Pay Transparency and Job Search

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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 establish a partial equilibrium job search model with subjective beliefs to illustrate how pay transparency can affect the gender gap in wage beliefs and, consequently, job search behavior and outcomes. The pay transparency law decreased the gender wage gap for job changers and job stayers by 11.1% and 1.6%, respectively. The narrowing of the gender wage gap was driven by an increase in female wages and a decrease in male wages. Compared to men, pay transparency increased women's job mobility and decreased women's employment.

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

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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. 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 West Coast states (California, Oregon, and Washington) 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.

Wage posting varied considerably across occupations in the pre-period, and middle-wage occupations had a higher fraction of wage posting (around 20%) than low-wage occupations (below 20%) and high-wage occupations (below 10%), which is consistent with Batra et al. (2023). 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. However, after the pay transparency law, there was less variation in wage posting across occupations. Non-compliance was not negligible in any 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 showed higher compliance, likely due to more established HR practices.

I evaluate the informativeness of posted wages by comparing LinkUp posted wages and CPS occupational median wages. I find a positive selection into wage posting for lower-wage occupations and a negative selection for higher-wage ones. I find that the lower bound of posted wages aligns more closely with actual wages from the CPS, providing more accurate salary expectations for job seekers than the upper bound. The transparency law has led to wider posted wage ranges across all occupations, which may indicate that employers are raising the upper bound to obfuscate true salary expectations and attract workers.

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 small increase in the minimum salary and the large increase in the maximum salary mirror the previous descriptive result that employers post wider wage ranges after the pay transparency law was enacted.

I establish a partial equilibrium job search model with subjective beliefs to illustrate how inaccurate beliefs about wages can affect labor search behavior and labor outcomes. My model builds upon both the original job search model from McCall (1970) as well as previous job search models with subjective beliefs, specifically Cortés et al. (2023) and Jiang and Zen (2023). The model implies that if women have lower beliefs than men, holding all else constant, they will have lower reservation wages and a lower unemployment rate. After the pay transparency law discloses wage information, the gender belief gap should decrease or disappear. The model predicts that the gender gap in reservation wages will decrease, leading to a decrease in the gender wage gap. Additionally, pay transparency may increase the probability of unemployment for women compared to men. This is because women tend to be more selective in accepting job offers after learning about expected wages in job postings, leading to higher reservation wages and a higher likelihood of unemployment.

Overall, 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 wage rates for either job changers or job stayers, although job changers are likely to be directly exposed to posted wage information.

The pay transparency law reduced the gender wage gap by about 2% in the full sample by reducing men's wages and increasing women's wages. For the subsample of job changers, there is an 11% within-occupation reduction in the gender wage gap, suggesting that women are more likely than men to switch to higher-paying employers as a result of the pay transparency law. Part of the reduction in the gender wage gap is due to a decrease in the wages of male job changers. Across specifications, the decrease in male wages for this group ranges from 4.4% to 6.2%, although none of the estimates are significant at the 5% significance level. Job stayers experience a small reduction in the gender wage gap (1.6%), suggesting that the pay transparency law also affects the gender wage gap through the bargaining channel. In sum, Colorado's pay transparency law proves effective in promoting pay equity, while some of this reduction is driven by adverse effects on male wages.

Compared to men, pay transparency increased the probability of women changing jobs by more than 1 percentage point and decreased the probability of women being employed by 1 percentage point. Conversely, pay transparency reduced men's probability of changing jobs by more than 1 percentage point, but did not affect men's employment rate. Thus, the increased wage information brought about by the pay transparency law promoted job mobility for women, but depressed job mobility for men. The empirical result is consistent with the model's prediction that women increase their reservation wages relative to men and become more "picky" about job offers after observing more wage information.

In the first robustness check, I use synthetic difference-in-differences (SDID) developed by Arkhangelsky et al. (2021) (1) to show that the above results are not driven by the choice of control group; and (2) to better deal with the nonparallel prior trends in some event study specifications. Using two donor pools: (1) West Coast states, and (2) ten states that had statewide salary history bans before 2020 (Alabama, California, Connecticut, Delaware, Illinois, Maine, Massachusetts, Oregon, Rhode Island, Vermont, and Washington), I obtain qualitatively similar results to DID, suggesting that my results are robust to different control group compositions.

In the second robustness check, I use a comparison within Colorado and compare the private sector to the public sector. One concern that is not addressed by the SDID design, or by any comparison between Colorado and other states, is that the effects on work outcomes may be driven by Colorado-specific confounders that are not the pay transparency law. To mitigate this concern, I use a comparison within Colorado, comparing the private sector to the public sector. In Colorado, public sector wages were public information prior to the pay transparency law, so the pay transparency law should not reveal much new information about wages to the labor market. Therefore, I use the public sector as the control group and the private sector as the treated group and repeat the DID analysis. Overall, the signs of the estimates are consistent with the cross-state DID and SDID estimates, although the estimates are very imprecise due to the small sample size.

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 pay transparency law and introduce the data. Section 3 will provide descriptive evidence on wage posting. Section 4 will report the results in job postings.

Section 5 will lay out a job search model with subjective beliefs. Section 6 will report the results on labor outcomes. Section 7 will present robustness checks and section 8 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 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]

[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.

[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.

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 ranges. The detailed description of the whole procedure is in Online 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. The distribution of occupations of job postings in Colorado is quite similar in Colorado versus the control states. [4] 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. 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 ($45,022) than in West Coast states ($54,249) and SHB states ($52,856). In Colorado, about 29% of job postings with salary information list annual wage rates and 66% list hourly wage rates. West Coast states have similar job postings with annual wage rates (29%) and slightly fewer job postings with hourly wage rates (63%) in proportion. SHB states have more job postings with annual wage rates (32%) and fewer job postings with hourly wage rates (61%).

[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.

[4] See Table A1 for a complete comparison of the occupational mix of job postings between Colorado and the control states.

2.3 CPS Data

The second dataset is the CPS (Flood et al., 2023). 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. [5]

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 Descriptive Evidence

3.1 LinkUp and CPS: Data Comparison

To assess the representativeness of the LinkUp data, I compare the LinkUp job posting data with the CPS wage data by occupation in Figure 1. 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 diamonds 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. 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. [6] The

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

[6] Apart from the CPS full sample, I also compare LinkUp job posting data with the CPS job changer

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 diamonds are close to the 45-degree line, indicating that posted wages are comparable to wages from a representative survey across occupations.

3.2 Wage Posting Pattern

Wage Posting and Occupation Which employers posted wage information in job vacancies before the pay transparency law required them to do so? Panel A of Figure A3 displays the fraction of job postings with salary information by occupation in Colorado, where blue bars represent the pre-period and orange bars represent increments (decrements) from the pre-period to the post-period. Occupations are ordered by CPS wage level from lowest to highest. Wage posting varied considerably across occupations in the pre-period, and middle wage occupations had higher fraction of wage posting (around 20%) than low wage occupations (below 20%) and high wage occupations (below 10%), which is consistent with Batra et al. (2023). 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. However, after the pay transparency law, there was less variation in wage posting across occupations, although middle wage occupations still had more wage information than low wage and high wage occupations overall. Non-compliance was not negligible in any occupation, ranging from 33% to 54%.

Panels B and C of Figure A3 show the fraction of job postings with salary information by occupation in West Coast and SHB states, respectively. The pattern of wage posting in the pre-period is very similar to that in Colorado. The pattern persisted from the pre-period to the post-period, with a small change for each occupation.

Wage Posting and Firm Size 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

subsample in Figure A1 and conclusion also holds for the job changer subsample. Job changers are defined as workers who can be credibly identified as having changed jobs in the CPS survey period.

and wage posting in Figure A4. Panel A shows that in Colorado, larger firms are more likely to post wage information in the post-period. In contrast, there was no relationship between wage posting and firm size when there was no regulation at all, as the blue lines in all panels show. Larger companies are more likely to have an established human resources department that tracks changes in laws and regulations. Their noncompliance is also more likely to be discovered by applicants and reported to the CDLE because they have more job openings. These reasons may explain why larger firms have higher compliance rates in Colorado.

3.3 Do Posted Wages Contain Useful Information?

Figure A7 compares posted minimum wages and CPS median wages by occupation. For each occupation, the y-axis shows the fraction of job postings that post a minimum wage above the CPS median wage, conditional on containing any wage information. Jobs in low-wage occupations positively select into wage posting, with 70% - 90% of job postings containing a minimum wage that is higher than the CPS median wage. In contrast, jobs in high-wage occupations negatively select into wage posting, with 20% - 40% of job postings containing a minimum wage that is higher than the CPS median wage. Negative selection into wage posting is weaker in Colorado in the post-period, as panel (b) shows, with at least 40% of job postings across nearly all occupations offering at least the CPS median wage. This pattern is also seen in the control states, but is not as striking. Overall, the pay transparency law induces more high-wage employers to post wage information.

Similarly, Figure A8 compares posted maximum wages and CPS median wages by occupation. For each occupation, the y-axis shows the fraction of job postings that post a maximum wage above the CPS median wage, conditional on containing any wage information. Jobs in low-wage occupations positively select into wage posting, with 80% - 100% of job postings having a maximum wage above the CPS median wage. There is substantial variation in wage posting for middle- and high-wage occupations, with 20% - 80% of job postings containing a maximum wage that is higher than the CPS median wage in all panels except panel (b). In Colorado, 20 out of 22 occupations have at least 60% of job postings that offer at least the CPS median wage in the post-period. This suggests that not all employees receive the upper range of posted wages, with the lower bound more reflective of realized wages.

Salary ranges are only informative to job seekers if they are narrow enough. Despite the pay transparency law, firms may post broad salary ranges, obscuring true salary expectations. 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 max-to-min salary ratio (maximum salary/minimum salary). Panel A of Figure A5 shows the histogram of the frequencies of job postings across the range of max-to-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. The average max-min ratio went from 1.13 to 1.27 after the pay transparency law went into effect. In contrast, in the control states, the variation across the range of ratios is small, as panels B and C of figure Figure A5 show.

Figure A6 breaks down the max-to-min ratio by occupation. Consistent with Batra et al. (2023), higher-wage occupations tend to have wider ranges across all states. However, as panel A shows, after the pay transparency law went into effect, the max-to-min wage ratio increased for all occupations in Colorado, while the max/min ratio decreased slightly for low-wage occupations and increased for high-wage occupations in the control states. The pay transparency law leads employers to post wider wage ranges across all occupations.

Taken together, this evidence suggests that the lower bound of posted wages is more reflective of actual wages than the upper bound, and is more useful for job seekers to infer true salary expectations. We do observe wider salary ranges in the post-period for all occupations. Given that over half of posted upper bounds are higher than the occupational median wage, wider ranges may indicate that employers are raising the upper bound to obfuscate true salary expectations and attract workers.

4 The Effect of Pay Transparency in Online Postings

4.1 Empirical Specification

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

$$Y_{ist} = \beta Treat_{ist} + \mu_{j(i)} + \theta_{c(i),t} + \epsilon_{ist}, \tag{1}$$

where Y_{ist} is (1) the binary variable for whether job posting i in state s at month t contains wage information or not, (2) log posted midpoint wages, (3) log posted minimum wages, and (4) log posted maximum wages. $Treat_{ist}$ is the binary variable that indicates whether the job posting is subject to the wage disclosure requirement in Colorado. $\mu_{j(i)}$ 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. β represents the difference in the outcome variable between Colorado and the control states in the post-period after taking out the difference in the period before the enactment of the pay transparency law.

For each outcome variable estimated by Equation 1, I also estimate an event study specification of the following form to estimate the dynamic effects:

$$Y_{ist} = \sum_{t=-12, t\neq -1}^{23} \beta_t Treat_{ist} + \mu_{j(i)} + \theta_{c(i),t} + \epsilon_{ist}. \tag{2}$$

The coefficient of interest in Equation 2 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 outcome variable 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.

4.2 Effect on Salary Posting

Figure 2 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.

4.3 Effect on Posted Salaries

The pay transparency law increased posted midpoint salaries. Columns (1) - (4) of Table 1 show estimated effects on posted midpoint salaries across different specifications. All four estimates are positive and significant at the 1% significance level. After controlling for occupation and firm fixed effects, the estimate shrinks from 13% (column (1)) to 5% (column (2)), which suggests that there is a larger increase in wage posting from high-wage occupations and firms than from low-wage occupations and firms. In the preferred specification (column (3)), the pay transparency law increased posted midpoint wages by 5%. [7] The green dots in Figure A10 show 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 minimum and maximum salaries in job postings. Columns (5) - (8) of Table 1 report estimated effects on posted minimum salaries. I find about a 1.3% increase for the lower bound of salary ranges using only within-occupation and within-firm variations. 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 (9) - (12) show. The orange and blue dots in Figure A10 display the event study estimates of the effects on posted maximum and minimum salaries respectively. 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 small (about 1%) increase in the minimum salary and the large (about 8%) increase in the maximum salary also mirror the previous descriptive result that employers post wider wage ranges after the pay transparency law was enacted.

The effect of the pay transparency law on posted wages also differs across occupations. I estimate Equation 2 separately for each 2-digit SOC occupation code and display the estimates in Figure A9. 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

[7] This is driven by increases in both salary rates and salary ranges. In the analysis where I split the sample by the wage setting approach - salary range or salary rate, the estimated effect is about 3% in each subsample, as Table A2 shows.

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.

4.4 Summary and Discussion

The pay transparency law in Colorado increased the share of job postings with salary information in Colorado by more than 40 percentage points. Using within-occupation and within-firm variation, the minimum salary increased by only about 1%, while the maximum salary increased by about 8%. As the comparison between posted wages and CPS median wages in section 3.3 shows, the minimum salary is more reflective of actual wages than the maximum salary. Therefore, although the maximum salary might be inflated, the minimum salary still provides useful information for inferring true salary expectations. In this sense, the pay transparency law substantially increased the amount of useful wage information available. This increase in information could affect workers' beliefs about expected wages, especially considering the empirical evidence that workers often have biased beliefs about expected wages (Conlon et al., 2018; Cortés et al., 2023; Jäger et al., 2022). In the next section, I will present a job search model with subjective beliefs to demonstrate the impact of additional wage information on job search.

5 Job Search Model with Subjective Beliefs

In this section, I establish a partial equilibrium job search model with subjective beliefs to illustrate how inaccurate beliefs about wages can affect labor search behavior and labor outcomes. My model builds upon both the original job search model from McCall (1970) as well as previous job search models with subjective beliefs, specifically Cortés et al. (2023) and Jiang and Zen (2023).

5.1 Setup

A risk-neutral unemployed worker seeks to maximize consumption via accepting or rejecting a job offer. In each period t, a worker receives an employment offer. If given an offer, the worker learns of the offer's attached wage w. The worker then chooses between (1) accepting the job and receiving wage w for the rest of time, or (2) rejecting the job, receiving a value of leisure b, and continuing the search next period.

Suppose that once a worker has accepted a job offer, she faces a constant job separation probability $s, 0 \leq s < 1$.

The worker solves:

$$\max \mathbb{E} \sum_{t=0}^{\infty} \beta^t y_t, \beta \in (0,1) \tag{3}$$

where:

$$y_t = \begin{cases} w\text{, accept job, receive wage w} \\ b\text{, reject job, receive leisure b and search again next period} \end{cases}$$

The worker has subjective beliefs. The worker does not observe the true distribution of wages, in which w is drawn from the distribution $F(log(w)) \sim N(\mu, \sigma)$. Assume the worker's belief is fixed and will not change over time.

The value of employment at wage w is thus:

$$W(w|\mu) = w + \beta(1-s)W(w|\mu) + \beta s V(\mu) \tag{4}$$

The value of unemployment for belief μ is:

$$V(\mu) = b + \beta \int_w max\left\{W(w|\mu), V(\mu)\right\} dF(w|\mu) \tag{5}$$

5.2 Reservation Wage

I define the reservation wage $\bar{w}(\mu)$ as the wage that satisfies:

$$W(\bar{w}(\mu), \mu) = V(\mu), \tag{6}$$

where the worker is indifferent between accepting the wage offer $\bar{w}$ and staying unemployed.

5.3 Unemployment Rate

We use the law of motion of unemployment to derive the steady-state level of unemployment. Start at time t with U_t unemployed workers. Out of the $1-U_t$ employed workers, $s(1-U_t)$ will become unemployed next period. Out of the U_t unemployed workers, those who do not find a job will remain unemployed. Therefore,

$$U_{t+1} = s(1-U_t) + F(\bar{w})U_t. \tag{7}$$

The unique steady-state unemployment rate is

$$\bar{U}(\mu) = \frac{s}{1 + s - F(\bar{w}|\mu)}. \tag{8}$$

The derivation of the steady-state unemployment rate is in appendix A.2.

5.4 Implications

The job search model leads to two implications regarding reservation wages and the unemployment rate. The proofs are in appendix A.3.

Proposition 1. *All else equal, reservation wages $\bar{w}(\mu)$ are increasing in beliefs μ, that is, $\frac{\partial \bar{w}}{\partial \mu} > 0$.*

Proposition 2. *All else equal, the unemployment rate $\bar{U}(\mu)$ is increasing in beliefs μ, that is, $\frac{\partial \bar{U}}{\partial \mu} > 0$.*

Proposition 1 and Proposition 2 imply that if women have lower beliefs than men, holding all else constant, they will have lower reservation wages and a lower unemployment rate. While this study does not directly measure beliefs, previous literature indicates that women have lower beliefs about expected wages than men (Cortés et al., 2023). After the pay transparency law discloses wage information, the gender belief gap should decrease or disappear. The model predicts that the gender gap in reservation wages will decrease, leading to a decrease in the gender wage gap. [8] Additionally, pay transparency may increase the probability of unemployment for women compared to men. This is because women tend to be more selective in accepting job offers after learning about expected wages in job postings, leading to higher reservation wages and a higher likelihood of unemployment.

Note that all of the model predictions here are based on a reduction in the gender gap in beliefs, and relate to gender differences in job search and labor outcomes. It is difficult to know how pay transparency affects the beliefs of all workers, men and women, as a whole because there is considerable individual-level heterogeneity in the accuracy of expected wages (Conlon et al., 2018; Jäger et al., 2022; Jiang and Zen, 2023).

[8] According to Roussille (2022), women tend to ask for lower wages than comparable men. However, if they are offered the median salary that firms are willing to offer to similar candidates, women would no longer ask for lower wages. Disclosing expected wages in job postings is likely to narrow the gender gap in expected wages in a similar way.

6 The Effect of Pay Transparency on Labor Outcomes

6.1 Empirical Specification

I first estimate a compressed DID specification:

$$Y_{ismt} = \beta Treat_{ismt} + X_{ismt}\Gamma + \lambda_s + \lambda_t + \lambda_m + \epsilon_{ismt} \tag{9}$$

where Y_{ismt} is the log of the realized hourly wage, or the binary indicator of being employed (versus unemployed), or the binary indicator of whether the worker has a different occupation than in the last survey month, of individual i in state s, year t, and calendar month m. I aggregate the data to the annual level to gain statistical power because the sample size per month in the CPS Outgoing Rotation Group is too small. $Treat_{ismt}$ is the binary variable indicating 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 level, 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 then use Equation 10 to estimate the dynamic effect of the pay transparency law on realized wages and test parallel pre-trends in the outcome:

$$Y_{ismt} = \sum_{t=-4, t\neq -1}^{1} \beta_t Treat_{ismt} + X_{ismt}\Gamma + \lambda_s + \lambda_t + \lambda_m + \epsilon_{ismt}. \tag{10}$$

To estimate the effect of the pay transparency law on the gender gap in each outcome, I use a triple difference specification:

$$\begin{aligned} Y_{ismt} = {} & \beta Treat_{ismt} Female_i + \alpha_1 Female_i + +\alpha_2 Treat_{ismt} \\ & + \alpha_3 Female_i CO_i + \alpha_4 Female_i Post_t + X_{ismt}\Gamma + \lambda_s + \lambda_t + \epsilon_{ismt} \end{aligned} \tag{11}$$

where $Female_i$ indicates whether the individual is a female and CO_i indicates whether the individual lives in Colorado. $Post_t$ indicates the years (2021 and 2022) after the pay transparency law went into effect. The coefficient of interest, β, represents the effect of the pay transparency law on the gender gap (female premium) in the outcome.

I modify Equation 10 and estimate an event-study specification of the following form to estimate the effect of the pay transparency law on the gender gap in each outcome:

$$Y_{ismt} = \sum_{t=-4, t\neq -1}^{1} \beta_t Treat_{ismt} Female_i + \alpha_1 Female_i + \alpha_2 Treat_{ismt} + \alpha_3 Female_i CO_i + X_{ismt}\Gamma + \lambda_s + \lambda_t + \epsilon_{ismt}. \quad (12)$$

6.2 Effect on Realized Salaries

Panel A of Figure 3 shows the effect on realized wages by year using data from CPS ORG. Before 2021, there was no discernible 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. Overall, the pay transparency law does not affect realized wages.

Columns (1)-(3) of Table 3 show the effect on realized wages for the full sample. I find a positive effect on realized wages in all specifications. Using my preferred specification (column (3)), where I control for state, occupation-year fixed effect, and industry-year fixed effect, I find a 0.8% ($p = 0.04$) increase in realized wages.

I then study separately the effects for the subsamples of job changers and job stayers. 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 out of the eight months of the survey, it is impossible to identify those who have changed employers in the other two months. As a result, they will be misclassified as job stayers. I expect that pay transparency law will have a greater impact on job changers, as they are more likely to be directly exposed to posted wage information compared to job stayers. According to the preferred specification (Columns (6) and (9)), job changers experience a 3% ($p = 0.22$) increase in wages, while job stayers experience a 0.7% ($p = 0.04$) increase in wages. The estimate for job changers is not statistically significant, likely due to the smaller sample size and/or greater heterogeneity in the treatment effects.

6.3 Effect on Gender Wage Gap

Colorado's pay transparency law is intended to promote pay equity and reduce the gender wage gap. According to the prediction from the job search model in Section 5, increased wage information should reduce the gender gap in wage beliefs and reduce the gender wage gap. In this section, I test the model's prediction and examine whether this law achieves its first intended goal of reducing the gender wage gap.

First, I present the time-varying effects of Colorado's pay transparency law on the gender wage gap. As panel A of Figure 3 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 Figure 3. Again, there are no significant changes in either male or female wages in 2021. However, the trends in male and female wages diverge in the second year. There is an increase in female wages and a decrease in male wages, both of which contribute to the decrease in the gender wage gap.

Table 4 shows the effect of the pay transparency law on the gender wage gap estimated by Equation 11. The primary coefficient of interest is $Female \times Treat$ (row 1), which represents the female wage premium. A positive value of this coefficient indicates 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) report the full sample estimates. Because the positive effect on female wages and the negative effect on male wages do not appear until the second year after the pay transparency law goes into effect, I observe only a small and suggestive reduction in the gender wage gap of about 1.8% ($p = 0.18$) in these specifications. This law appears to have a minimal negative impact on male wages in the full sample, with a decrease of less than 0.5% ($p > 0.23$), according to columns (1)-(3).

Since the wage transparency law is likely to have a stronger effect on job seekers than on those not actively pursuing new job opportunities, I report estimates using the subsamples of job changers (columns (4)-(6)) and job stayers (columns (7)-(9)). For job changers, the gender wage gap decreases by 2.2% ($p = 0.17$) when I do not control for occupation or industry. The effect increases to 8.3% ($p = 0.002$) (column (5)) when I control for occupation and to 11.1% ($p = 0.008$) (column (6)) when I control for both occupation and industry. This shows that within occupations, women are more likely than men to switch to higher-paying employers due to the pay transparency law, while between occupations, women are not more likely than men to switch to higher-paying occupations. Part of the reduction in the gender wage gap is due to a decrease in the wages of male job changers. Across specifications, the decline in male wages for this group ranges from 4.4% to 6.2%, although none of the estimates are significant at the 5% significance level.

Not only job changers but also job stayers experience a decrease in the gender wage gap. The gender wage gap shrank by about 1.6% ($p = 0.26$), slightly smaller than the estimate for the full sample. The pay transparency law has a negligible effect on male job stayers, with estimates ranging from -0.2% to 0.2% and none is statistically significant at the 10% significance level.

In sum, Colorado's pay transparency law proves effective in reducing the gender wage gap, while some of this reduction is driven by adverse effects on male wages. There is a large within-occupation reduction in the gender wage gap among job changers, which suggests that women are more likely than men to switch to higher-paying employers than men due to the pay transparency law. Job stayers experience a small decrease (1.6%) in the gender wage gap, which indicates that the pay transparency law also affects the gender wage gap through the bargaining channel.

6.4 Effect on Gender Mobility and Employment Gap

Job Mobility The first three columns of Table 5 show that pay transparency increased women's probability of changing jobs relative to men by over 1 percentage point, which is an increase of over 50% given that the baseline probability of changing jobs is 2%. Conversely, pay transparency reduced men's probability of changing jobs by more than 1 percentage point. Thus, the increased wage information brought about by the pay transparency law promoted job mobility for women but depressed job mobility for men.

Employment According to the prediction of the job search model in Section 5, increased wage information should reduce the gender gap in wage beliefs and increase the unemployment rate of women relative to men. Columns (4) - (5) of Table 5 show the effect of the pay transparency law on the probability of being employed. Relative to men, women are 1 percentage point less likely to be employed due to pay transparency, and the estimate is significant at the 5% level. At the same time, the effect on men's probability of being employed is very small. The empirical result is consistent with the model's prediction that women increase their reservation wages relative to men and become more "picky" about job offers after observing more wage information.

7 Robustness

7.1 SDID Procedure

In this section, I use synthetic difference-in-differences (SDID) developed by Arkhangelsky et al. (2021) (1) to show that the above results are not driven by the choice of the control group; and (2) to better handle the unparallel pre-trends in some event-study specifications. Using two donor pools: (1) West Coast states, and (2) ten states that have had state-wide salary history bans before 2020 (Alabama, California, Connecticut, Delaware, Illinois, Maine, Massachusetts, Oregon, Rhode Island, Vermont, and Washington), I get qualitatively similar results as DID, which suggests that my results are robust to different compositions of the control group.

SDID bridges the DID and synthetic control (SC) procedures. I use the sdid command to implement the SDID analyses in Stata (Clarke et al., 2023). The SDID estimator is defined as:

$$\left(\widehat{\tau}^{sdid}, \widehat{\mu}, \widehat{\alpha}, \widehat{\beta}\right) = \underset{\tau,\mu,\alpha,\beta}{\arg\min} \left\{ \sum_{s=1}^{N} \sum_{t=1}^{T} \left(Y_{st} - \mu - \alpha_s - \beta_t - Treat_{st}\tau\right)^2 \widehat{\omega}_s^{sdid} \widehat{\lambda}_t^{sdid} \right\}, \tag{13}$$

where $\widehat{\tau}^{sdid}$ estimates the average treatment effect on the treated (ATT). Y_{st} is the state-year aggregate outcome. $Treat_{st}$ is the binary indicator for the treatment status. α_s is the state fixed effect and β_t is the year fixed effect.

To add covariates that are used in DID specifications and keep things parallel, I add the same control variables and fixed effects to SDID analyses following the procedure described by Kranz (2022). [9] I first run the following individual-level two-way fixed effect regression

[9] I control for age, race, education, state, month, worker classification, occupation, occupation×year, industry, industry×year, and calendar month fixed effects in all regressions. I also control for the state×female fixed effect when the outcome is the gender gap. Unfortunately, I cannot replicate the DID analyses with individual fixed effects using the SDID-where the outcome is whether one is employed or has changed jobs. This is because the SDID requires a balanced panel over the entire study period (2017 - 2022), while the CPS is a short individual-level panel that interviews respondents for a total of eight months, which prevents me from constructing a balanced panel where individual fixed effects are removed. Because the CPS survey period is only eight months, the majority of CPS respondents observed in the post-period in Colorado ($treat = 1$) were not observed in the pre-period and do not enter the covariate adjustment procedure, and their individual fixed effects cannot be removed.

sub-setting to observations that are not treated or not treated yet (i.e. $Treat_{ismt} = 0$): [10]

$$Y_{ismt} = X_{ismt}\Gamma + \lambda_s + \lambda_t + \epsilon_{ismt}. \tag{14}$$

Then I compute individual-level adjusted outcomes

$$Y_{ismt}^{adj} = Y_{ismt} - X_{ismt}\widehat{\Gamma}, \tag{15}$$

which is also $\widehat{\lambda}_s + \widehat{\lambda}_t + \widehat{\epsilon}_{ismt}$. Lastly, I aggregate adjusted outcomes Y_{ismt}^{adj} to the state-year level and apply SDID.

7.2 SDID Results

I show all SDID and DID results in event-study style figures in Figure A11 -Figure **??** to facilitate the comparison between DID and SDID results.

Compared with SDID with the West Coast donor pool and DID with any control group, SDID designs with the larger donor pool (i.e., states with state-wide salary history bans) generally match pre-trends better.

No matter whether the control group (donor pool) is the West Coast states or states with statewide salary history bans, the DID estimates are qualitatively similar to the respective SDID estimates: the signs and the significance levels are usually the same. The similarity in DID estimates and SDID estimates suggests that the results in labor outcomes are robust to different compositions of the control group.

7.3 Within-Colorado DID: Public vs. Private Sector

One concern that is not solved by the SDID design, or by any comparison between Colorado and other states, is that effects on labor outcomes may be driven by Colorado-specific confounders that are not the pay transparency law. To mitigate this concern, I use a within-Colorado comparison and compare the private sector with the public sector. In Colorado, wages for public sector employees had been public information before the pay transparency law, so the pay transparency law should not reveal much new information about wages to the labor market. Therefore, I use the public sector as the control group

[10] Regressing individual-level outcomes such as wages on demographics and then aggregating residuals to the state-year level is consistent with Peri and Yasenov (2018), although they apply SC rather than SDID in the next step.

and the private sector as the treated group and repeat the DID analysis. Based on the classification of workers in CPS, I define public sector employees as federal, state, or local government employees.

The first row of Table A4 displays the within-Colorado DID estimates of effects on gender gaps in labor outcomes. Overall, the signs of the estimates are aligned with between-state DID and SDID estimates, although the estimates are very imprecise because of the small sample size. Therefore, although I cannot rule out the possibility that Colorado-specific confounders exist, it is very unlikely that the effects on the gender gaps in labor outcomes are purely driven by Colorado-specific confounders.

8 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 establish a partial equilibrium job search model with subjective beliefs to illustrate how pay transparency can affect the gender gap in wage beliefs and, consequently, job search behavior and outcomes. The pay transparency law decreased the gender wage gap for job changers and job stayers by 11.1% and 1.6%, respectively. The narrowing of the gender wage gap was driven by an increase in female wages and a decrease in male wages. Compared to men, pay transparency increased women's job mobility and decreased women's employment.

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Appendix

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

	(1) Colorado	(2) West Coast	(3) SHB States	(4) (1) - (2)	(5) p-value	(6) (1) - (3)	(7) p-value
Panel A: All Job Postings							
Contains Salary Info	0.07	0.07	0.07	-0.00	0.00	-0.00	0.00
Occupational Mix (Top 5 in Colorado)							
Sales	0.15	0.14	0.14	0.01	0.00	0.01	0.00
Computer	0.10	0.10	0.10	-0.00	0.00	-0.00	0.00
Medicine	0.10	0.11	0.11	-0.01	0.00	-0.01	0.00
Food Preparation	0.10	0.09	0.09	0.01	0.00	0.01	0.00
Office Admin	0.09	0.09	0.09	0.00	0.00	0.00	0.00
Observations	1393129	8808452	14917173				
Number of Firms	6001	12866	16388				
Panel B: Job Postings with Salary Info							
Mean Posted Salary (annual $)							
Mid Posted Salary	45022	54249	52856	-9227	0.00	-7834	0.00
Min Posted Salary	41710	48997	48461	-7287	0.00	-6751	0.00
Max Posted Salary	48335	59502	57251	-11167	0.00	-8916	0.00
Pay Structure							
Annual	0.29	0.29	0.32	-0.00	0.13	0.03	0.00
Hourly	0.66	0.63	0.61	0.04	0.00	-0.06	0.00
Monthly	0.04	0.07	0.06	-0.03	0.00	0.02	0.00
Weekly	0.01	0.01	0.01	0.00	0.01	0.00	0.00
Observations	98298	636462	896908				
Number of Firms	1219	3597	5052				

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. West Coast states are California, Oregon, and Washington. SHB states are states that had statewide pay history bans before 2021 (Alabama, California, Connecticut, Delaware, Illinois, Maine, Massachusetts, Oregon, Rhode Island, Vermont, 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 mid, min, and max wages are all equal to the wage rate. If the job posting includes a wage *range*, the min and max salaries refer to the low and high ends of the range, and the mid 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.

Table 2: Effect of Pay Transparency Law on Posted Salaries, LinkUp Job Posting

	Mid Salary				Min Salary				Max Salary			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Treat	0.131***	0.050***	0.050***	0.053***	0.071**	0.012*	0.013**	0.011	0.180***	0.081***	0.081***	0.088***
	(0.033)	(0.010)	(0.010)	(0.015)	(0.029)	(0.007)	(0.006)	(0.011)	(0.036)	(0.015)	(0.014)	(0.020)
Month FE	X			X	X			X	X			X
Zipcode FE	X				X				X			
Occ-Month FE		X	X			X	X			X	X	
Firm-occ-zip FE		X	X			X	X			X	X	
Ind-Month FE			X				X				X	
State FE				X				X				X
Occ FE				X				X				X
Ind FE				X				X				X
Occ×Year FE				X				X				X
Ind×Year FE				X				X				X
Observations	1877126	1773154	1773124	1986480	1877126	1773154	1773124	1986480	1877126	1773154	1773124	1986480
Adjusted R^2	0.160	0.879	0.879	0.729	0.152	0.859	0.860	0.694	0.162	0.885	0.885	0.732
Mean	47314.485	47035.501	47035.622	47340.518	43006.859	42749.299	42749.393	43044.515	51141.401	50842.705	50842.848	51155.198

Note: This table shows the effect of the pay transparency law on posted wages using the LinkUp job posting data estimated with Equation 1. The outcome variable for columns (1) - (4) is the log of the midpoint salary. The outcome variable for columns (5) - (8) is the log of the minimum salary. The outcome variable for columns (9) - (12) is the log of the maximum salary. Columns (1), (5), and (9) control for month and zipcode fixed effects. Columns (2), (6), and (10) control for the interaction between occupation and month and the interaction between firm, occupation, and zipcode. Columns (3), (7), and (11) also control for the interaction between industry (2-digit NAICS code) and month in addition to the above interactions. Columns (4), (8), and (12) control for the same group of fixed effects as the later analysis using the CPS data to facilitate the comparison between the effect on posted and realized wages. Standard errors are clustered at the firm level.

Table 3: 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	0.004	0.005*	0.008**	-0.011	0.008	0.031	0.005	0.005*	0.007**
	(0.003)	(0.002)	(0.002)	(0.016)	(0.017)	(0.020)	(0.002)	(0.002)	(0.002)
Control	X	X	X	X	X	X	X	X	X
State FE	X	X	X	X	X	X	X	X	X
Year FE	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	104669	101486	100258	6754	6442	6328	97915	94957	93819
Adjusted R^2	0.425	0.524	0.536	0.435	0.551	0.560	0.424	0.524	0.536
Mean	20.525	20.430	20.421	19.777	19.639	19.651	20.578	20.485	20.476

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 9. 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 4: 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	0.018	0.014	0.018	0.022	0.083***	0.111***	0.017	0.017	0.016
	(0.008)	(0.009)	(0.010)	(0.012)	(0.008)	(0.017)	(0.010)	(0.010)	(0.011)
Female	-0.144***	-0.105***	-0.100***	-0.108***	-0.068**	-0.068**	-0.147***	-0.147***	-0.103***
	(0.014)	(0.007)	(0.007)	(0.017)	(0.018)	(0.017)	(0.014)	(0.014)	(0.007)
Female×CO	-0.031	-0.025	-0.026	-0.010	-0.002	-0.005	-0.033	-0.033	-0.026
	(0.016)	(0.013)	(0.014)	(0.023)	(0.025)	(0.030)	(0.016)	(0.016)	(0.014)
Treat	-0.005	-0.002	0.000	-0.044	-0.062*	-0.047	-0.002	-0.002	0.002
	(0.003)	(0.004)	(0.003)	(0.019)	(0.024)	(0.027)	(0.004)	(0.004)	(0.004)
Female×Post	0.018	0.026***	0.024***	0.008	-0.002	0.004	0.019	0.019	0.025**
	(0.008)	(0.004)	(0.004)	(0.013)	(0.021)	(0.019)	(0.010)	(0.010)	(0.004)
Control	X	X	X	X	X	X	X	X	X
State FE	X	X	X	X	X	X	X	X	X
Year FE	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	104669	101486	100258	6811	6497	6386	97858	97858	93764
Adjusted R^2	0.425	0.525	0.537	0.433	0.550	0.559	0.425	0.425	0.536
Mean	20.525	20.430	20.421	19.680	19.521	19.532	20.585	20.585	20.486

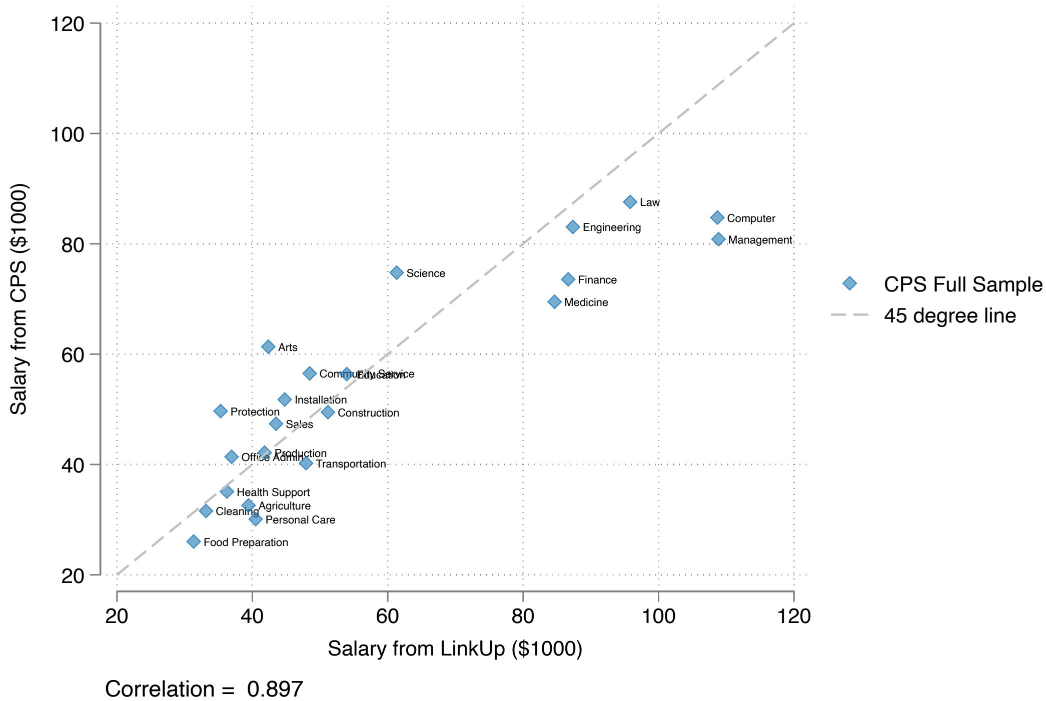
Note: This table shows the effects of the pay transparency law on the gender wage gap using data from the Current Population Survey Outgoing Rotation Group estimated with Equation 11. All columns control for age, race, education, state, month, and worker classification. The coefficient on 'Treat' denotes 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.

Table 5: Effect of Pay Transparency Law on Gender Gaps in Job Mobility and Employment, CPS Basic Monthly

	Changing Job			Employed	
	(1)	(2)	(3)	(4)	(5)
Female×Treat	0.006**	0.012*	0.013*	-0.010**	-0.010**
	(0.002)	(0.004)	(0.005)	(0.002)	(0.003)
Treat	-0.010***	-0.013***	-0.015***	-0.002	-0.001*
	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)
Female×Post	-0.003	0.000	0.000	0.010**	0.010**
	(0.002)	(0.004)	(0.004)	(0.002)	(0.002)
Control	X	X	X		X
State FE	X	X	X	X	X
Year FE	X	X	X	X	X
Individual FE	X	X	X	X	X
Occupation		X	X		
Occupation×Year		X	X		
Industry			X		
Industry×Year			X		
Observations	237082	229229	226148	419862	419862
Adjusted R^2	0.059	0.068	0.071	0.246	0.246
Mean	0.021	0.020	0.020	0.976	0.976

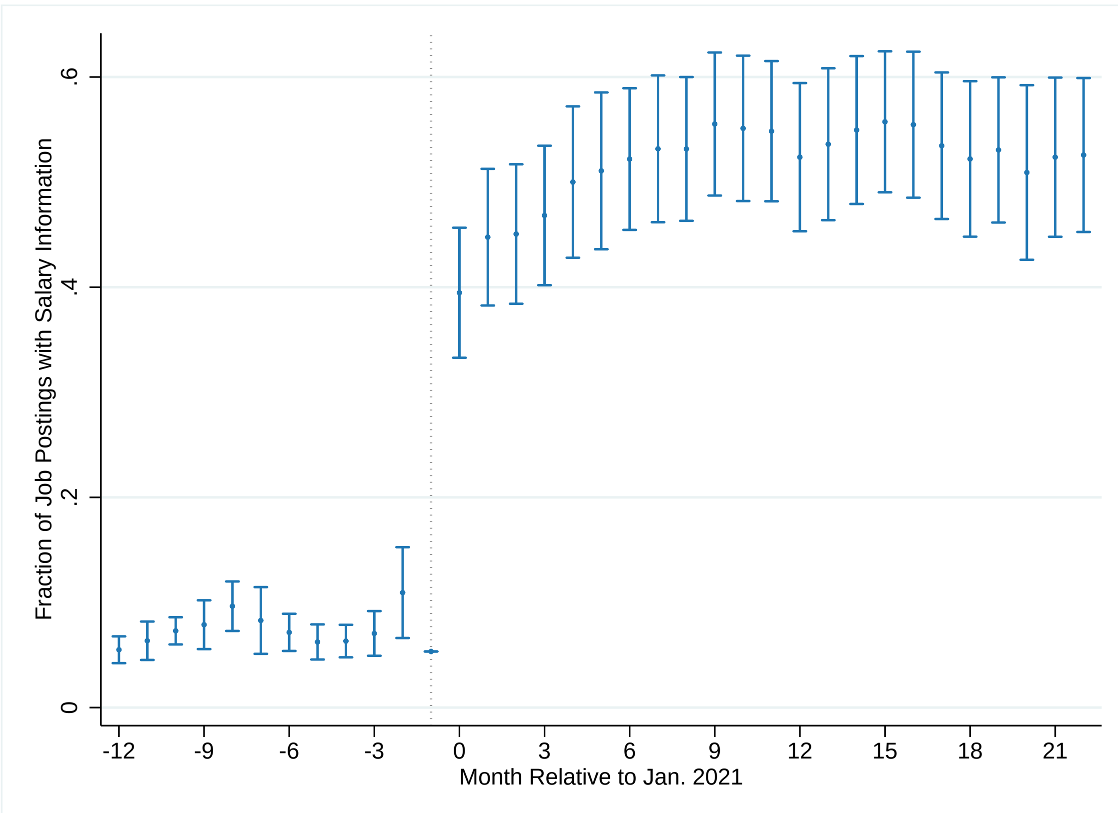
Note: This table shows the effects of the pay transparency law on gender gaps in employment and Occupation Changes using data from the Current Population Survey Basic Monthly estimated with Equation 11. All columns except for Column (4) control for age, race, and education. Columns (1)-(3) additionally control for worker classification, full-time/part-time status, and whether paid hourly. The coefficient on 'Treat' denotes the effect on men, and that on 'Female×Treat' is the effect on the gender gap. The outcome for columns (4)-(5) is a binary indicator that takes one if the individual is employed and zero if the individual is unemployed. The outcome for columns (1)-(3) is a binary indicator that takes one if the worker changes occupation from the last survey month and zero otherwise. Standard errors are clustered at the state level.

Figure 1: Comparison Between LinkUp Job Postings Data and CPS Wage Data by Occupation



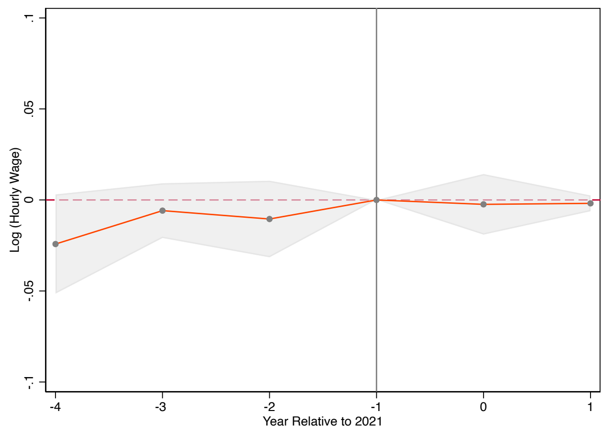
Note: This figure compares mean annual wages by occupation between the LinkUp job posting data and wage data from the CPS. Blue diamonds display the mean wage of the respective occupation from the LinkUp data on the x-axis and the CPS full sample on the y-axis. Both axes use units of thousands to denote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

Figure 2: Effect of Pay Transparency Law on Fraction of Job Postings with Salary Information, LinkUp Job Posting

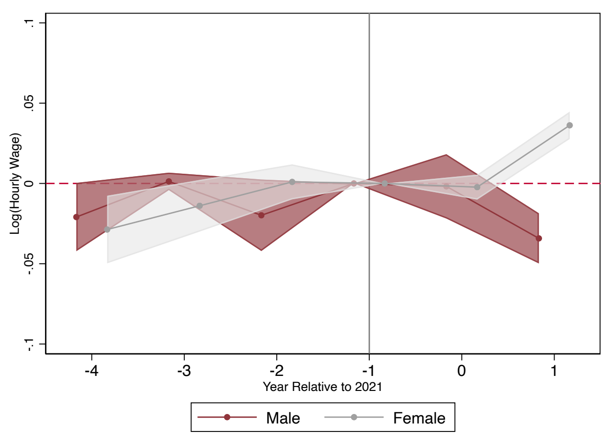


Note: This figure reports the effect of the pay transparency law on the fraction of job postings with salary information by month estimated with Equation 2. The corresponding econometric specification controls for interaction (1) between occupation (6-digit ONet code) and month and (2) between firm,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

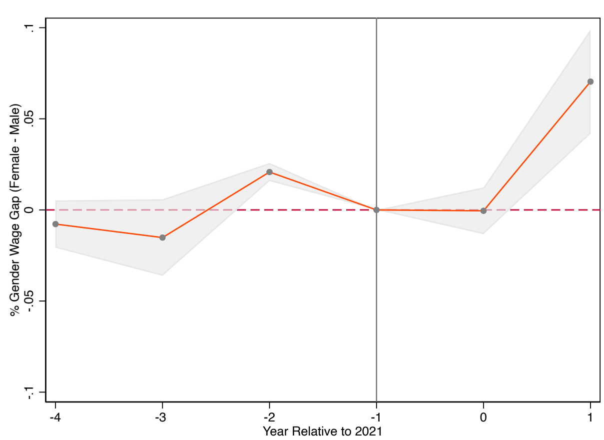
Figure 3: Effect of Pay Transparency Law on Realized Wages by Year and Gender, CPS ORG



(a) Effect on Wages



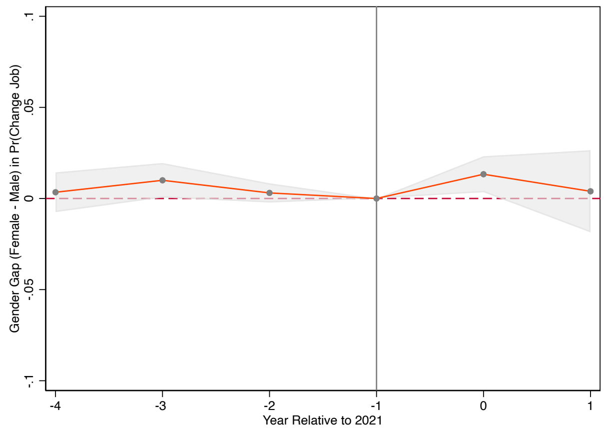
(b) Effect on Wages by Gender



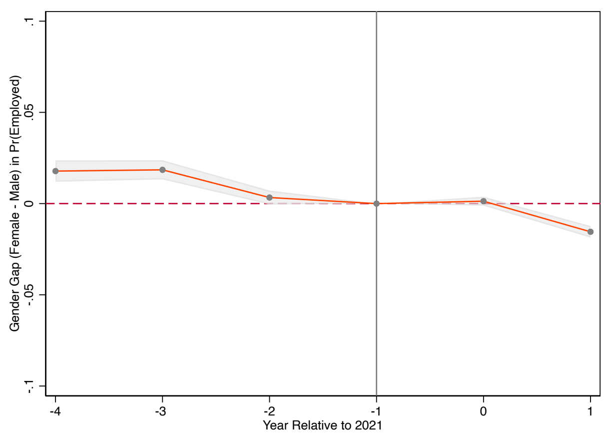
(c) Effect on Gender Wage Gap

Note: Panel A reports the point estimates and the 95% confidence intervals of the effect of the pay transparency law on realized hourly wages estimated with Equation 11. Panel B reports the point estimates and the 95% confidence intervals of the effect of the pay transparency law on male and female wages. Panel C reports the point estimates and the 95% confidence intervals of the effect of the pay transparency law on the gender wage gap. Panels B and c are estimated with Equation 12. Standard errors are clustered at the state level. Data source: CPS ORG.

Figure 4: Effect of Pay Transparency Law on the Gender Gap in Mobility and Employment, CPS Basic Monthly



(a) Effect on the Gender Gap in Pr(Changing Jobs)



(b) Effect on the Gender Gap in Pr(Employed)

Note: Panel A reports the point estimates and the 95% confidence intervals of the effect of the pay transparency law on the gender gap in the probability of changing job. Panel B reports the point estimates and the 95% confidence intervals of the effect of the pay transparency law on the gender gap in the probability of being employed. Both panels are estimated with Equation 12. Standard errors are clustered at the state level. Data source: CPS Basic Monthly.

Appendix A Job Search Model

A.1 Model Derivation

A risk-neutral unemployed worker seeks to maximize consumption via accepting or rejecting a job offer. In each period t, a worker receives an employment offer. If given an offer, the worker learns of the offer's attached wage w. The worker then chooses between (1) accepting the job and receiving wage w for the rest of time, or (2) rejecting the job, receiving a value of leisure b, and continuing the search next period.

Suppose that once a worker has accepted a job offer, she faces a constant job separation probability $s, 0 \leq s < 1$.

The worker solves:

$$\max \sum_{t=0}^{\infty} \beta^t y_t, \beta \in (0,1)$$

where:

$$y_t = \begin{cases} w, \text{ accept job, receive wage w} \\ b, \text{ reject job, receive leisure b and search again next period} \end{cases}$$

Using value functions, an employed worker receives:

$$W(w|\mu) = w + \beta(1-s)W(w|\mu) + \beta s V(\mu). \tag{16}$$

An unemployed worker receives:

$$V(\mu) = b + \beta \int_w \max\{W(w|\mu), V(\mu)\} \, dF(w|\mu). \tag{17}$$

I define the reservation wage $\bar{w}(\mu)$ as the wage that satisfies:

$$W(\bar{w}|\mu) = V(\mu), \tag{18}$$

where the worker is indifferent between accepting the wage offer $\bar{w}$ and staying unemployed.

Then we know when $w = \bar{w}$, Equation 16 = Equation 17, and we get

$$V(\mu) = \frac{\bar{w}}{1-\beta}. \tag{19}$$

Substituting Equation 19 into Equation 17:

$$\frac{\bar{w}}{1-\beta} = b + \beta \int_0^{\bar{w}} \frac{\bar{w}}{1-\beta} dF(w|\mu) + \beta \int_{\bar{w}}^{\infty} \frac{w + \beta s \left(\frac{\bar{w}}{1-\beta}\right)}{1-\beta(1-s)} dF(w|\mu)$$

Rewrite the left-hand side and simplify:

$$\frac{\bar{w}}{1-\beta} \int_0^{\bar{w}} dF(w|\mu) + \frac{\bar{w}}{1-\beta} \int_{\bar{w}}^{\infty} dF(w|\mu) = b + \beta \int_0^{\bar{w}} \frac{\bar{w}}{1-\beta} dF(w|\mu) + \beta \int_{\bar{w}}^{\infty} \frac{w + \beta s \left(\frac{\bar{w}}{1-\beta}\right)}{1-\beta(1-s)} dF(w|\mu)$$

$$\bar{w} \int_0^{\bar{w}} dF(w|\mu) = b + \beta \int_{\bar{w}}^{\infty} \left(\frac{w + \beta s \left(\frac{\bar{w}}{1-\beta}\right)}{1-\beta(1-s)} - \frac{\bar{w}}{\beta(1-\beta)} \right) dF(w|\mu)$$

$$\bar{w}\int_0^{\bar{w}} dF\left(w|\mu\right)+\bar{w}\int_{\bar{w}}^{\infty} dF\left(w|\mu\right)=b+\beta\int_{\bar{w}}^{\infty}\left(\frac{w+\beta s\left(\frac{\bar{w}}{1-\beta}\right)}{1-\beta(1-s)}-\frac{\bar{w}}{\beta(1-\beta)}+\frac{\bar{w}}{\beta}\right)dF\left(w|\mu\right)$$

$$\bar{w}-b=\frac{\beta}{1-\beta(1-s)}\int_{\bar{w}}^{\infty}\left(w-\bar{w}\right)dF\left(w|\mu\right) \tag{20}$$

Re-formulate the right-hand side of Equation 20 to prove Proposition 1 by adding and subtracting $\frac{\beta}{1-\beta(1-s)}\int_0^{\bar{w}}(w-\bar{w})dF(w|\mu)$:

$$\bar{w}-b=\frac{\beta}{1-\beta(1-s)}\int_0^{\infty}(w-\bar{w})dF(w|\mu)-\frac{\beta}{1-\beta(1-s)}\int_0^{\bar{w}}(w-\bar{w})dF(w|\mu)$$

$$\bar{w}-b=\frac{\beta}{1-\beta(1-s)}E(w|\mu)-\frac{\beta\bar{w}}{1-\beta(1-s)}-\frac{\beta}{1-\beta(1-s)}\int_0^{\bar{w}}(w-\bar{w})dF(w|\mu)$$

$$(1+\beta s)(\bar{w}-b)=\beta[E(w|\mu)-b]-\beta\int_0^{\bar{w}}(w-\bar{w})dF(w|\mu) \tag{21}$$

Using integration by parts, we know $\int_0^{\bar{w}} wdF(w|\mu)=wF(w|\mu)|_0^{\bar{w}}-\int_0^{\bar{w}} F(w|\mu)dw$, which simplifies to

$$\int_0^{\bar{w}} u(w)dF(w|\mu)=\bar{w}F(\bar{w}|\mu)-\int_0^{\bar{w}} F(w|\mu)dw.$$

Then, Equation 21 becomes:

$$(1+\beta s)(\bar{w}-b)=\beta[E(w|\mu)-b]+\beta\int_0^{\bar{w}} F(w|\mu)dw \tag{22}$$

We can use Equation 22 to prove Proposition 1.

A.2 Derivation of Unemployment Rate

We use the law of motion of unemployment to derive the steady-state level of unemployment. Start at time t with U_t unemployed workers. Out of the $1-U_t$ employed workers, $s(1-U_t)$ will become unemployed next period. Out of the U_t unemployed workers, those who do not find a job will remain unemployed. Therefore,

$$U_{t+1}=s(1-U_t)+F(\bar{w})U_t.$$

Subtracting U_t from both sides:

$$U_{t+1}-U_t=s(1-U_t)+[F(\bar{w}|\mu)-1]U_t.$$

If the period length is arbitrary, this can be written as

$$U_{t+\Delta t}-U_t=s(1-U_t)\Delta t+[F(\bar{w}|\mu)-1]U_t\Delta t+o(\Delta t).$$

Dividing by Δt and taking limits as $\Delta t\to 0$, we obtain the continuous time version

$$\dot{U}_t=s(1-U_t)+[F(\bar{w}|\mu)-1]U_t.$$

The unique steady-state unemployment rate where $U_{t+1}=U_t$ (or $\dot{U}_t=0$) given by

$$\bar{U}(\mu)=\frac{s}{1+s-F(\bar{w}|\mu)}. \tag{23}$$

We can use Equation 23 to prove Proposition 2.

A.3 Proofs of Propositions

Proposition 1. *All else equal, reservation wages $\bar{w}(\mu)$ are increasing in beliefs μ, that is,* $\frac{\partial \bar{w}}{\partial \mu} > 0$.

Proof. Differentiate Equation 22 to find $\frac{\partial \bar{w}}{\partial \mu}$:

$$(1 + \beta s) \frac{\partial \bar{w}}{\partial \mu} = \beta \frac{\partial E(w|\mu)}{\partial \mu} + \beta F(\bar{w}|\mu) \frac{\partial \bar{w}}{\partial \mu}.$$

Rearranging, we get:

$$[1 + \beta s - \beta F(\bar{w}|\mu)] \frac{\partial \bar{w}}{\partial \mu} = \beta \frac{\partial E(w|\mu)}{\partial \mu}.$$

Transforming the left-hand side:

$$\{\beta[1 - F(\bar{w}|\mu)] + [1 - \beta(1 - s)]\} \frac{\partial \bar{w}}{\partial \mu} = \beta \frac{\partial E(w|\mu)}{\partial \mu}.$$

On the left-hand side, we know , $\beta > 0$, $[1 - F(\bar{w}|\mu)] > 0$, and $[1 - \beta(1 - s)] > 0$. Thus,

$$\{\beta[1 - F(\bar{w}|\mu)] + [1 - \beta(1 - s)]\} > 0.$$

On the right-hand side, we know $\beta > 0$ and$\frac{\partial E(w|\mu)}{\partial \mu} > 0$. Thus,

$$\beta \frac{\partial E(w|\mu)}{\partial \mu} > 0.$$

Therefore,

$$\frac{\partial \bar{w}}{\partial \mu} > 0.$$

□

Proposition 2. *All else equal, the unemployment rate $\bar{U}(\mu)$ is increasing in beliefs μ, that is,* $\frac{\partial \bar{u}}{\partial \mu} > 0$.

Proof. Differentiate Equation 23 to find $\frac{\partial \bar{w}}{\partial \mu}$:

$$\frac{\partial \bar{U}}{\partial \mu} = \frac{s \frac{\partial F(\bar{w}|\mu)}{\partial \bar{w}} \frac{\partial \bar{w}}{\partial \mu}}{[1 + s - F(\bar{w}|\mu)]^2}.$$

On the right-hand side, we know $s > 0$, $\frac{\partial F(\bar{w}|\mu)}{\partial \bar{w}} > 0$, $\frac{\partial \bar{w}}{\partial \mu} > 0$ (from Proposition 1), and $[1 + s - F(\bar{w}|\mu)] > 0$. It follows that $\frac{\partial \bar{U}}{\partial \mu} > 0$.

□

Appendix B Additional Figures and Tables

Table A1: Job Postings in CO vs. Control States By Occupation (2017 - 2020)

Occupation	(1) Colorado	(2) West Coast States	(3) SHB States	(4) (1) - (2)	(5) p-value	(6) (1) - (3)	(7) p-value
Management	0.07	0.10	0.10	-0.03	0.00	-0.03	0.00
Finance	0.06	0.06	0.06	-0.01	0.00	-0.01	0.00
Computer	0.10	0.10	0.10	-0.00	0.00	-0.00	0.00
Engineering	0.03	0.03	0.03	-0.01	0.00	-0.01	0.00
Science	0.01	0.02	0.02	-0.01	0.00	-0.01	0.00
Community Service	0.02	0.02	0.02	-0.00	0.00	-0.00	0.00
Law	0.00	0.00	0.00	-0.00	0.00	-0.00	0.00
Education	0.03	0.03	0.03	-0.00	0.00	-0.00	0.00
Arts	0.02	0.02	0.02	-0.00	0.00	-0.00	0.00
Medicine	0.10	0.11	0.11	-0.01	0.00	-0.01	0.00
Health Support	0.04	0.03	0.03	0.01	0.00	0.01	0.00
Protection	0.02	0.03	0.03	-0.01	0.00	-0.01	0.00
Food Preparation	0.10	0.09	0.09	0.01	0.00	0.01	0.00
Cleaning	0.02	0.02	0.02	0.00	0.00	0.00	0.00
Personal Care	0.01	0.01	0.01	0.00	0.00	0.00	0.00
Sales	0.15	0.14	0.14	0.01	0.00	0.01	0.00
Office Admin	0.09	0.09	0.09	0.00	0.00	0.00	0.00
Agriculture	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Construction	0.01	0.01	0.01	0.00	0.00	0.00	0.00
Installation	0.03	0.02	0.02	0.01	0.00	0.01	0.00
Production	0.01	0.01	0.01	-0.00	0.00	-0.00	0.00
Transportation	0.07	0.06	0.06	0.01	0.00	0.01	0.00
Observations	1393129	8809770	14917173				

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. West Coast states are California, Oregon, and Washington. SHB states are states that had statewide pay history bans before 2021 (Alabama, California, Connecticut, Delaware, Illinois, Maine, Massachusetts, Oregon, Rhode Island, Vermont, and Washington).

Table A2: 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 1. 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 A3: Effect of Pay Transparency Law on the Realized Wages, Within-Colorado Comparison, CPS ORG

Outcome: log(hourly wage)	(1)	(2)	(3)
Private×Post	-0.020	-0.017	-0.013
	(0.013)	(0.014)	(0.014)
Private	0.054***	0.009	0.005
	(0.009)	(0.020)	(0.021)
Control	X	X	X
Metropolitan Area FE	X	X	X
Year FE	X	X	X
Occupation		X	X
Industry			X
Observations	10931	10919	10861
Adjusted R^2	0.382	0.448	0.506
Mean	20.691	20.690	20.692

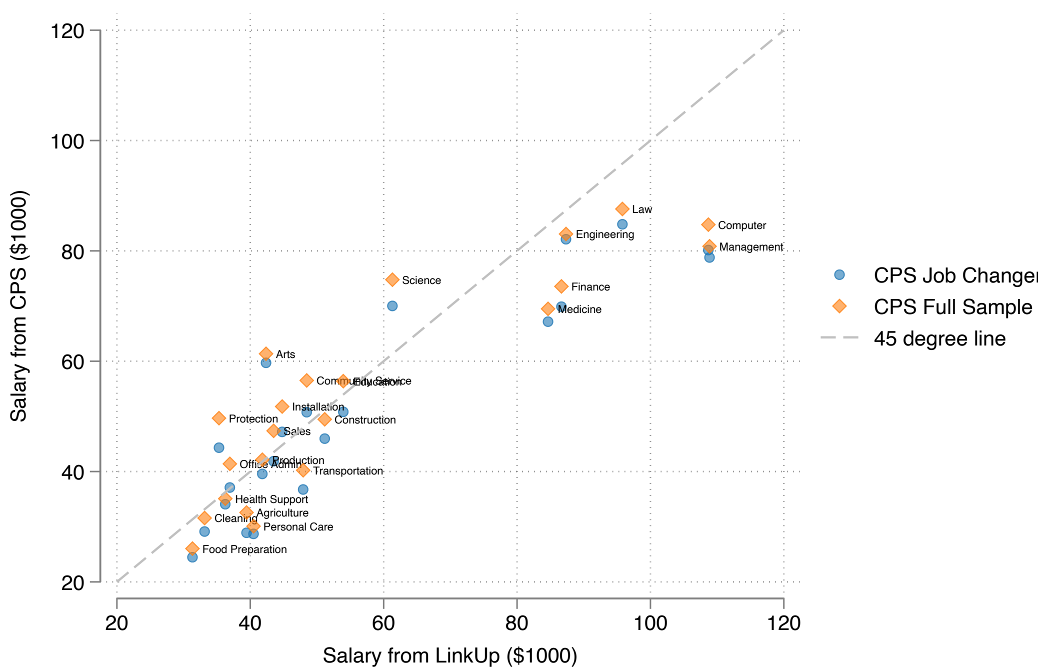
Note: This table shows the effects of the pay transparency law on realized wages using data from the Current Population Survey Outgoing Rotation Group estimated with Equation 9. All columns control for age, race, education, calendar month, full-time/part-time status, and whether paid hourly. The coefficient on 'Private×Post' denotes the effect on men. Standard errors are clustered at the metropolitan area level.

Table A4: Effect of Pay Transparency Law on Gender Gaps in Labor Outcomes, Within-Colorado Comparison, CPS

	log(wage)			Changing Jobs		Employed	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Female×Private×Post	0.076*	0.046	0.046	0.033	0.036	-0.016	-0.021
	(0.035)	(0.038)	(0.038)	(0.050)	(0.051)	(0.013)	(0.011)
Private×Post	-0.048	-0.039	-0.039	-0.032	-0.034	0.015*	0.018*
	(0.033)	(0.028)	(0.028)	(0.019)	(0.019)	(0.007)	(0.007)
Female×Private	0.015	0.009	0.009	-0.052*	-0.055*	-0.040**	-0.040**
	(0.028)	(0.026)	(0.026)	(0.024)	(0.024)	(0.015)	(0.015)
Female×Post	-0.018	0.007	0.007	-0.022	-0.024	0.017	0.020
	(0.034)	(0.033)	(0.033)	(0.045)	(0.044)	(0.013)	(0.014)
Private	0.032	-0.001	-0.001	0.045*	0.046*	0.045**	0.044**
	(0.022)	(0.022)	(0.022)	(0.018)	(0.019)	(0.013)	(0.013)
Control	X	X	X		X		X
Metropolitan Area FE	X	X	X	X	X	X	X
Year FE	X	X	X	X	X	X	X
Individual FE				X	X	X	X
Occupation		X	X				
Industry			X				
Observations	10565	10508	10508	25102	25102	38871	38871
Adjusted R^2	0.387	0.497	0.497	0.069	0.069	0.236	0.238
Mean	20.720	20.723	20.723	0.021	0.021	0.981	0.981

Note: This table shows the effects of the pay transparency law on the gender gaps in labor outcomes using data from the Current Population Survey estimated with Equation 11. Columns (1)-(3) control for age, race, education, calendar month, full-time/part-time status, and whether paid hourly. Columns (5) and (7) control for age, race, education, and calendar month. The coefficient on 'Private×Post' denotes the effect on men, and that on 'Female×Private×Post' is the effect on the gender gap in labor outcomes. Outcomes for columns (1)-(3), (4)-(5), (6)-(7) are log(hourly wage), whether the worker has changed jobs from last month, and whether employed (versus unemployed) respectively. Standard errors are clustered at the metropolitan area level.

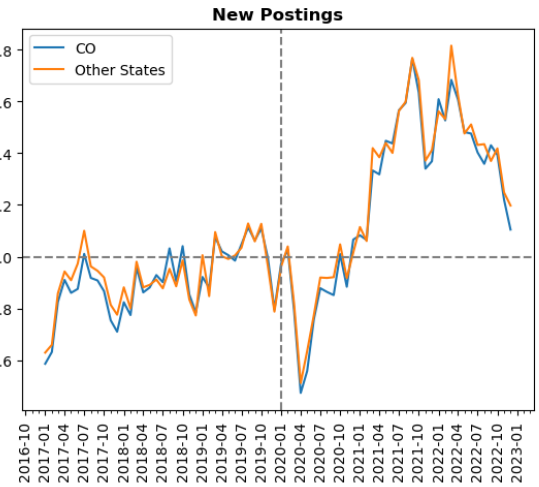
Figure A1: Comparison Between LinkUp Job Postings Data and CPS Wage Data by Occupation



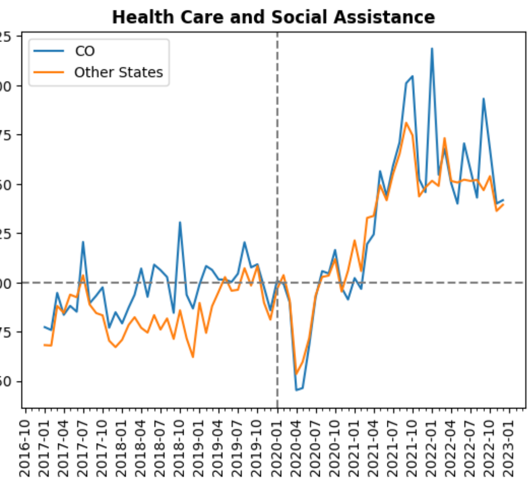
Correlation = 0.897(full sample); 0.907(job changers)

Note: This figure compares mean annual wages by occupation between the LinkUp job posting 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.

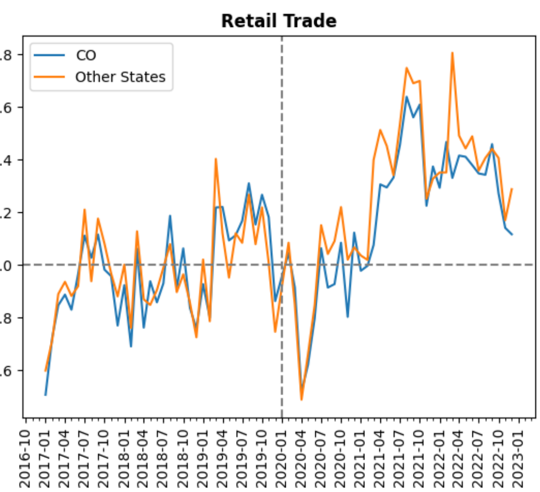
Figure A2: Impact of COVID-19 Pandemic on Number of New Job Postings, LinkUp Job Posting



(a)



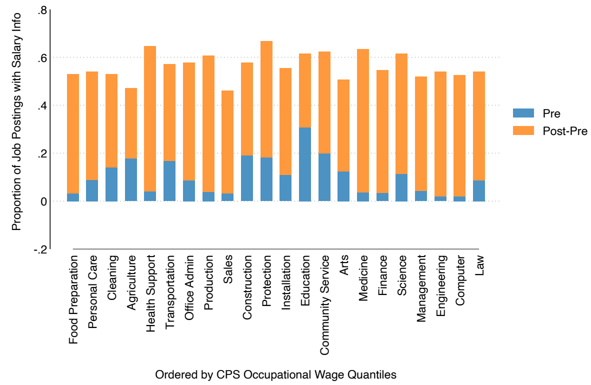
(b)



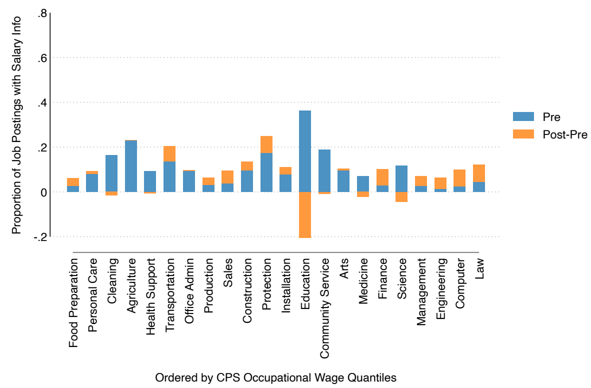
(c)

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.

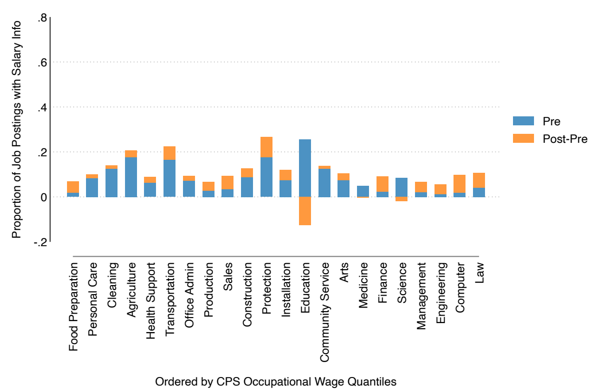
Figure A3: Fraction of Job Postings with Salary Information by Occupation: Pre vs. Post, LinkUp Job Posting



(a) Colorado



(b) West Coast States

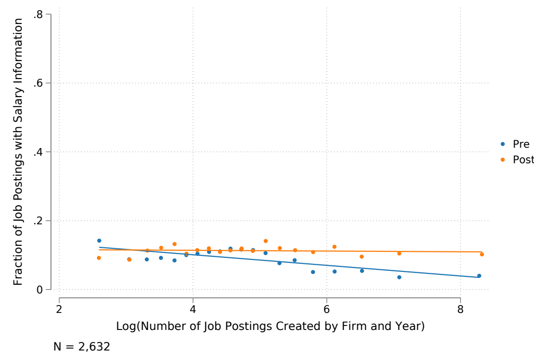


(c) SHB States

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; Panel B is for West Coast states (California, Oregon, and Washington); Panel C is for SHB states, which are states that had statewide pay history bans before 2021 (Alabama, California, Connecticut, Delaware, Illinois, Maine, Massachusetts, Oregon, Rhode Island, Vermont, and Washington). Pre-period refers to 2017-2020, and post-period refers to 2021-2022.

Figure A4: Fraction of Job Postings with Salary Information by Firm Size in Colorado: Pre vs. Post, LinkUp Job Posting

(a) Colorado

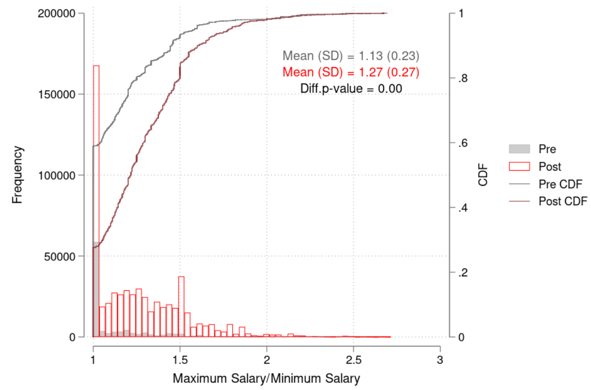


(b) West Coast States

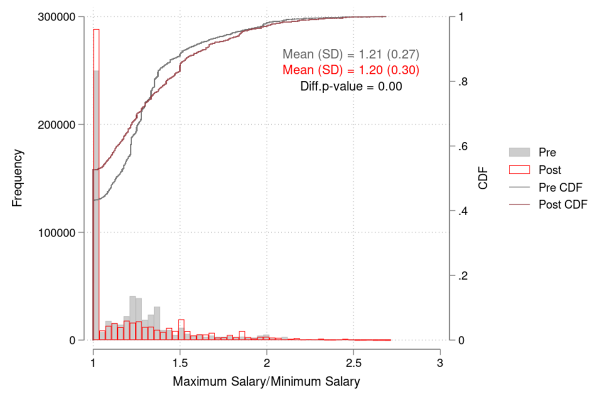
(c) SHB States

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. Panel A is for Colorado; Panel B is for West Coast states (California, Oregon, and Washington); Panel C is for SHB states, which are states that had statewide pay history bans before 2021 (Alabama, California, Connecticut, Delaware, Illinois, Maine, Massachusetts, Oregon, Rhode Island, Vermont, 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. For Panel C, the sample is restricted to firms that post at least 10 jobs per year in any of Alabama, California, Connecticut, Delaware, Illinois, Maine, Massachusetts, Oregon, Rhode Island, Vermont, and Washington. This sample consists of 3637 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.

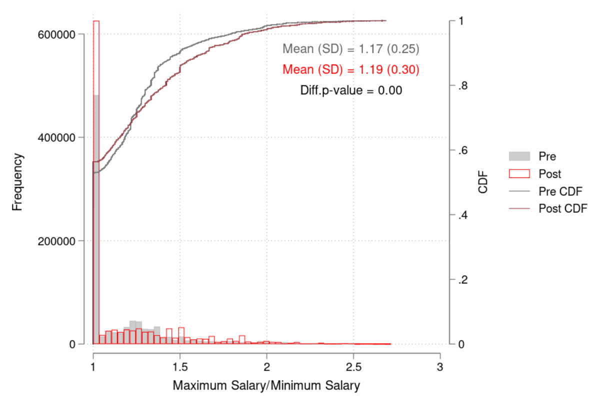
Figure A5: Histograms of Maximum Salary/Minimum Salary: Pre vs. Post, LinkUp Job Posting



(a) Colorado



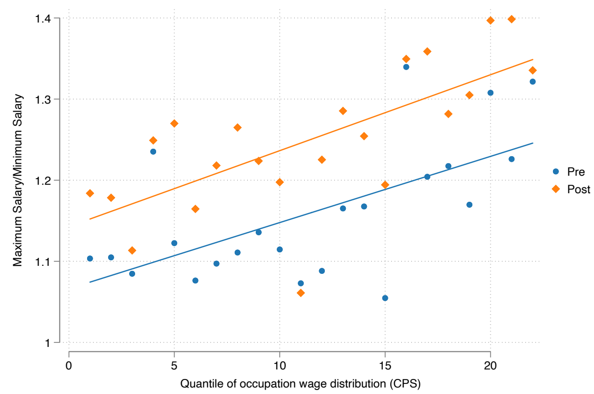
(b) West Coast States



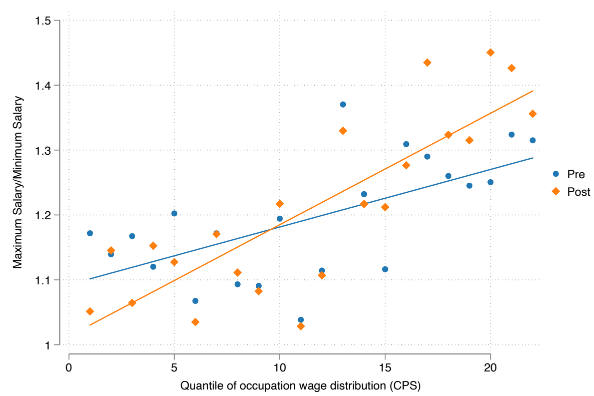
(c) SHB States

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; Panel B is for West Coast states (California, Oregon, and Washington); Panel C is for SHB states, which are states that had statewide pay history bans before 2021 (Alabama, California, Connecticut, Delaware, Illinois, Maine, Massachusetts, Oregon, Rhode Island, Vermont, 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.

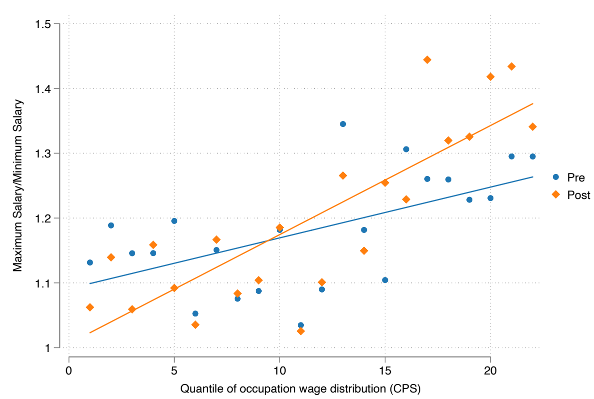
Figure A6: Maximum Salary/Minimum Salary by Occupation: Pre vs. Post, LinkUp Job Posting



(a) Colorado



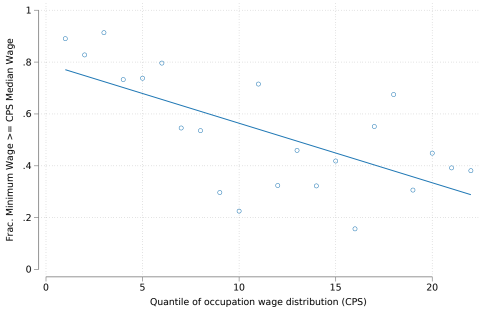
(b) West Coast States



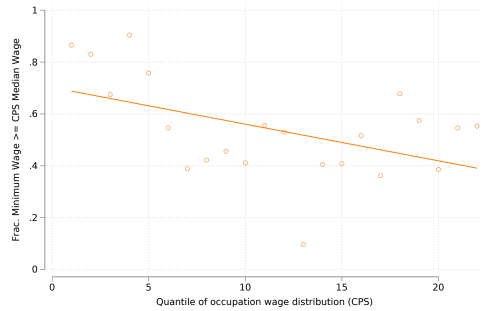
(c) SHB States

Note: This scatter plot shows the ratio of the maximum salary to the minimum salary in the pre-period and post-period. Panel A is for Colorado; Panel B is for West Coast states (California, Oregon, and Washington); Panel C is for SHB states, which are states that had statewide pay history bans before 2021 (Alabama, California, Connecticut, Delaware, Illinois, Maine, Massachusetts, Oregon, Rhode Island, Vermont, 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.

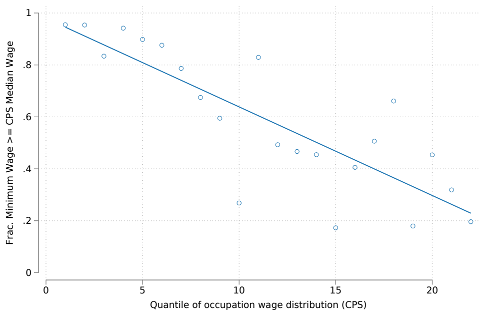
Figure A7: Minimum Posted Salary by Occupation: Pre vs. Post, LinkUp Job Posting and CPS ORG



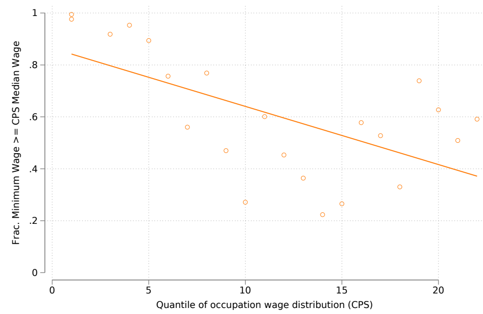
(a) Colorado - Pre



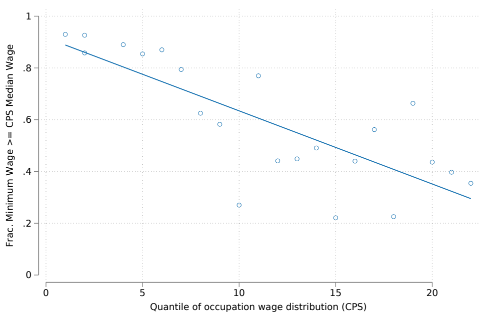
(b) Colorado - Post



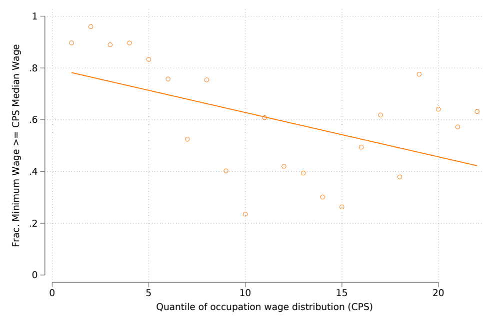
(c) West Coast States - Pre



(d) West Coast States - Post



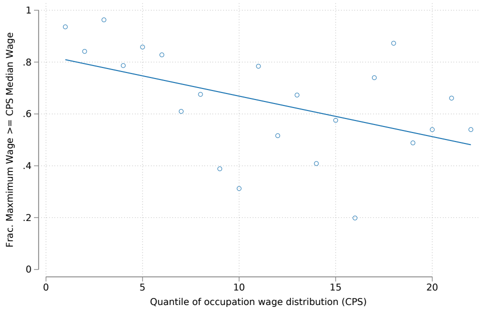
(e) SHB States - Pre



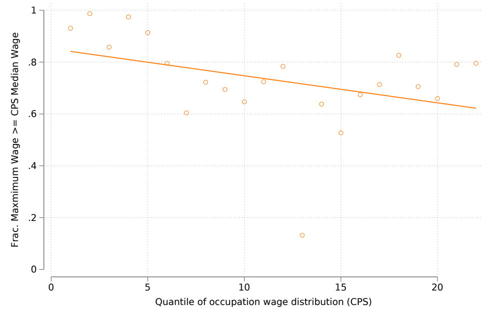
(f) SHB States - Post

Note: This scatter plot displays the proportion of job postings that have a minimum salary higher than the CPS occupational median wage, given that they have any wage information, for each occupation in the pre-period and post-period. Panels A and B are for Colorado; Panels C and D are for West Coast states (California, Oregon, and Washington); Panels E and F are for SHB states, which are states that had statewide pay history bans before 2021 (Alabama, California, Connecticut, Delaware, Illinois, Maine, Massachusetts, Oregon, Rhode Island, Vermont, and Washington). Pre-period refers to 2017-2020, and post-period refers to 2021-2022. Data source: LinkUp Job Posting Data and CPS ORG.

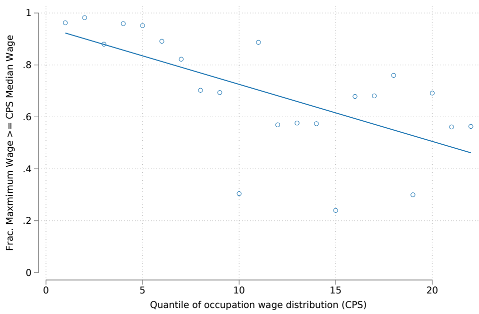
Figure A8: Maximum Posted Salary by Occupation: Pre vs. Post, LinkUp Job Posting and CPS ORG



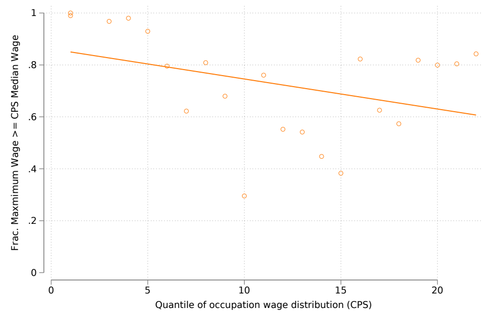
(a) Colorado - Pre



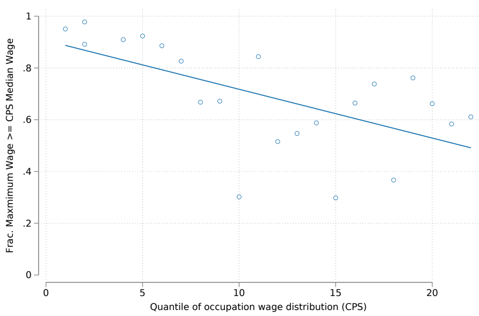
(b) Colorado - Pre



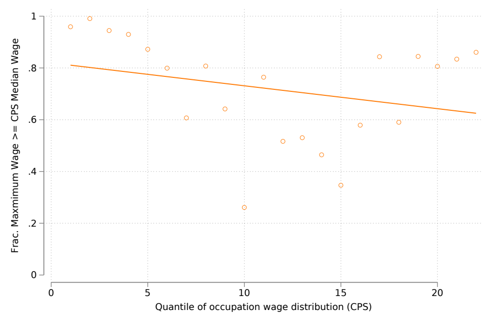
(c) West Coast States - Pre



(d) West Coast States - Post



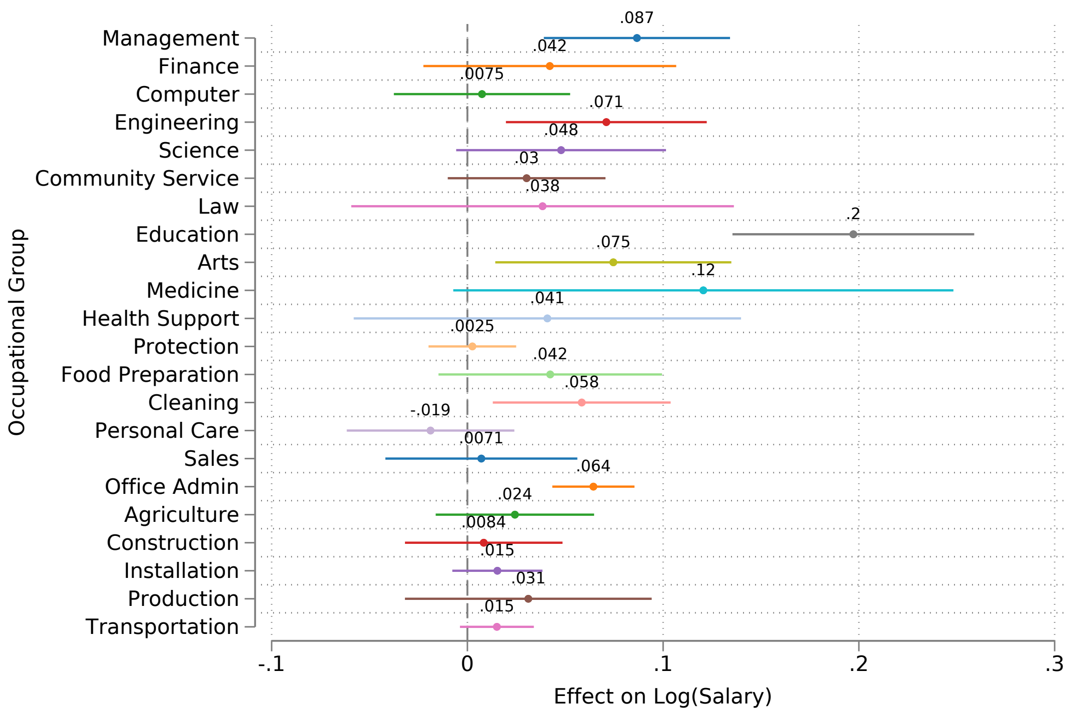
(e) SHB States - Pre



(f) SHB States - Post

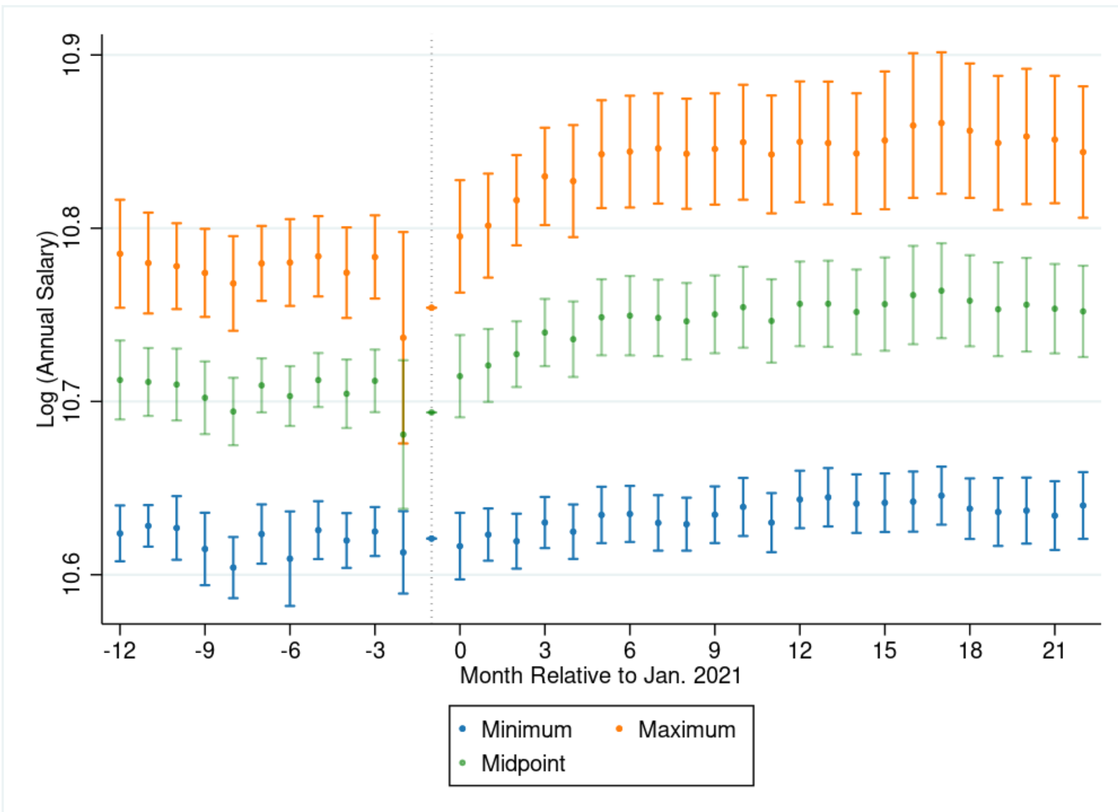
Note: This scatter plot displays the proportion of job postings that have a minimum salary higher than the CPS occupational median wage, given that they have any wage information, for each occupation in the pre-period and post-period. Panels A and B are for Colorado; Panels C and D are for West Coast states (California, Oregon, and Washington); Panels E and F are for SHB states, which are states that had statewide pay history bans before 2021 (Alabama, California, Connecticut, Delaware, Illinois, Maine, Massachusetts, Oregon, Rhode Island, Vermont, and Washington). Pre-period refers to 2017-2020, and post-period refers to 2021-2022. Data source: LinkUp Job Posting Data and CPS ORG.

Figure A9: Effect of Pay Transparency Law on Posted Salaries by Occupation, LinkUp Job Posting



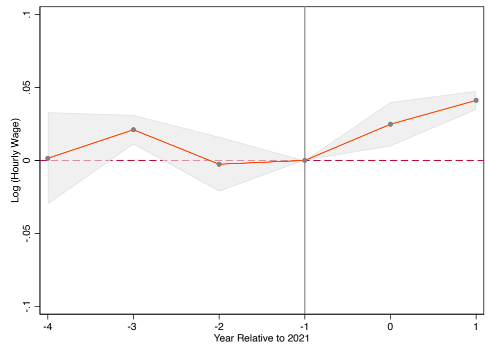
Note: This figure reports the point estimates and the 95% confidence intervals of the effect of pay transparency law on posted midpoint wages by occupation. Data source: LinkUp Job Posting Data.

Figure A10: Effect of Pay Transparency Law on Posted Salaries, LinkUp Job Posting

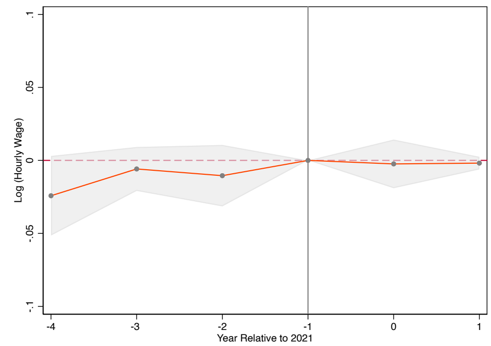


Note: This figure reports the effect of the pay transparency law on the log of the posted midpoint wage by month. The corresponding econometric specification controls for interaction (1) between occupation (6-digit ONet code) and month and (2) between firm, occupation, and zipcode. All coefficients are 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.

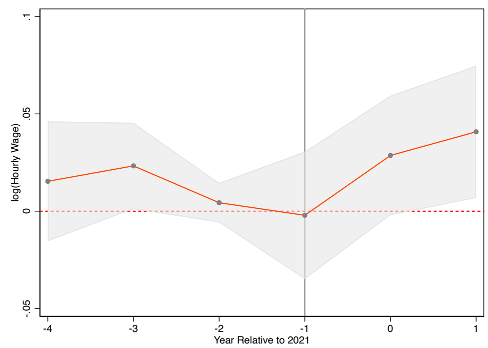
Figure A11: Effect of Pay Transparency on Realized Wages Using West Coast Control, DID vs. SDID, CPS ORG



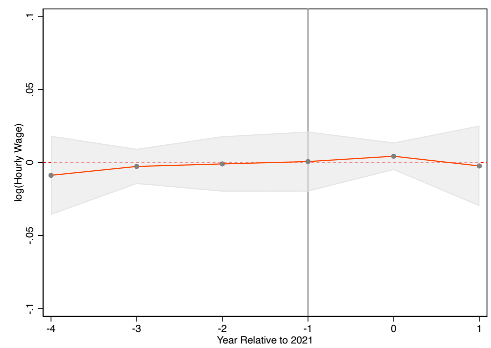
(a) DID without controls



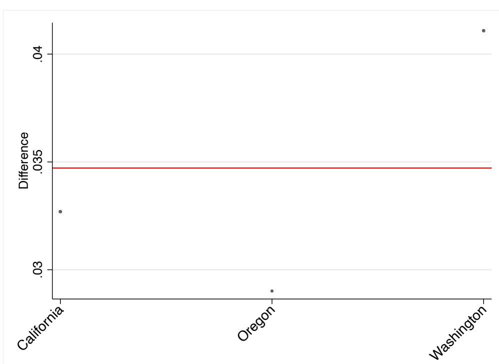
(b) DID with controls



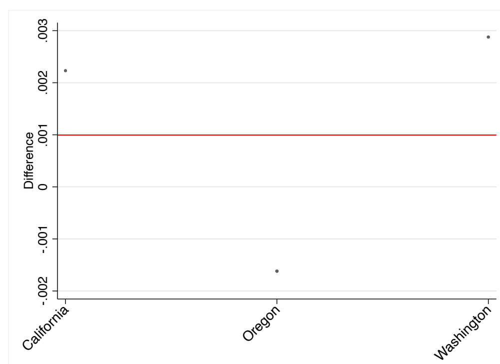
(c) SDID without controls



(d) SDID with controls



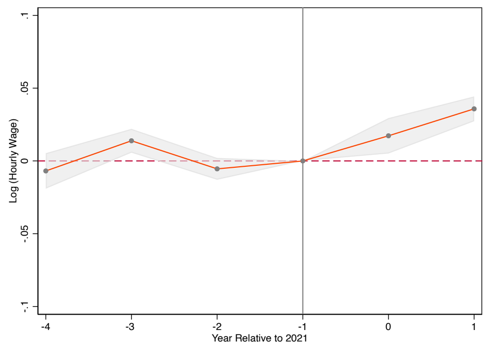
(e) SDID without controls



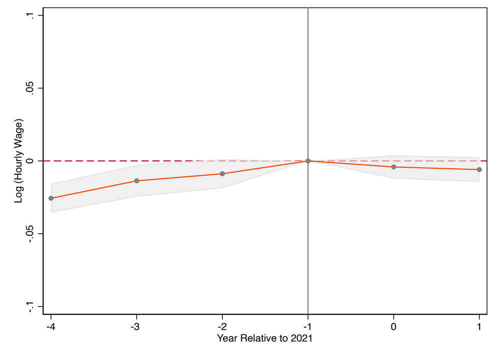
(f) SDID with controls

Note: The outcome is the log of the hourly wage. The treated group is Colorado and the control group (donor pool) is West Coast states (California, Oregon, and Washington). Panels A and B report the point estimates and the 95% confidence intervals of the effect of the pay transparency law on log(hourly wage) estimated by DID with and without control variables respectively. Standard errors are clustered at the state level. Panels C and D report the point estimates and the 95% confidence intervals of the effect of the pay transparency law on log(hourly wage) estimated by SDID with and without control variables respectively. Standard errors are computed using a placebo, or permutation-based, inference procedure with 1000 repetitions. Control variables include age, race, education, calendar month, full-time/part-time status, whether paid hourly, occupation, industry, occupation×year, and industry×year. Panels E and F report the unit-specific weight for each West Coast state used to construct the synthetic Colorado for Panels C (without controls) and D (with controls) respectively. Data source: CPS Outgoing Rotation Group.

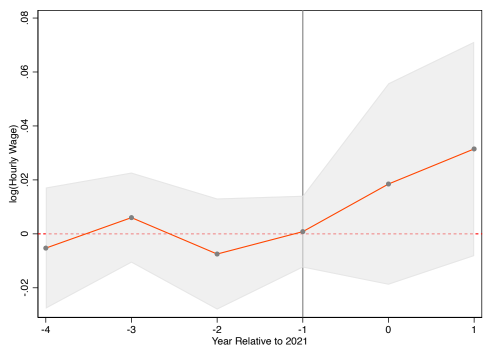
Figure A12: Effect of Pay Transparency on Realized Wages Using SHB States Control, DID vs. SDID, CPS ORG



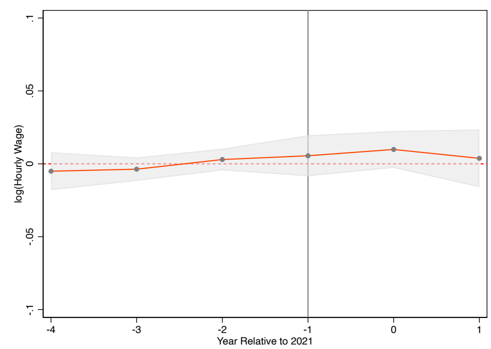
(a) DID without controls



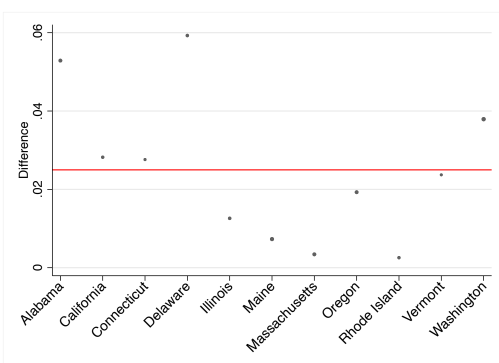
(b) DID with controls



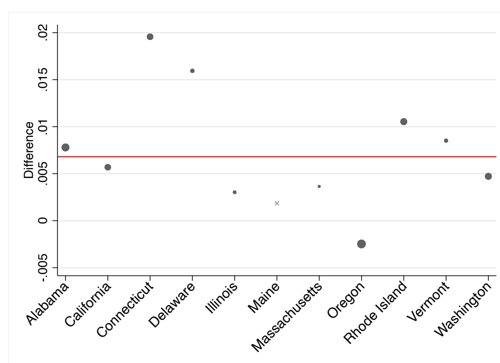
(c) SDID without controls



(d) SDID with controls



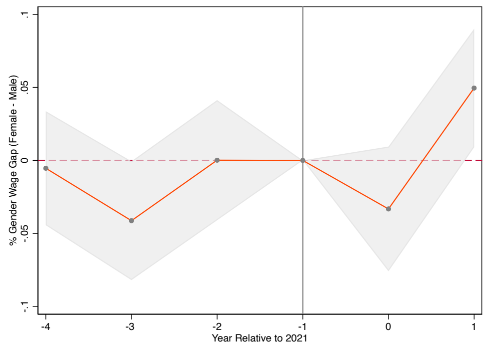
(e) SDID without controls



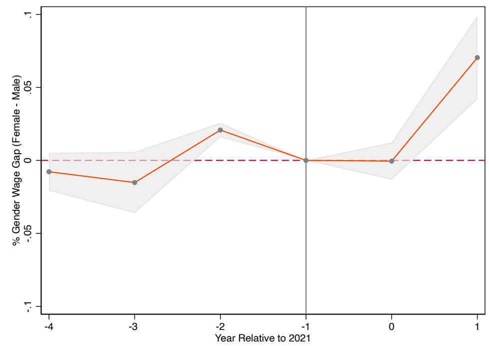
(f) SDID with controls

Note: The outcome is the log of the hourly wage. The treated group is Colorado, and the control group (donor pool) is states that had statewide pay history bans before 2021 (Alabama, California, Connecticut, Delaware, Illinois, Maine, Massachusetts, Oregon, Rhode Island, Vermont, and Washington). Panels A and B report the point estimates and the 95% confidence intervals of the effect of the pay transparency law on log(hourly wage) estimated by DID with and without control variables respectively. Standard errors are clustered at the state level. Panels C and D report the point estimates and the 95% confidence intervals of the effect of the pay transparency law on log(hourly wage) estimated by SDID with and without control variables respectively. Standard errors are computed using a placebo, or permutation-based, inference procedure with 1000 repetitions. Control variables include age, race, education, calendar month, full-time/part-time status, whether paid hourly, occupation, industry, occupation×year, and industry×year. Panels E and F report the unit-specific weight for each West Coast state used to construct the synthetic Colorado for Panels C (without controls) and D (with controls) respectively. Data source: CPS Outgoing Rotation Group.

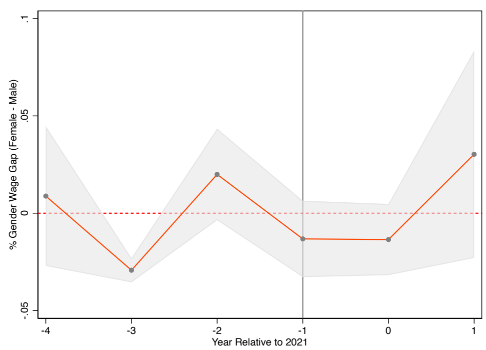
Figure A13: Effect of Pay Transparency on the Gender Wage Gap Using West Coast Control, DID vs. SDID, CPS ORG



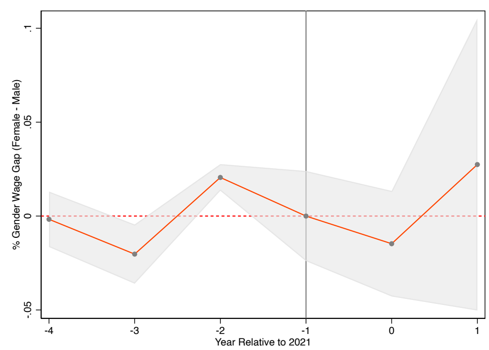
(a) DID without controls



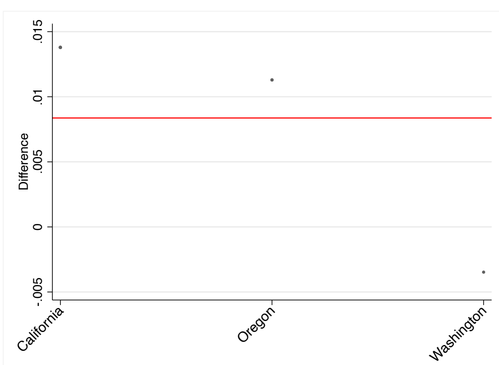
(b) DID with controls



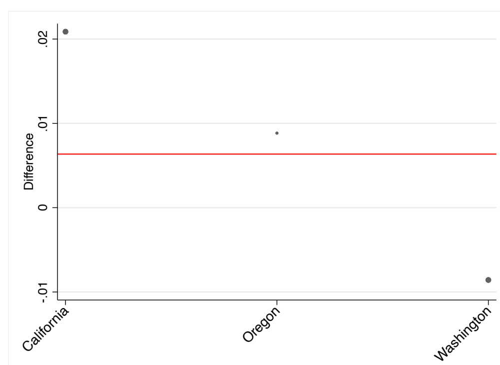
(c) SDID without controls



(d) SDID with controls



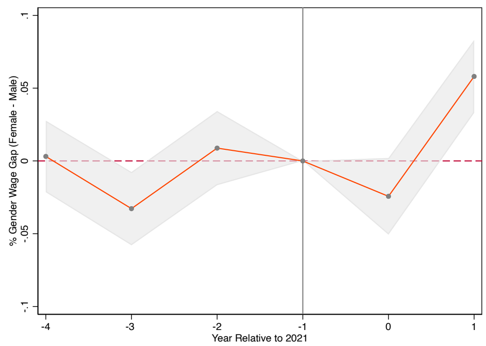
(e) SDID without controls



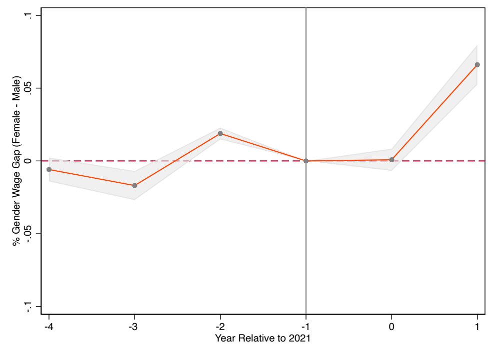
(f) SDID with controls

Note: The outcome is the gender wage gap. The treated group is Colorado and the control group (donor pool) is West Coast states (California, Oregon, and Washington). Panels A and B report the point estimates and the 95% confidence intervals of the effect of the pay transparency law on the gender wage gap estimated by DID with and without control variables respectively. Standard errors are clustered at the state level. Panels C and D report the point estimates and the 95% confidence intervals of the effect of the pay transparency law on the gender wage gap estimated by SDID with and without control variables respectively. Standard errors are computed using a placebo, or permutation-based, inference procedure with 1000 repetitions. Control variables include age, race, education, calendar month, full-time/part-time status, whether paid hourly, occupation, industry, occupation×year, and industry×year. Panels E and F report the unit-specific weight for each West Coast state used to construct the synthetic Colorado for Panels C (without controls) and D (with controls) respectively. Data source: CPS Outgoing Rotation Group.

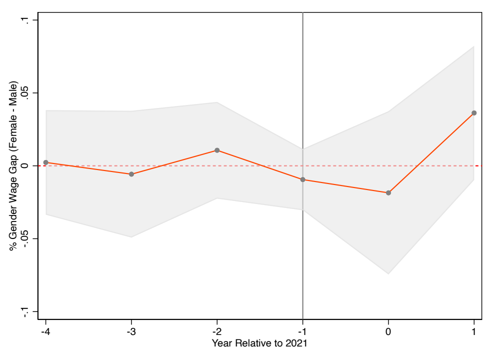
Figure A14: Effect of Pay Transparency on the Gender Wage Gap Using SHB States Control, DID vs. SDID, CPS ORG



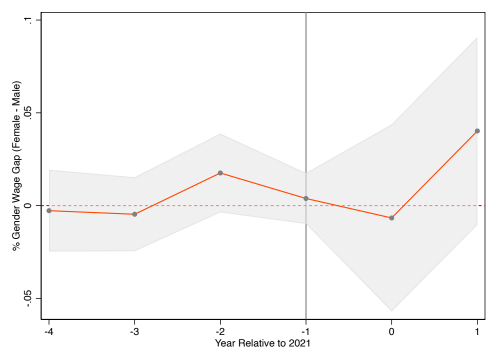
(a) DID without controls



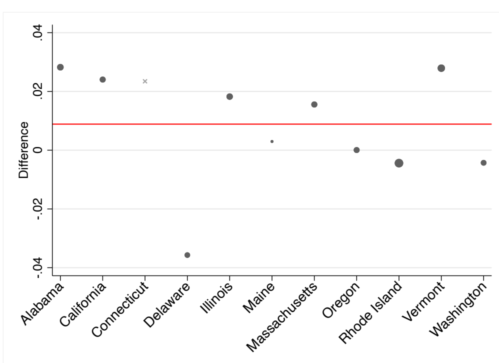
(b) DID with controls



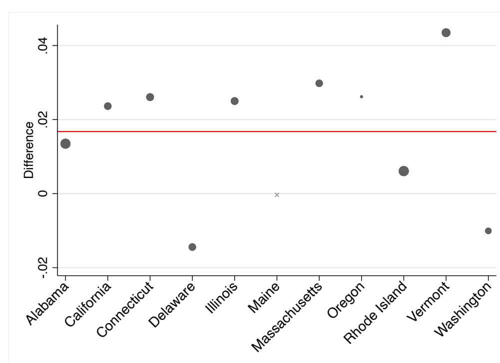
(c) SDID without controls



(d) SDID with controls



(e) SDID without controls



(f) SDID with controls

Note: The outcome is the gender wage gap. The treated group is Colorado, and the control group (donor pool) is states that had statewide pay history bans before 2021 (Alabama, California, Connecticut, Delaware, Illinois, Maine, Massachusetts, Oregon, Rhode Island, Vermont, and Washington). Panels A and B report the point estimates and the 95% confidence intervals of the effect of the pay transparency law on the gender wage gap estimated by DID with and without control variables respectively. Standard errors are clustered at the state level. Panels C and D report the point estimates and the 95% confidence intervals of the effect of the pay transparency law on the gender wage gap estimated by SDID with and without control variables respectively. Standard errors are computed using a placebo, or permutation-based, inference procedure with 1000 repetitions. Control variables include age, race, education, calendar month, full-time/part-time status, whether paid hourly, occupation, industry, occupation×year, and industry×year. Panels E and F report the unit-specific weight for each West Coast state used to construct the synthetic Colorado for Panels C (without controls) and D (with controls) respectively. Data source: CPS Outgoing Rotation Group.

Appendix C 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 A15 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.

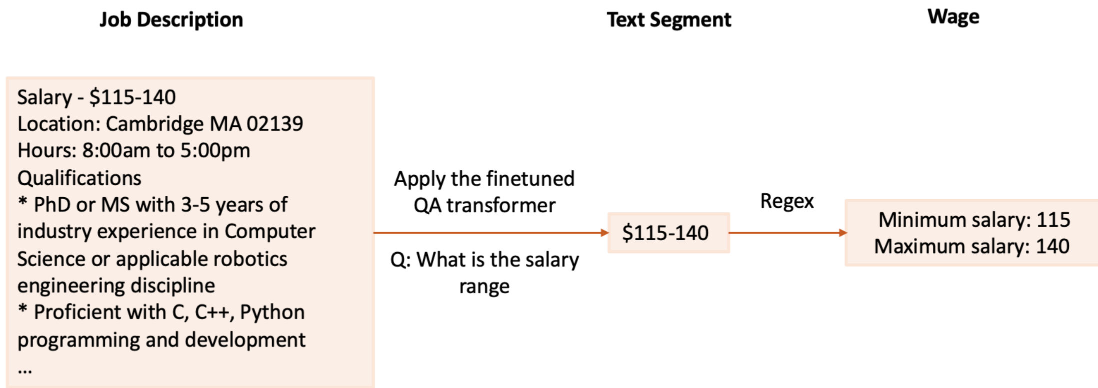
  I finetuned a pre-trained transformer to achieve better performance in extracting wage information from job descriptions. The pre-trained model used for finetuning is `deberta-v3-large-squad2`. This model is trained using a large set of English Wikipedia articles and has learned general-purpose representations 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 A5 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" 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.**

Figure A15: 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.

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 A5: 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.