identification Assumption

The key identifying assumption for the DID design is that in the absence of Colorado's pay transparency law, job posting outcomes in Colorado would have had the same trend as in the control states. Even if there is no pre-trend, the assumption may not hold because of shocks that occur contemporaneously with the policy change.

There are two threats to the parallel trend assumption. The first is the confounding effects of the COVID-19 pandemic and the associated recession. The COVID-19 pandemic broke out in March 2020 and lasted well into 2021 and 2022, largely overlapping with the post period. During the COVID-19 pandemic, the labor market collapsed across the U.S. If the pandemic affected Colorado's labor market differently than the control states,

[5] Cortés et al. (2023) collect survey data on beliefs about expected future earnings from undergraduates of Boston University's Questrom School of Business.

particularly in 2021 and 2022, the estimated effects are not causal. Although a number of papers provide evidence that the labor market collapsed in March and April 2020 in all states, regardless of the state-level policies imposed, occupations, and almost all industries (Forsythe et al., 2020), the pandemic might still affect Colorado differently in 2021 and 2022.

To address the first threat, I compare the general and sector-specific trends of job postings in Colorado versus other states before and after the COVID-19 pandemic outbreak and find no large differences. In Panel (a) of Figure 3, I plot and compare the number of new job postings in Colorado versus all other states, relative to the number of postings in January and February 2020. As Panel (a) shows, there were large shifts in the number of new postings over the course of 2020-2022: the number of new postings dropped sharply at the beginning of the pandemic and then rebounded in 2021 and 2022. However, the shifts and general trends are nearly identical in Colorado and other states. Panels (b) and (c) show the number of new postings by sector. I choose two sectors: health care and social assistance and retail trade, because (1) these sectors are most affected by the pandemic, and (2) these sectors have the largest number of job postings in Colorado. As Panels (b) and (c) show, the sector-specific trends in job postings in Colorado are similar to those in other states. In sum, the COVID-19 pandemic did not affect the structure of job postings in Colorado very differently from other states.

7 Conclusion

Pay transparency laws are increasingly discussed and have been implemented in several jurisdictions in the United States as a means of improving pay equity. Pay transparency laws increase the amount of publicly available market wage information, but little is known about how employers and workers respond to this increased wage information. I examine the effects of the pay transparency law by exploiting a Colorado law that required the inclusion of wage information in job postings, using online job posting data and CPS data. Using a difference-in-differences design, I find that the pay transparency law increased the fraction of job postings with salary information by nearly 50 percentage points. The pay transparency law increased posted wages by about 5 percent. Specifically, the law increased the lower bound of posted salaries by 1.3% and the upper bound by 8.1%. I do not find significant effects on realized wages, suggesting that the increase in posted wages was driven by a disproportionate increase in the posting of wages for higher-paying jobs. The pay transparency law decreased the gender wage gap for job changers and job stayers by 8.9% and 1.1%, respectively. The narrowing of the gender wage gap was driven by an increase in female wages and a decrease in male wages.

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Appendix

Table 1: Summary Statistics of LinkUp Job Postings Data in CO vs. Control States (2017 - 2020)

	(1) Colorado	(2) Control States
Panel A: All Job Postings		
Contains Salary Info	0.07	0.07
	(0.26)	(0.26)
Observations	1393129	8808452
Number of Firms	6001	12866
Panel B: Job Postings with Salary Information		
Mean Posted Salary		
Midpoint Posted Salary (annual $)	45022.10	54249.49
	(28108.94)	(35278.90)
Minimum Posted Salary (annual $)	41709.56	48997.11
	(23646.55)	(31248.94)
Maximum Posted Salary (annual $)	48334.65	59501.87
	(33978.02)	(40839.25)
Pay Structure		
Annual	0.29	0.29
	(0.45)	(0.46)
Hourly	0.66	0.63
	(0.47)	(0.48)
Monthly	0.04	0.07
	(0.19)	(0.26)
Weekly	0.01	0.01
	(0.07)	(0.08)
Biweekly	0.00	0.00
	(0.05)	(0.02)
Observations	98298	636462
Number of Firms	1219	3597

Note: This table shows summary statistics of the LinkUp job posting data from 2017-2020, the period before the period prior to Colorado's pay transparency law. Control states are California, Oregon, and Washington. Panel A includes all job postings. Panel B includes only job postings with salary information. I convert posted wages to annual rates regardless of the original pay schedule. If the job posting includes a wage *rate*, the midpoint, minimum, and maximum wages are all equal to the wage rate. If the job posting includes a wage *range*, the minimum and maximum salaries refer to the low and high ends of the range, and the midpoint salary is the average of the low and high ends. Pay structure refers to whether the job posting specifies an annual, hourly, monthly, weekly, or biweekly wage rate. Standard deviations are shown in parentheses.

Table 2: Job Postings in CO vs. Control States By Occupation (2017 - 2020)

	Control States	Colorado	Diff.	P-value
Management	0.096	0.067	0.028	0.000
Finance	0.061	0.055	0.006	0.000
Computer	0.103	0.100	0.003	0.000
Engineering	0.032	0.028	0.005	0.000
Science	0.021	0.012	0.009	0.000
Community Service	0.018	0.017	0.001	0.000
Law	0.003	0.002	0.001	0.000
Education	0.032	0.030	0.001	0.000
Arts	0.020	0.019	0.001	0.000
Medicine	0.106	0.100	0.006	0.000
Health Support	0.033	0.040	-0.007	0.000
Protection	0.029	0.018	0.012	0.000
Food Preparation	0.088	0.103	-0.015	0.000
Cleaning	0.017	0.020	-0.003	0.000
Personal Care	0.012	0.014	-0.002	0.000
Sales	0.140	0.155	-0.015	0.000
Office Admin	0.088	0.092	-0.004	0.000
Agriculture	0.000	0.000	0.000	0.001
Construction	0.005	0.009	-0.004	0.000
Installation	0.024	0.034	-0.010	0.000
Production	0.012	0.010	0.002	0.000
Transportation	0.061	0.074	-0.013	0.000
Observations	8809770	1393129		

Note: This table shows the occupational mix of the LinkUp job posting data from 2017-2020, the period before the period prior to Colorado's pay transparency law. Control states are California, Oregon, and Washington.

Table 3: Effect of Pay Transparency Law on Posted Salaries, LinkUp Job Posting

	log(Mid Salary)			log(Min Salary)			log(Max Salary)		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Treat	0.131***	0.050***	0.050***	0.071**	0.012*	0.013**	0.180***	0.081***	0.081***
	(0.033)	(0.010)	(0.010)	(0.029)	(0.007)	(0.006)	(0.036)	(0.015)	(0.014)
Month FE	X			X			X		
Zipcode FE	X			X			X		
SOC-Month FE		X	X		X	X		X	X
Firm-SOC-zip FE		X	X		X	X		X	X
Sector-Month FE			X			X			X
Observations	1877126	1773154	1773124	1877126	1773154	1773124	1877126	1773154	1773124
Adjusted R^2	0.160	0.879	0.879	0.152	0.859	0.860	0.162	0.885	0.885
Mean	47314.485	47035.501	47035.622	43006.859	42749.299	42749.393	51141.401	50842.705	50842.848

Note: This table shows the effect of the pay transparency law on posted wages using the LinkUp job posting data estimated with Equation 2. The outcome variable for columns (1), (2), and (3) is the log of the midpoint salary. The outcome variable for columns (4), (5), and (6) is the log of the minimum salary. The outcome variable for columns (7), (8), and (9) is the log of the maximum salary. Columns (1), (4), (7) control for month and zipcode fixed effects. Columns (2), (5), and (8) control for the interaction between occupation and month and the interaction between firm, occupation, and zipcode. Columns (3), (6), and (9) also control for the interaction between industry (2-digit NAICS code) and month in addition to the above interactions. Standard errors are clustered at the firm level.

Table 4: Effect of Pay Transparency Law on Posted Salaries by Wage Setting Approach, LinkUp Job Posting

Dep var: log(midpoint posted wage)	Subsample: Salary Range			Subsample: Salary Rate		
	(1)	(2)	(3)	(4)	(5)	(6)
Treat	0.006	0.027**	0.026**	0.090***	0.028***	0.030***
	(0.052)	(0.012)	(0.012)	(0.032)	(0.010)	(0.010)
Month FE	X			X		
Zipcode FE	X			X		
SOC-Month FE		X	X		X	X
Firm-SOC-zipcode FE		X	X		X	X
Sector-Month FE			X			X
Observations	1060486	989071	989032	816423	759271	759247
Adjusted R^2	0.210	0.882	0.882	0.149	0.891	0.891
Mean	54452.219	54209.226	54209.316	39421.731	39033.261	39033.091

Note: This table shows the effects of the pay transparency law on posted wages using the LinkUp job posting data estimated with Equation 2. The outcome variable is the log of the midpoint salary. Columns (1), (2), and (3) restrict to the subsample of job postings with salary ranges and columns (4), (5), and (6) restrict to the subsample of job postings with salary rates. Columns (1) and (4) control for month and zipcode fixed effects. Columns (2) and (5) also control for the interaction between firm, occupation, and zipcode. Columns (3) and (6) also control for the interaction between industry (2-digit NAICS code) and month in addition to the above interactions. Standard errors are clustered at the firm level.

Table 5: Effect of Pay Transparency Law on Posted Maximum/Minimum Salary Ratios, LinkUp Job Posting

	Max/Min > 1.5?			Max/Min > 1.75?		
	(1)	(2)	(3)	(4)	(5)	(6)
Treat	0.065***	0.053***	0.055***	0.017	0.012*	0.011
	(0.018)	(0.018)	(0.017)	(0.011)	(0.007)	(0.007)
Month FE	X			X		
Zipcode FE	X			X		
SOC-Month FE		X	X		X	X
Firm-SOC-zipcode FE		X	X		X	X
Sector-Month FE			X			X
Observations	2510633	2362141	2362117	2510633	2362141	2362117
Adjusted R^2	0.105	0.708	0.710	0.085	0.697	0.700
Mean	0.132	0.132	0.132	0.060	0.061	0.061

Note: This table shows the effect of the pay transparency law on the ratio of posted maximum salary to posted minimum salary using LinkUp job posting data estimated with Equation 2. The outcome variables are binary indicators for whether the ratio of maximum salary to minimum salary is above 1.5 and above 1.7. Columns (1) and (4) control for month and zip code fixed effects. Columns (2) and (5) also control for the interaction between firm, occupation, and zip code. Columns (3) and (6) also control for the interaction between industry (2-digit NAICS code) and month in addition to the above interactions. Standard errors are clustered at the firm level.

Table 6: Effect of Pay Transparency Law on Realized Wage Rates, CPS ORG

Outcome: log(hourly wage)	Full Sample			Subsample: Job Changer			Subsample: Job Stayer		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Treat	-0.001	0.001	0.004	-0.011	-0.005	0.013	0.000	0.002	0.005
	(0.003)	(0.001)	(0.002)	(0.014)	(0.014)	(0.018)	(0.002)	(0.001)	(0.002)
Control	X	X	X	X	X	X	X	X	X
State FE	X	X	X	X	X	X	X	X	X
Month FE	X	X	X	X	X	X	X	X	X
Occupation		X	X		X	X		X	X
Occupation×Year		X	X		X	X		X	X
Industry			X			X			X
Industry×Year			X			X			X
Observations	96598	93669	92530	6774	6465	6350	89824	87117	86067
Adjusted R^2	0.422	0.521	0.532	0.418	0.536	0.542	0.422	0.520	0.532
Mean Wage	23.153	23.048	23.041	22.143	21.968	21.977	23.232	23.132	23.124

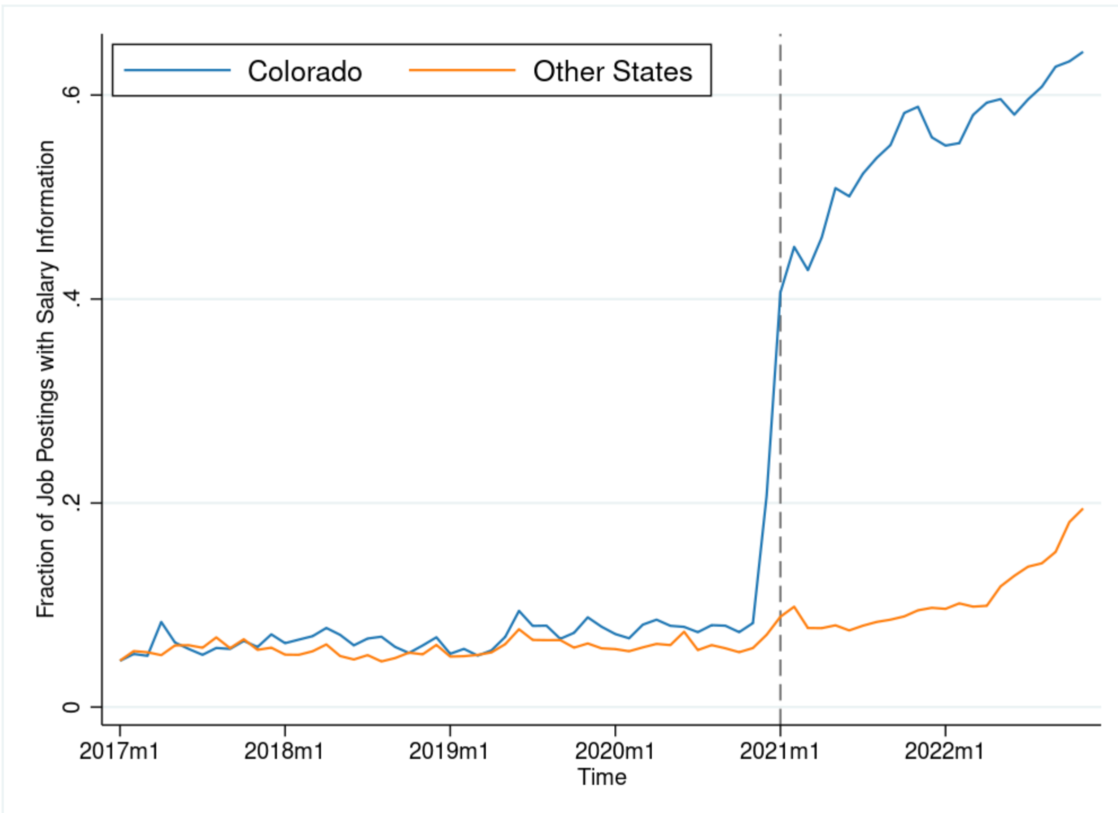
Note: This table shows the effects of the pay transparency law on realized wages using data from the Current Population Survey Outgoing Rotation Group estimated with Equation 3. The CPS Outgoing Rotation Group only records the earnings of respondents in the 4th and 8th months of the survey period. Columns (1)-(3) keep the full sample of workers regardless of whether they have changed jobs between the 4th and 8th months. Columns (4)-(6) keep a subsample of workers who can be credibly identified as having changed jobs during the CPS survey period. Columns (7)-(9) keep a subsample of workers who are not job changers. All columns control for age, race, education, worker classification, state, calendar month, full-time/part-time status, and whether paid hourly. Standard errors are clustered at the state level.

Table 7: Effect of Pay Transparency Law on the Gender Wage Gap, CPS ORG

Outcome: log(hourly wage)	Full Sample			Subsample: Job Changer			Subsample: Job Stayer		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Female×Treat	0.014	0.012	0.014	0.024***	0.062**	0.089**	0.012	0.012	0.011
	(0.006)	(0.008)	(0.008)	(0.004)	(0.018)	(0.023)	(0.007)	(0.007)	(0.009)
Female	-0.145***	-0.107***	-0.102***	-0.118***	-0.079**	-0.077**	-0.147***	-0.147***	-0.104***
	(0.012)	(0.006)	(0.006)	(0.016)	(0.016)	(0.014)	(0.012)	(0.012)	(0.005)
Female×CO	-0.026	-0.021	-0.022	-0.010	0.011	0.006	-0.027	-0.027	-0.022
	(0.014)	(0.012)	(0.012)	(0.019)	(0.025)	(0.028)	(0.014)	(0.014)	(0.012)
Treat	-0.007*	-0.004	-0.002	-0.026	-0.033	-0.025	-0.005	-0.005	-0.000
	(0.003)	(0.003)	(0.002)	(0.016)	(0.019)	(0.016)	(0.004)	(0.004)	(0.003)
Female×Post	0.020*	0.029***	0.027***	0.012*	-0.000	0.005	0.021*	0.021*	0.028***
	(0.007)	(0.003)	(0.003)	(0.004)	(0.013)	(0.014)	(0.007)	(0.007)	(0.003)
Control	X	X	X	X	X	X	X	X	X
State FE	X	X	X	X	X	X	X	X	X
Month FE	X	X	X	X	X	X	X	X	X
Occupation		X	X		X	X		X	X
Occupation×Year		X	X		X	X		X	X
Industry			X			X			X
Industry×Year			X			X			X
Observations	96598	93669	92530	6774	6465	6350	89824	89824	86067
Adjusted R^2	0.423	0.521	0.532	0.429	0.538	0.544	0.422	0.422	0.532
Mean	23.153	23.048	23.041	22.143	21.968	21.977	23.232	23.232	23.124

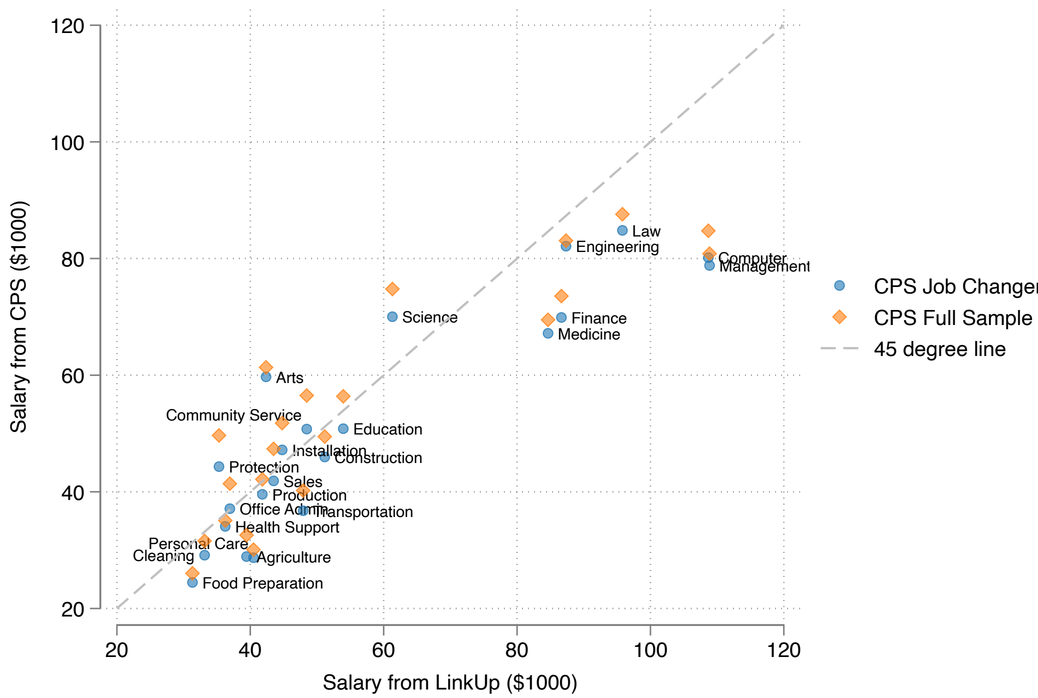
Note: This table shows the effects of the pay transparency law on the gender wage gap using data from the Current Population Survey Outgoing Rotation Group estimated with Equation 6. All columns control for age, race, education, state, month, and worker classification. The coefficient on 'Treat' denotes the effect on men, and that on 'Female×Treat' is the effect on the gender wage gap. The coefficient on 'Female' is the baseline gender wage gap in the control states. The coefficient on 'Female×CO' shows the baseline difference in the gender wage gap between Colorado and the control states. Columns (1)-(3) keep the full sample of workers regardless of whether they have changed jobs between the 4th and 8th months. Columns (4)-(6) keep a subsample of workers who can be credibly identified as having changed jobs during the CPS survey period. Columns (7)-(9) keep a subsample of workers who are not job changers. All columns control for age, race, education, worker classification, state, calendar month, full-time/part-time status, and whether paid hourly. Standard errors are clustered at the state level.

Figure 1: Fraction of Job Postings with Salary Information in CO vs. All Other States



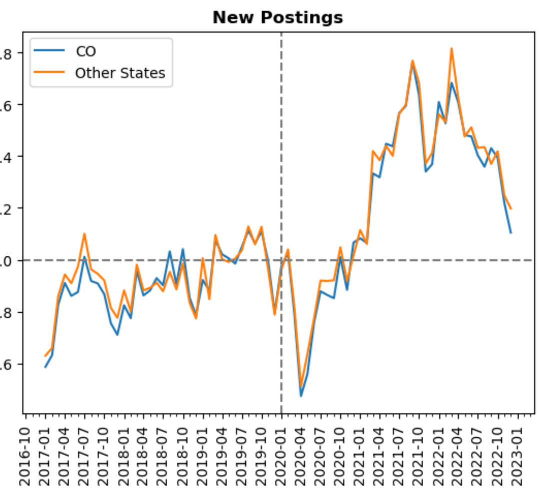
Note: This figure illustrates the fraction of job postings with salary information for Colorado versus all other U.S. states by month.

Figure 2: Comparison Between LinkUp Job Postings Data and CPS Wage Data by Occupation

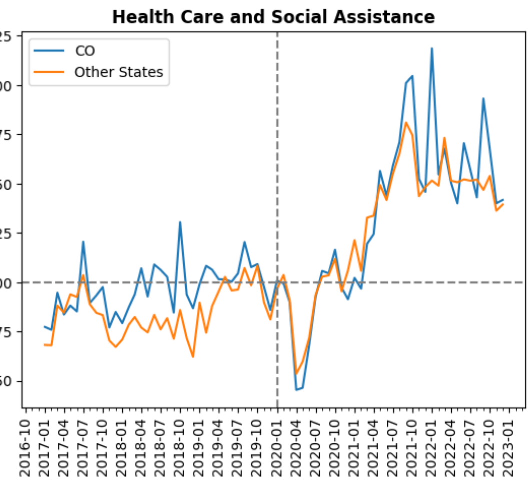


Note: This figure compares mean annual wages by occupation between the LinkUp job postings data and wage data from the CPS. Blue dots display the mean wage of the respective occupation from the LinkUp data on the x-axis and the CPS full sample on the y-axis. Orange diamonds display the mean wage of the respective occupation from the LinkUp data on the x-axis and the mean wage of the respective occupation from the CPS job changer subsample on the y-axis. Both axes use units of thousands to denote the x- and y-coordinates of each circle.

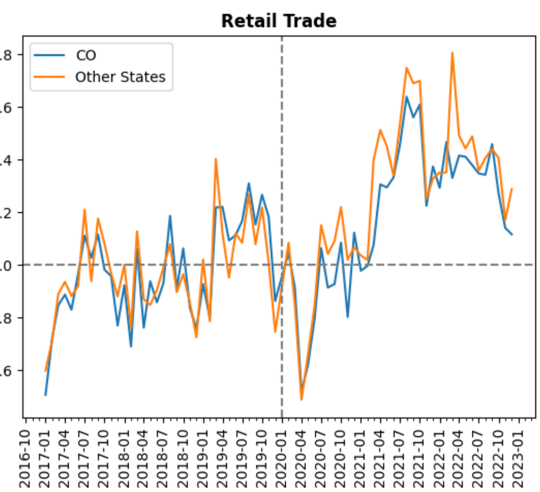
Figure 3: Impact of COVID-19 Pandemic on Number of New Job Postings, LinkUp Job Posting



(a)



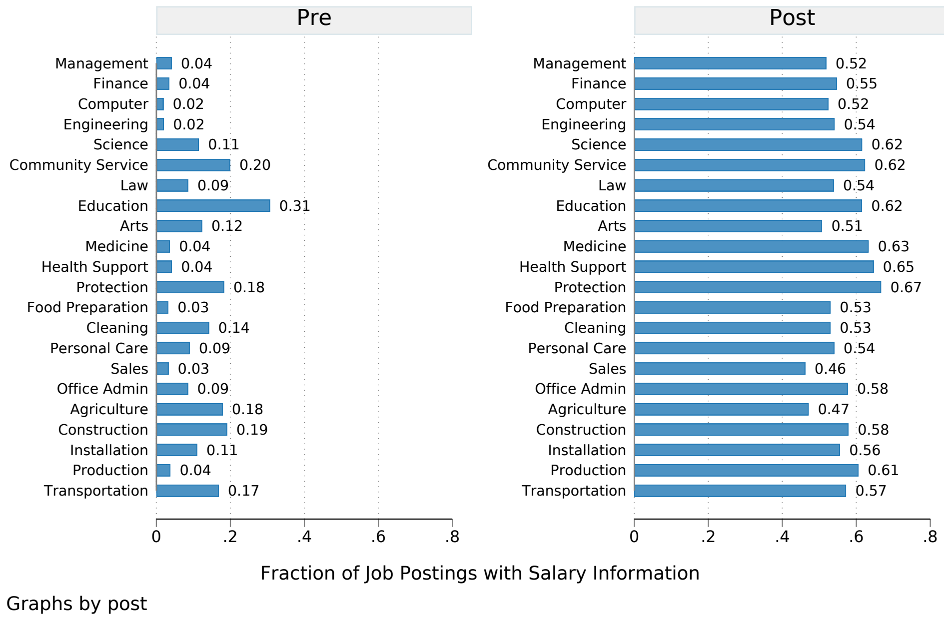
(b)



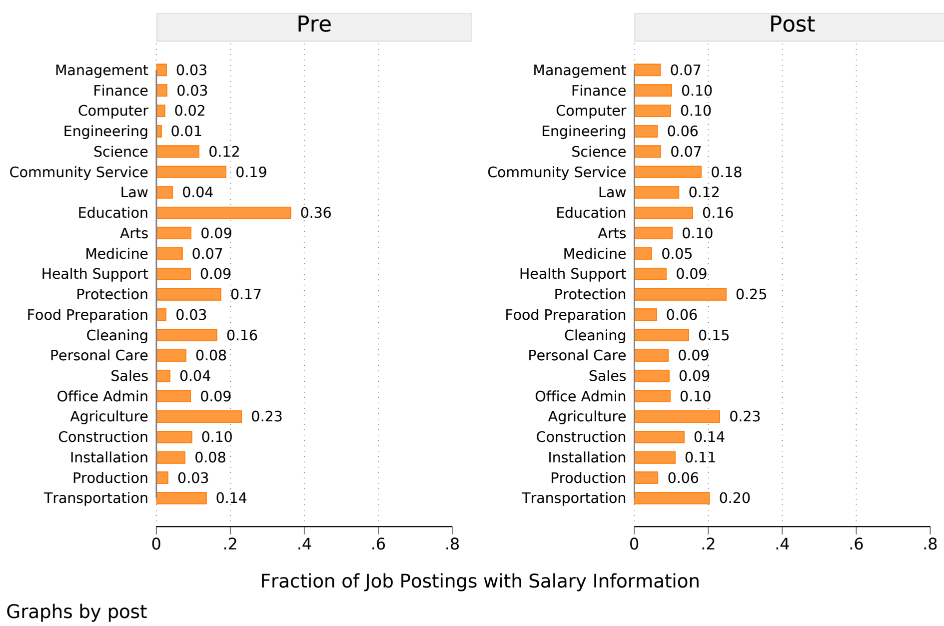
(c)

Note: These figures display the total number of newly created job postings and the number by sector in Colorado versus all other states relative to the average number of postings in January and February 2020 (pre-COVID). The values for both Colorado and other states are mechanically close to one in January and February 2020. Sectors are defined by the NAICS 2-digit industry code: Health Care and Social Assistance is NAICS code 62; Retail Trade is NAICS codes 44 and 45.

Figure 4: Fraction of Job Postings with Salary Information by Occupation: Pre vs. Post, LinkUp Job Posting



(a) Colorado

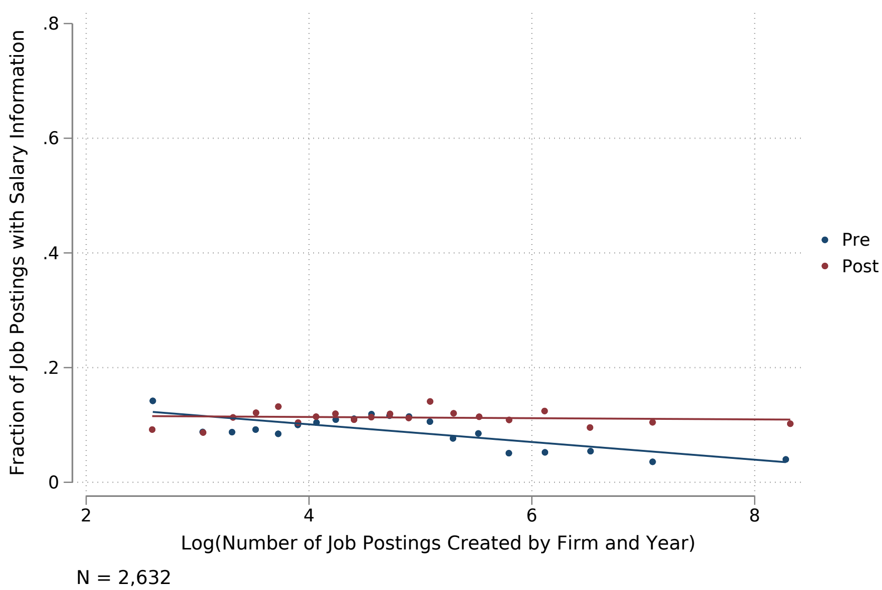


(b) Control States

Note: This figure shows the fraction of job postings with salary information by occupation in the pre- and post-period separately. Panel A is for Colorado and Panel B is for the control states. Control states are West Coast states: California, Oregon, and Washington. Pre-period refers to 2017-2020, and post-period refers to 2021-2022.

Figure 5: Fraction of Job Postings with Salary Information by Firm Size in Colorado: Pre vs. Post, LinkUp Job Posting

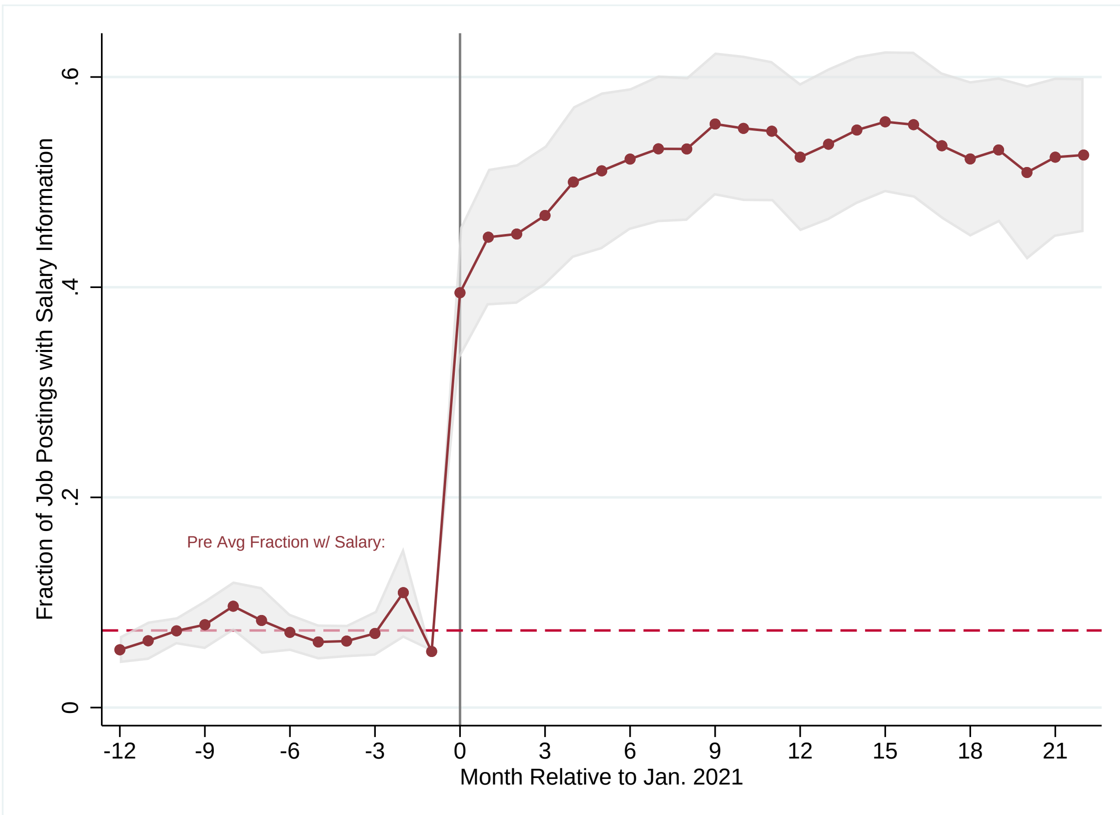
(a) Colorado



(b) Control States

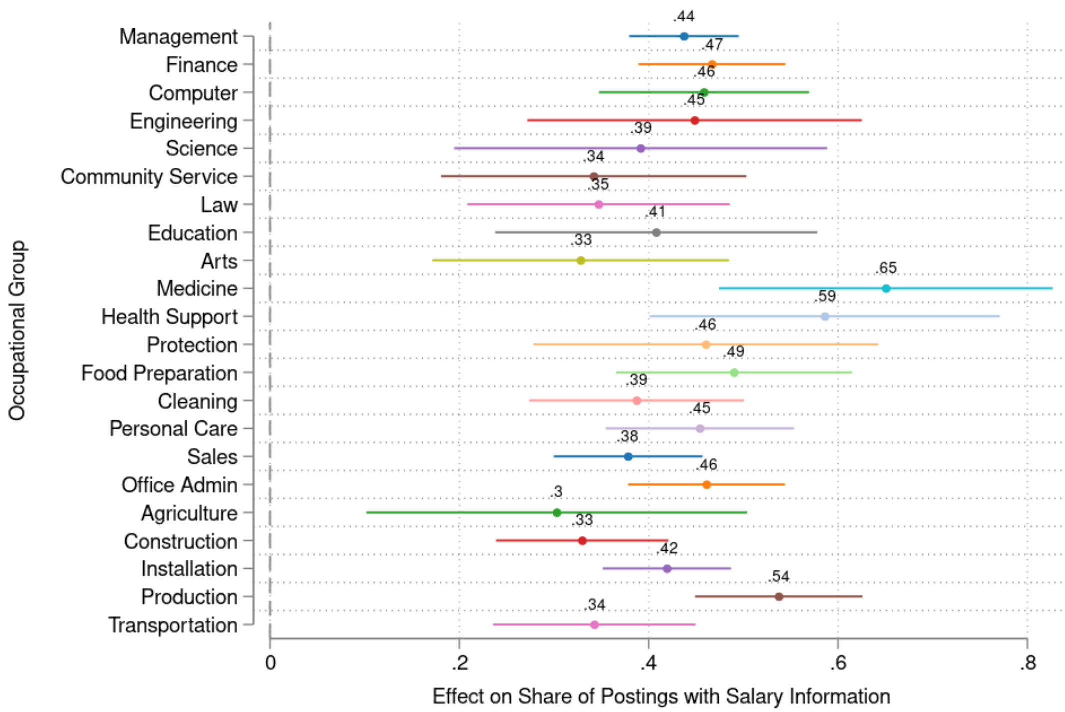
Note: This binscatter plots the fraction of job postings with salary information by firm and year as a function of the log of the number of job postings by the same firm and in the same year in the pre- and post-period separately. Control states are West Coast states: California, Oregon, and Washington. For Panel A, the sample is restricted to firms that post at least 10 jobs in Colorado per year throughout the study period. This sample consists of 788 firms. For Panel B, the sample is restricted to firms that post at least 10 jobs per year in any of California, Oregon, and Washington throughout the study period. This sample consists of 2632 firms. Linear fitted lines are plotted. The red dots and lines represent data from 2017 to 2020, and the blue dots and lines represent data from 2021 to 2022.

Figure 6: Effect of Pay Transparency Law on Fraction of Job Postings with Salary Information, LinkUp Job Posting



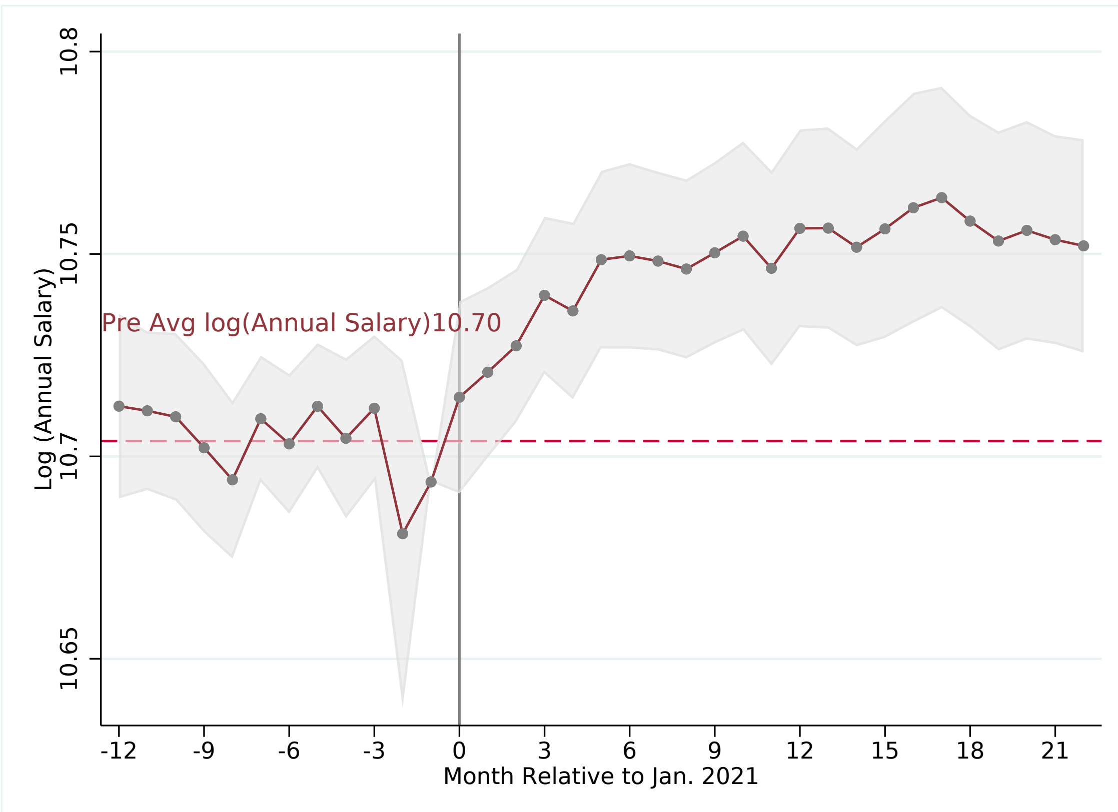
Note: This figure reports the effect of the pay transparency law on the fraction of job postings with salary information by month estimated with Equation 1. The corresponding econometric specification controls for interaction (1) between occupation (6-digit ONet code) and month and (2) between firm, occupation, and zipcode. All coefficients are shifted such that the pre-treatment coefficients average to the pre-treatment mean of log salary.

Figure 7: Effect of Pay Transparency Law on Fraction of Job Postings with Salary Information by Occupation, LinkUp Job Posting



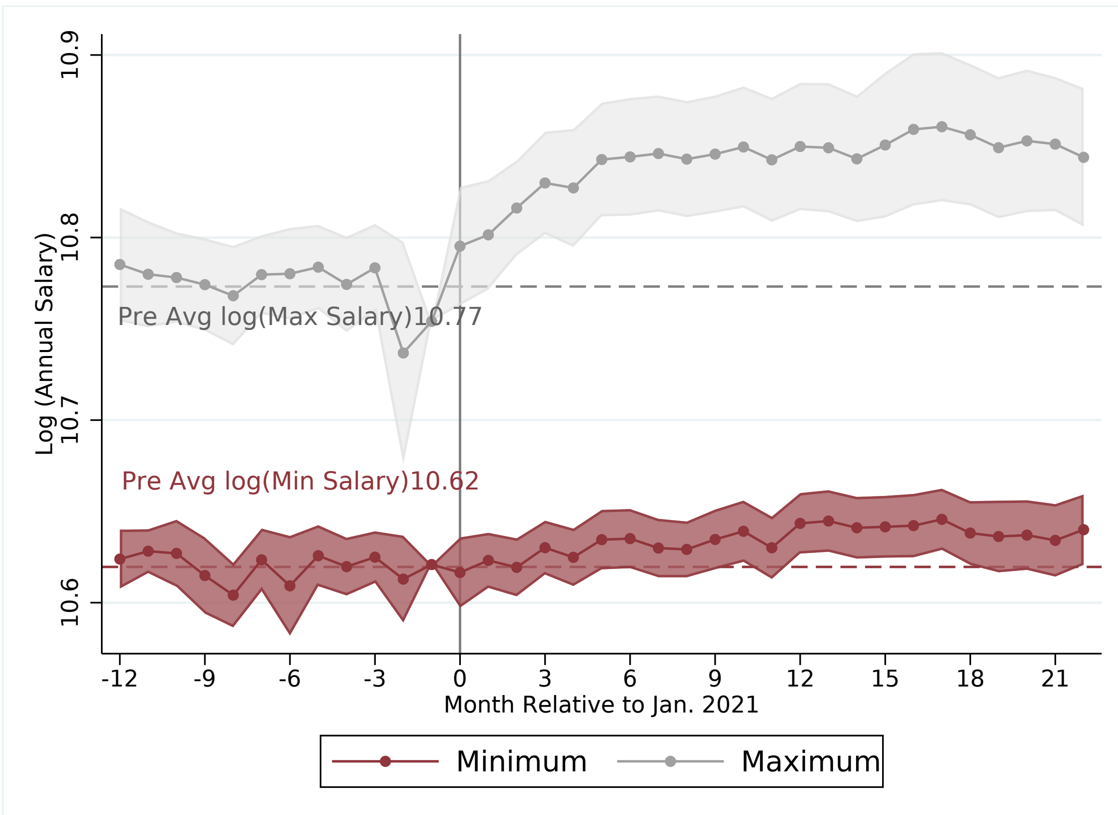
Note: This figure reports the point estimates and the 95% confidence intervals of the effect of pay transparency law on the fraction of job postings with salary information by occupation estimated with **??**. Data source: LinkUp Job Posting Data.

Figure 8: Effect of Pay Transparency Law on Posted Salaries, LinkUp Job Posting



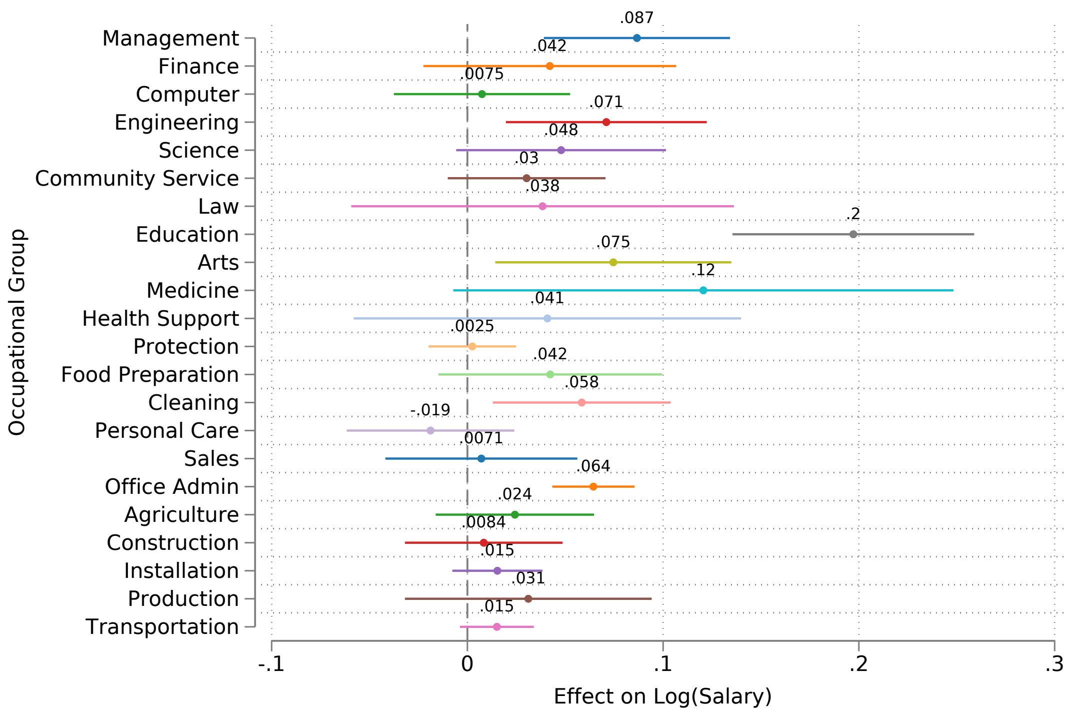
Note: This figure reports the effect of the pay transparency law on the log of the posted midpoint wage by month. The corresponding econometric specification controls for interaction (1) between occupation (6-digit ONet code) and month and (2) between firm, occupation, and zipcode estimated with Equation 1. All coefficients are shifted such that the pre-treatment coefficients average to the pre-treatment mean of log salary. The band represents the 95% confidence interval. Standard errors are clustered at the firm level. Data source: LinkUp Job Posting Data.

Figure 9: Effect of Pay Transparency Law on Posted Minimum and Maximum Salaries, LinkUp Job Posting



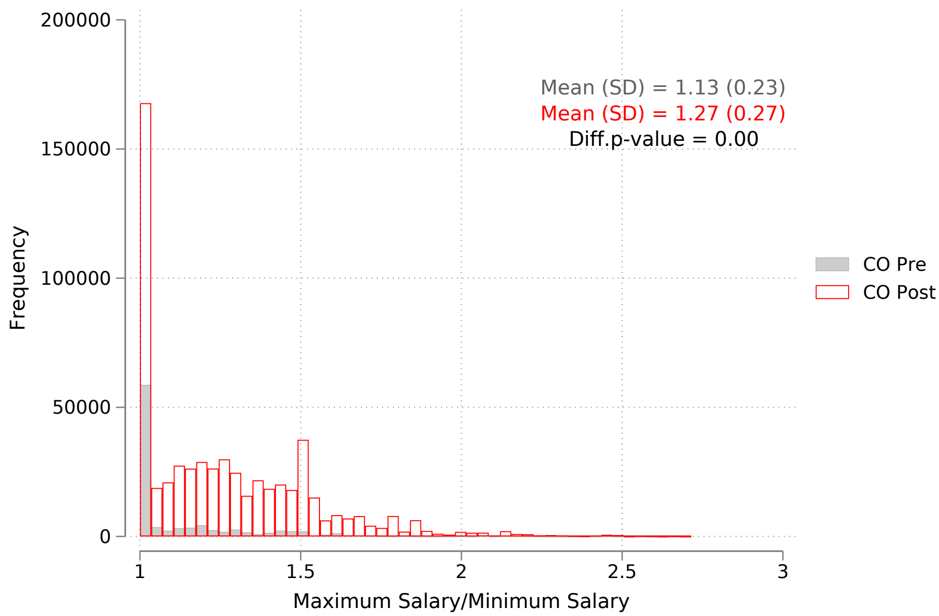
Note: This figure reports the effect of the pay transparency law on the log of the posted midpoint wage by month. The corresponding econometric specification controls for interaction (1) between occupation (6-digit ONet code) and month and (2) between firm, occupation, and zipcode. All coefficients are shifted such that the pre-treatment coefficients average to the pre-treatment mean of log salary. The band represents the 95% confidence interval. Standard errors are clustered at the firm level. Data source: LinkUp Job Posting Data.

Figure 10: Effect of Pay Transparency Law on Posted Salaries by Occupation, LinkUp Job Posting

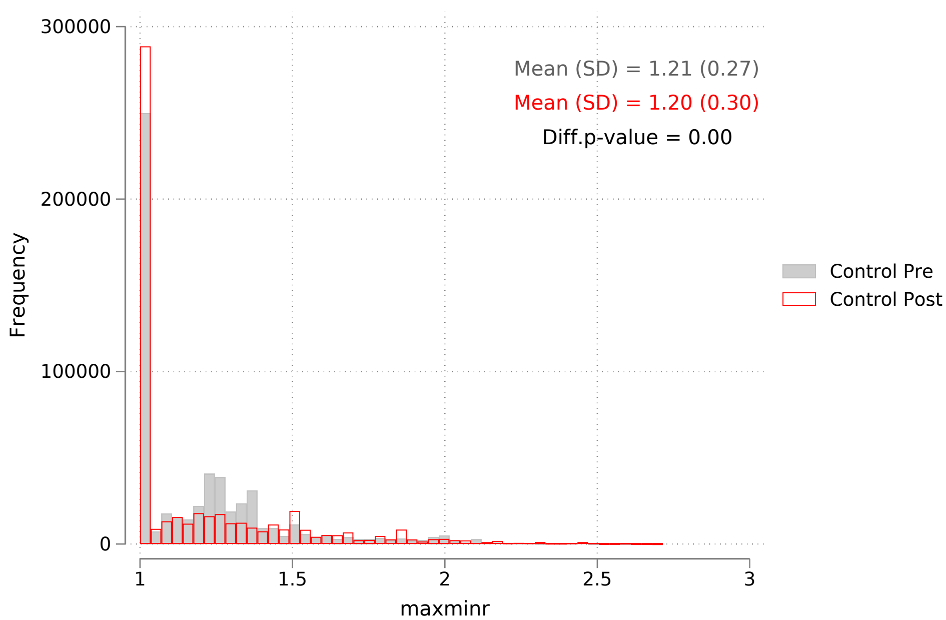


Note: This figure reports the point estimates and the 95% confidence intervals of the effect of pay transparency law on posted midpoint wages by occupation. Data source: LinkUp Job Posting Data.

Figure 11: Histograms of Maximum Salary/Minimum Salary: Pre vs. Post, LinkUp Job Posting



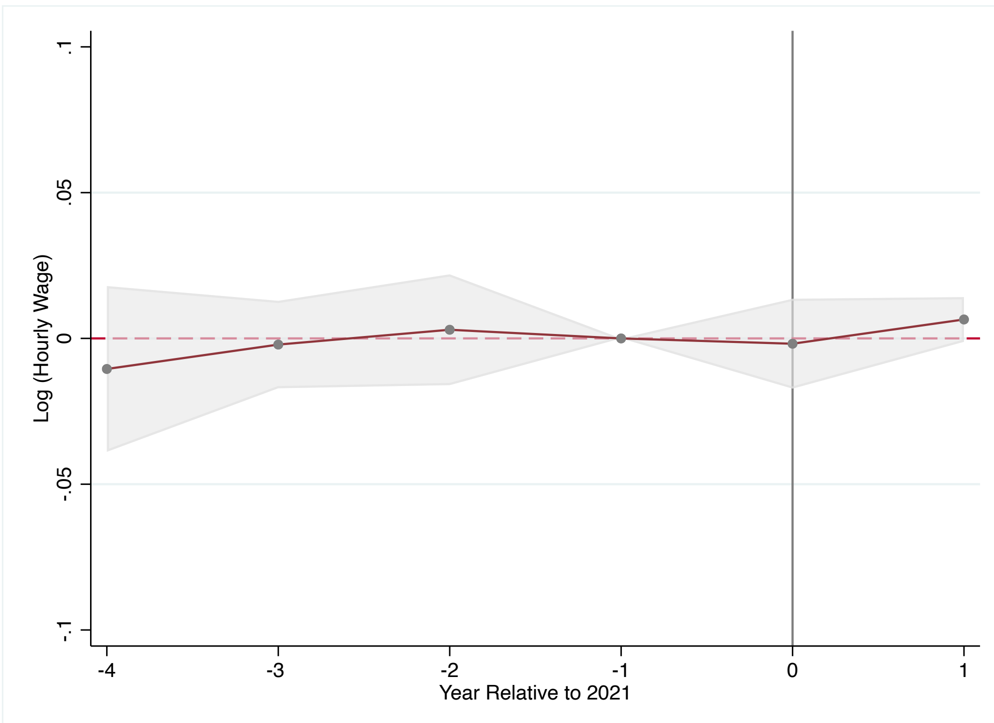
(a) Colorado



(b) Control States

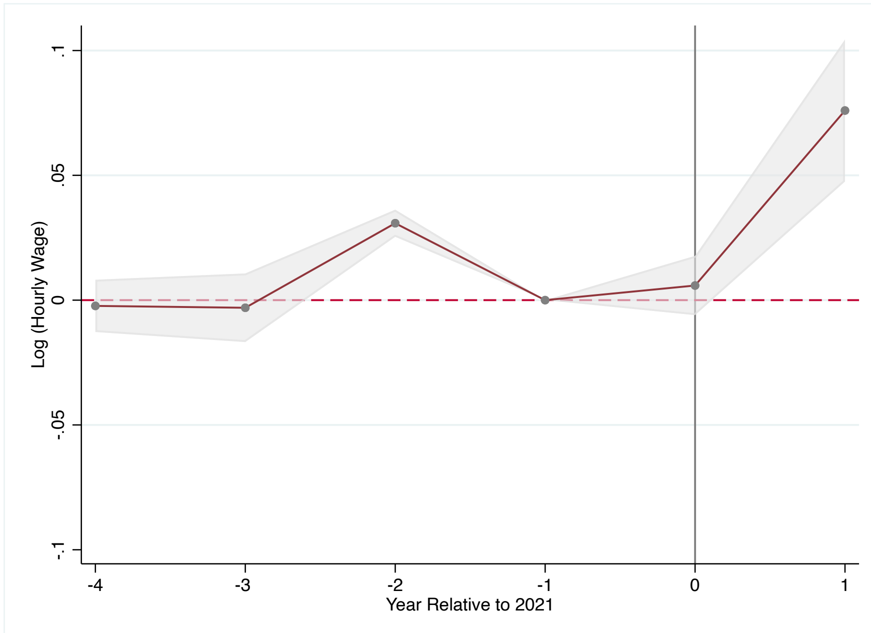
Note: This histogram shows the ratio of the maximum salary to the minimum salary in the pre- and post-period separately. Panel A is for Colorado and Panel B is for the control states. Control states are West Coast states: California, Oregon, and Washington. Pre-period refers to 2017-2020, and post-period refers to 2021-2022. The y-axis is the frequency. Data source: LinkUp Job Posting Data.

Figure 12: Effect of Pay Transparency Law on Realized Salaries by Year, CPS ORG

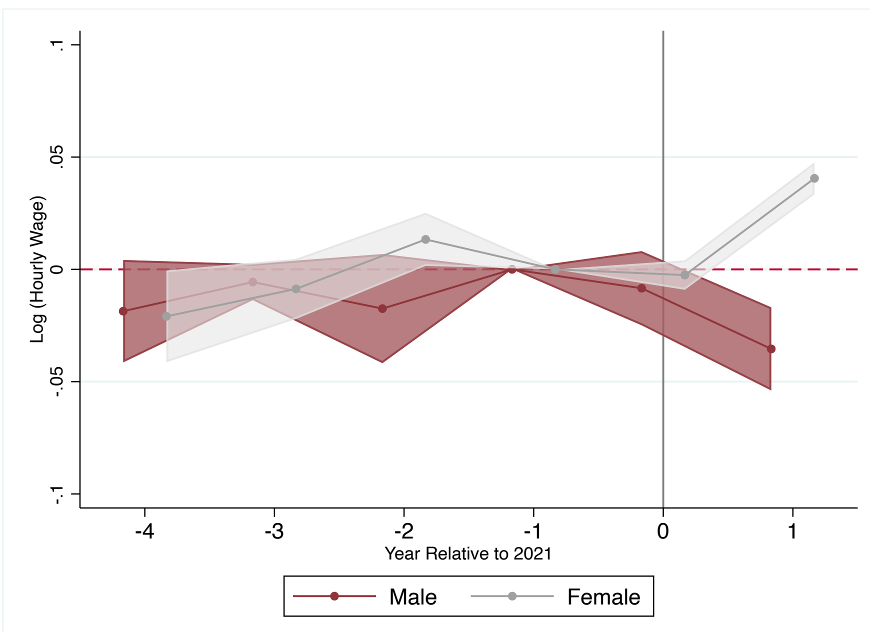


Note: This figure reports the point estimates and the 95% confidence intervals of the effect of the pay transparency law on realized hourly wages estimated with Equation 6. Standard errors are clustered at the state level. Data source: CPS ORG.

Figure 13: Effect of Pay Transparency Law on Realized Wages by Year and Gender, CPS ORG



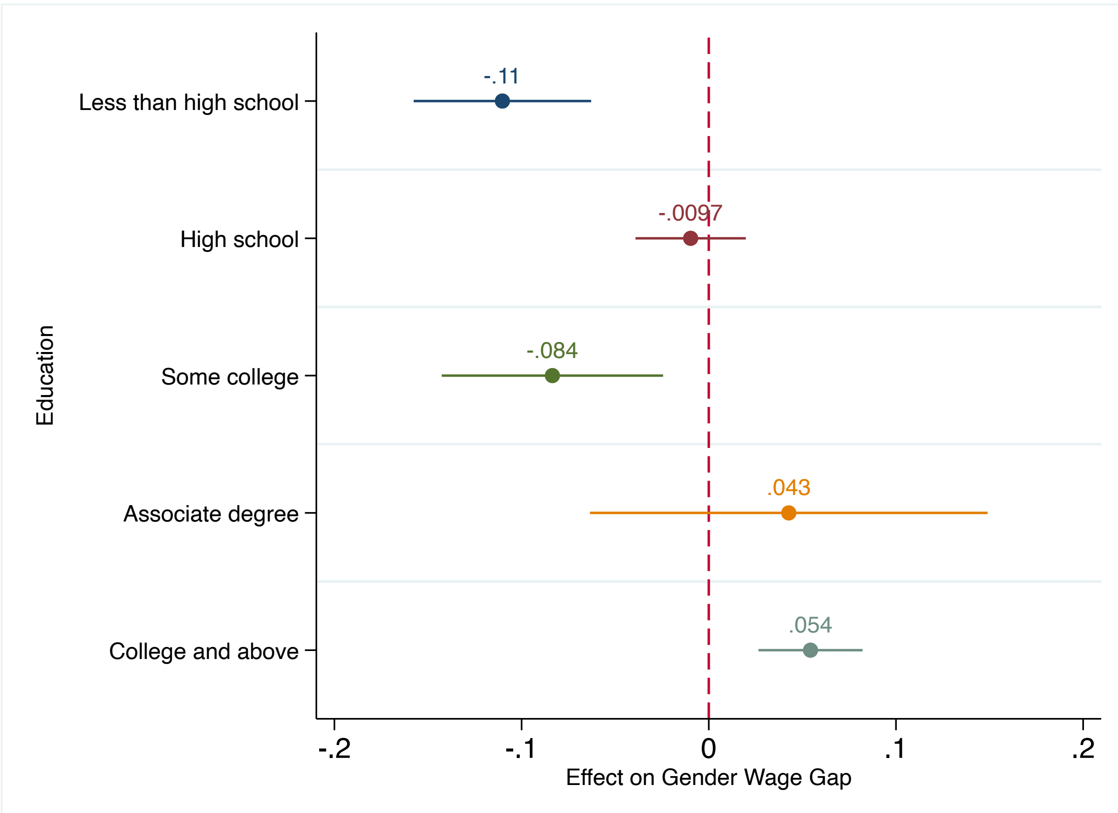
(a) Effect on Gender Wage Gap



(b) Effect by Gender

Note: Panel A reports the point estimates and the 95% confidence intervals of the effect of the pay transparency law on the gender wage gap. Panel B reports the point estimates and the 95% confidence intervals of the effect of the pay transparency law on male and female wages. Both panels are estimated with Equation 5. Standard errors are clustered at the state level. Data source: CPS ORG.

Figure 14: Effect of Pay Transparency Law on the Gender Wage Gap by Education, CPS ORG



Note: This figure reports the point estimates and the 95% confidence intervals of the effect of the pay transparency law on the gender wage gap by educational attainment estimated with Equation 6. Standard errors are clustered at the state level. Data source: CPS ORG.

Online Appendix

Data Appendix: Extracting Wages from Job Descriptions

The job posting data from LinkUp only contains raw job descriptions and does not contain wage information. I use the following procedure to extract posted wages from text-based job postings. Figure A1 illustrates the procedure graphically.

- **Step 1: Extract text chunks containing a dollar sign followed by a digit (e.g., $12, $9, $52,000) from job descriptions.**

  Since raw job descriptions can be very long and contain a lot of information irrelevant to wage information, I keep only sentences in job postings that contain $ followed by a digit or digits. If a job description contains wage information, posted wages should be in these sentences. Without cutting raw job descriptions into shorter sentences, Step 2 can be very time-consuming.

- **Step 2: Use a finetuned question-answering transformer to extract text segments containing wage information from text chunks.**

  After obtaining the sentences that may contain wage information, I use a question-answering transformer to extract phrases that contain posted wages from those sentences. Transformers are a type of neural network architecture that has gained widespread use in NLP tasks such as language modeling, translation, and question-answering. They were first introduced in 2017 by Vaswani et al. (2017).

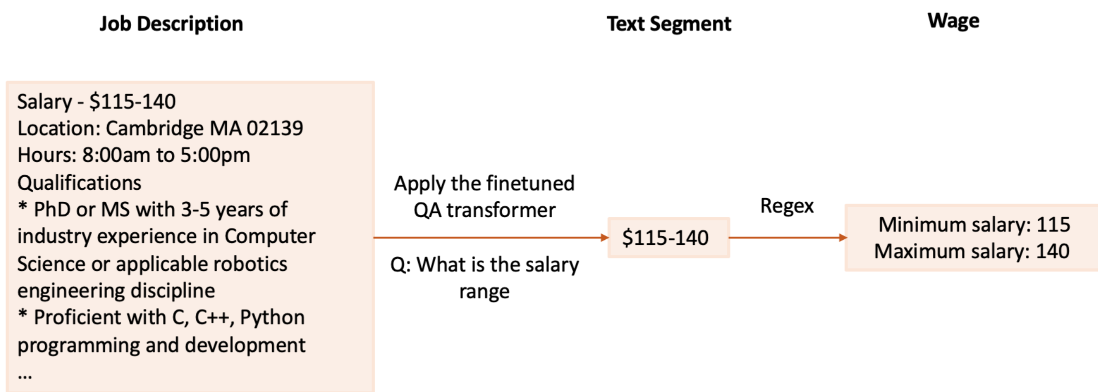
  A question-answering transformer requires two inputs to extract an answer: a question and a context. The transformer will extract the answer to the question from the context and produce a confidence score of the answer. The score ranges from 0 to 1. The more confident the transformer is about the extracted answer, the higher the score. If the context does not contain an answer to the question, the transformer will still extract an "answer", but the score will usually be close to 0.

  I finetuned a pre-trained transformer to achieve better performance in extracting wage information from job descriptions. The pre-trained model used for finetuning is `deberta-v3-large-squad2`. This model is trained using a large set of English Wikipedia articles and has learned general-purpose representations of language that can be finetuned for the downstream task, wage extraction, with relatively little labeled job postings data. The pre-trained transformer learns domain-specific language patterns in job postings during finetuning.

  I randomly drew about 18000 job postings and constructed a labeled dataset with job descriptions and correct wage information for finetuning. The question input of the transformer is "What is the salary range". After finetuning, the accuracy of the transformer improved remarkably. Table A1 shows the evaluation metrics of the original and the finetuned models. The F1 score increased from 66 to 94, and exact matches increased from 54% to 88%.

  In rare cases, the text segment containing the complete wage range is too long to be extracted by the transformer. For example, if the text segment containing the full range is "*Range minimum: $18.00 /hr + bonus * Range maximum: $31.00 /hr + bonus", the answer generated by the transformer to the question will be "Range maximum: $31.00 /hr + bonus". For these cases, I change the question from "What is the salary range" to "What is the maximum salary"

Figure A1: Procedure of Wage Extraction from Job Descriptions



Note: This figure illustrates the procedure of extracting wages from text-based job descriptions using an excerpt of a job posting.

and "What is the minimum salary" and apply the finetuned transformer to extract maximum and minimum salaries separately.

- **Step 3: Use a regular expression to extract wage numbers from text segments containing wage information.**

  After getting text segments containing wages, I use a regular expression to extract all numbers following a dollar sign in text segments. I code the smallest number as the minimum salary and the largest as the maximum salary.

Table A1: Evaluation Metrics of the Finetuned and the Original Transformers

Metric	Finetuned	Original
% Exact Match	88.05	54.08
F1 Score	93.76	66.39
Sample Size	2694	2694

Note: This table compares the performance of the fintuned and the original transformers. For each question+answer pair, if the characters of the model's prediction exactly match the characters of (one of) the True Answer(s), Exact match = 1; otherwise, Exact match = 0. The F1 score is the harmonic mean of the precision and recall.

References

Vaswani, A., Shazeer, N., Parmar, N., Uszkoreit, J., Jones, L., Gomez, A. N., Kaiser, Ł., and Polosukhin, I. (2017). Attention is all you need. *Advances in neural information processing systems*, 30.