Wage Inequality and Labor Rights Violations*

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Abstract

Wage inequality does not fully capture differences in job quality. Jobs also differ along other key dimensions, including the prevalence of labor-rights violations. Yet, there is little systematic evidence on this non-wage dimension of job quality and how it contributes to overall inequality. We use a combination of systematic legal violations data from federal agencies, and local industry employment data. We construct novel measures of labor violation rates and show they are positively correlated with worker survey reports of adverse working conditions, establishing their validity. Within local industries over time, a 10% increase in the average local industry wage is associated with a 0.15% decrease in the number of violations per employee and a 4% decrease in fines per dollar of pay. Increases in worker power measured by reduced labor market concentration and increased unionization are also associated with reductions in labor violations. Overall, we conclude that labor violations are regressive: they deepen wage inequality by increasing inequality in job quality.

JEL codes: J31, J83, J32, J33, J28, K31, K42

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Wage inequality in the U.S. is considerable, and has been growing since the 1980s (e.g. Kopczuk, Saez and Song, 2010). But the difference between better and worse jobs is not just about pay. Employers violate workers' legal rights (Anderson, 2019) by requiring work under unsafe conditions (Weil, 2001; Levine, Toffel and Johnson, 2012; Pouliakas and Theodossiou, 2013), failing to pay them fully (Bobo, 2014; Galvin, 2016), and more. To what extent does inequality in job quality deepen wage inequality? Scholars, activists, and public officials lack systematic data on the prevalence of worker rights violations. Cross-sectional worker survey evidence on labor violations exists for a few cities in low-wage industries (Bernhardt et al., 2013) and there is a cross-sectional nationally-representative survey of working conditions (Maestas et al., 2017). Measures based on administrative data offer a relatively inexpensive way to measure variation in labor violations at a fine geographic level and over time, but there is little evidence on the properties and relevance of such measures nor is it commonly put in the context with complementary data on workforce or by combining information across multiple enforcement agencies.

The present study works towards improving systematic, quantitative view of labor-rights violations in the U.S. and understanding how such violations can reinforce wage inequality. Do wages serve as a compensating differential for illegal working conditions (wages positively correlated with illegal working conditions)? Or are illegal working conditions and lower wages simply two aspects of bad jobs (wages negatively correlated with illegal working conditions)? Sorkin (2018) refers to these two mechanisms as the Rosen and Mortensen motives, respectively. Using panel regressions, we show that local industry wage increases are associated with decreases in the prevalence and severity of labor-rights violations caught by federal agencies. Therefore, our results suggest that wage inequality understates the inequality in job quality in the U.S. They are not consistent with a simple compensating differentials model, but are consistent with the "Mortensen" view that low wages and illegal working conditions are two aspects of bad jobs.

To reach this conclusion, this study leverages a unique, relatively-new database that merges and harmonizes data on enforcement actions against companies across agencies.[1] A nonprofit,

[1] Gaining a view of firm activities across regulatory agencies' domains is challenging. In recognition of this, the U.S. Commission on Evidence-Based Policymaking's final report pushed for greater integration of administrative data-

Good Jobs First, constructed the Violation Tracker (VT) database precisely to facilitate research into corporate behavior across multiple domains. Each record is a case with at least one violation citation by an enforcement agency, a date, a cited establishment or firm at a location, a type of primary violation, and a penalty amount. We focus on labor rights enforced by federal agencies that report violating establishments' industry: the Occupational Safety and Health Administration (OSHA), the U.S. Department of Labor's Wage and Hours Division (WHD), and the National Labor Relations Board (NLRB).[2] In most analysis, we sum violations across OSHA, WHD, and NLRB to build a holistic measure of labor-rights violations.

Labor-violation citations must be understood as resulting from a combination of firm, worker, and enforcement agency behavior: this means that actual violations can easily differ from legally-sanctioned violations. Cited violations depend on both the true intensity of violations and the likelihood that real violations convert into citations (Marinescu, 2011; Sojourner and Yang, 2020), which depends on workers' willingness to report violations to enforcement agencies and to co-operate with investigators.[3] Enforcement policy can change with each presidential administration (Weil, 2010), and we will check whether our key relationships of interest hold within an enforcement regime. Grittner and Johnson (2020) find evidence that, on average, local industries where workplace injury rates are higher are also those where workers are more likely to file complaints,

sets and need for stable, reliable firm identifiers across agencies and within agency over time (U.S. Commission on Evidence-Based Policymaking's Employer Data Matching Workgroup, 2017; U.S. Commission on Evidence-Based Policymaking, 2017).

[2]The records of another federal agency, the Equal Employment Opportunity Commission (EEOC), do not report violating companies' industry, so we cannot include their enforcement actions in the analysis. In the VT data nationally, OSHA, WHD, and NLRB cite 124 times as many violations and 4.6 times larger aggregate penalties as the EEOC.

[3]When comparing social-benefit use reports between surveys and administrative data (Meyer et al., 2015), the administrative dataset can be credibly understood as accurate because the question of interest is about the administered program. However, our situation is closer to the challenge of understanding crime broadly, where survey and administrative data might provide two imperfect measures of a hard-to-observe phenomenon. For instance, the F.B.I.'s Uniform Crime Report (U.C.R.) system harmonizes data from state and local agencies on victim reports to agencies and their arrests. This gives one partial view of differences over geographies and time in crime rates. The Bureau of Justice Statistics also runs a separate survey of the U.S. population and asks about victimization. This gives an alternative view that does not depend on official complaints or successful investigation and enforcement. Unfortunately, official surveys of workers provide little insight into the worst aspects of jobs and little fine-grained power to understand sub-group variation. This is analogous to asking if places with higher crime rates reported to police in U.C.R. are also the places with higher crime rates reported in population surveys about victimization. A small difference is that our administrative measure is not based on complaints to enforcement agencies but on findings of wrong-doing, so more like criminal convictions rather than crime reports.

suggesting that cited violation rates will proxy well for underlying true violation rates.

Consider two workers who are identical in productivity but one worker has less bargaining power in her employment relationship than the other. An employer might claim greater value from the employment relationship both by paying lower wages and by violating the worker's labor rights, such as requiring work in unsafe or unhealthy conditions (OSHA), shorting on overtime pay (WHD), or discouraging union organizing by threatening to fire union sympathizers (NLRB). The lower-power worker would have both lower wage and more violations of her labor rights. However, workers with less power may be less likely to to *report* these violations to enforcement agencies, leading to measurement error in cited violations that's negatively correlated with true violations. This echoes another Grittner and Johnson (2020) finding, true violation intensity is negatively correlated with complaint rates among Hispanic workers in low-wage industries. Echoing this, Hertel-Fernandez (2020) shows that lower-income workers and workers with fewer outside options are less comfortable discussing workplace problems with their coworkers. Thus, even if the relationship between wages and true violations is negative, the relationship between wages and *legally-sanctioned* violations might appear positive if the reporting channel dominates. This reporting channel would create positive bias in the estimated relationship between wages and cited-violations, pushing against finding a negative relationship between wages and violations.

Our new measures of labor-violation intensity put violation records in the context of their labor markets. We measure the number of workers in each industry-year or industry-locale-year, their pay, and their characteristics using standard data sources such as the Quarterly Census of Employment and Wages (QCEW), Quarterly Workforce Indicators (QWI), and the Current Population Survey (CPS). Violation measures become the numerators and the workforce measures the denominators, yielding labor-violation rates. We compute two measures: the *prevalence* of violations measured as the number of violation citations per employee, and the *severity* of violations measured by the dollar value of penalties assessed per million dollars of payroll. Loosely, the former focuses on the extensive margin of violation prevalence and the latter on the intensive margin of severity. The severity measure allows us to quantify violations in dollar terms, and express them as a kind of tax on wages levied by employers. Harnessing these new measures, we make three primary empirical contributions.

First, we contribute by providing new measures of labor violation intensity and testing their validity. To validate these measures, we assess whether cited violations predict employee reports of abuse and working conditions across industries in the 2015 American Working Conditions Survey (Maestas, Mullen, Powell, Von Wachter and Wenger, 2017). This analysis is motivated by the theory that the two kinds of measures share a common factor, underlying job quality. We find that higher levels of labor-rights violations from administrative records correlate positively with worker survey reports of abuse on the job, bad bosses, bad workplaces, exposure to physical risks, and being forced into last-minute schedule changes. Thus, violations are not merely a regulation and reporting outcome but reflect employees' experience.

Second, we contribute to the measurement of inter-industry wage inequality by examining a new dimension of job quality: labor-rights violations. Using a panel regression with industry by commuting zone (CZ) and year fixed effects, we find that a 10% increase in the average industry-CZ pay is associated with an average 0.15% decrease in the number of violations per employee and a 4% decrease in fines per dollar of payroll. To the extent that the reporting channel described above operates, this understates the magnitude of the negative relationship between labor rights violations and wages. The relationship between local industry wages and violations is stronger conditional on having labor violations: among local industries that do have labor violations, a 10% increase in wages is associated with an *equal* decrease in violations. Overall, we conclude that the labor violations wage "tax" is regressive and contributes to increasing inequality. This contributes to a literature showing that higher paying jobs also tend to have other desirable amenities, that the Mortensen pattern tends to dominate the Rosen pattern (Bonhomme and Jolivet, 2009; Maestas et al., 2018; Sorkin, 2018).

Our third contribution is to examine how other aspects of worker bargaining power relate to violation intensity. We study how violation intensity relates to worker educational attainment, union density, and the concentration of employment in local industries across employers. Results are mixed. Increases in the share of workers with a bachelors' degree do not relate to violation intensity. Increased unionization decreases the prevalence of labor rights violations, consistent with unions increasing worker bargaining power (Freeman and Medoff, 1984; Breda, 2015; Knepper, 2018) and protecting workers' legal rights (Weil, 1991; Fine, 2017). Increased labor market concentration – which should reduce worker bargaining power – may increase labor violations. While we do not find evidence for this using OLS, we do find a positive effect of labor market concentration on labor violations when using an instrumental-variables estimator (Azar et al., 2020; Qiu and Sojourner, 2019).

The paper is organized as follows. In section 1, we discuss our data, focusing on the labor rights violations dataset. In section 2, we validate our measures of labor rights violations against survey measures of working conditions. In section 3, we present our analysis of the relationship between industry wages and labor violations, and we examine the relationship between worker power and labor violations. Section 4 concludes.

1 Measuring Violation Intensity

Our primary analysis focuses on variation in labor conditions in local industries by year. Using the Violation Tracker (VT) database allows us to build systematic, quantitative measures of the extent of labor-rights violations at fine levels of detail. The primary concept we want to understand is the intensity of labor-rights violations among firms in an industry-locale-year, which we measure with cited violations.

Labor-rights violations intensity: To measure violation prevalence, we compute violation rates by dividing total violation counts across agencies by the number of thousands of employees at risk. To measure violation severity, we add up total associated penalties and divide by the total payroll of employees at risk in millions of dollars. This gives a violation rate (prevalence) per thousand employees and a penalty rate (severity) per million dollars of payroll. Each of these rates can be computed by year, by industry, by geography, or by any combination of these. Keeping the industry (NAICS4) and calendar year definitions fixed, we use multiple, different levels of geography – national, state, and commuting zone (CZ) – to match different supplemental data sources at various points in this study.

The underlying data on cases with cited violations comes from the Violation Tracker (VT) Database, produced by the nonprofit Good Jobs First. The VT data runs from the years 2000 to 2019. Although we don't use it all, the database collects and partially harmonizes violation case records from more than 40 federal, state, and local agencies. It focuses on cases that brought at least a $5,000 penalty.[4] For each case, the record contains company name, location (often but not always state, city, street address, and zip code), description of primary offense, penalty date, penalty amount[5], and enforcement agency name.

To measure labor-rights violations, we focus on violations enforced by federal agencies with a primary-offense type implying harm centered on workers. We ignore agencies with harm centered on investors (e.g. Securities and Exchange Commission), on consumers (e.g. Consumer Product Safety Commission), or neighbors (e.g. Environmental Protection Agency). State attorney generals do not always have jurisdiction over labor regulation and do very limited labor enforcement (Strong, 2014). Restricting attention to federal agencies ensures relatively-uniform measurement properties across states and prevents confounding a state's vigorous enforcement action with higher violation intensity. Appendix Table A.1 shows all agencies present in VT involved in labor violations and what share of violations each represents. Among all cited violations in VT, 71 percent are labor-related. However, they account for only 5 percent of monetary penalties paid by firms, reflecting labor-violations' relatively low average penalty per citation compared to other agencies.

To enable study of variation across industries, we focus on agencies that report each violating company's industry. The U.S. Occupational Safety and Health Administration (OSHA), U.S. Department of Labor's Wage and Hour Division (WHD), and the National Labor Relations Board (NLRB) do report company detailed NAICS industry codes. These three agencies account for

[4]For actions enforced by Occupational Safety and Health Administration (OSHA), only penalties designated as willful, repeat or serious are included in the database.

[5]We inflate penalty amount to 2019 dollars.

244,876 cases, which are 84 percent of all cited labor-rights violations across all state and federal agencies in VT.[6]

In much of our analysis, the unit of observation is the industry by commuting zone by year, defined as the interaction between a 4-digit 2012 NAICS (NAICS4) code, 2000 commuting zone (CZ), and calendar year. For each observed violation, we map the 5-digit zip code of the violating company to its CZ, through county.[7] To identify the 2012 4-digit NAICS associated with each observation, we use the reported NAICS codes in the VT database. 94 percent of OSHA, WHD, and NLRB records have NAICS code observed. To harmonize different versions of NAICS codes, we use the crosswalks among different versions of NAICS codes provided by the Census.[8]

This process yields an analytic sample based on 214,364 labor-related violations in 348 industries, 698 CZs, 20 years, and which form 40,487 local industries (NAICS4-CZ), and 112,942 industry-CZ-years with any violations. Counts or sums of violations and penalties are not particularly meaningful without scaling them for variation in the underlying workforce at risk. Otherwise, one cannot tell if a high count comes from higher violation risk or more workers at risk. Scaling the number of violations in a local industry by employment counts and penalties by payroll makes them more interpretable.

Employment and Payroll: employment and payroll data come from the annual averages file of Quarterly Census of Employment and Wages (QCEW), the nation's most reliable measures of these variables. The QCEW covers 98% of U.S. jobs and its pay data include salaries, bonuses, stock options, profit distributions and other benefits. We only use data for the private sector. We measure employment and pay at the same unit, NAICS4$\times$CZ$\times$year, to match to the violations

[6]Two main federal labor enforcement agencies are excluded because their records do not classify cited companies by industry: the Equal Employment Opportunity Commission (EEOC) with 1,977 cases and the Mining Safety and Health Administration (MSHA) with 27,573 cases. Though we know all MSHA violations are labor violations in the mining sector, classification into detailed industry (NAICS4) comparable with OSHA, WHD, and NLRB is not available.

[7]Another advantage of the OSHA, WHD, and NLRB agency data is that the zip code pertains to the establishment where the violation occurred, not the corporate headquarters. The crosswalk between 5-digit zip code and county is at `https://anthonylouisdagostino.com/a-better-zip5-county-crosswalk/`. The crosswalk between county and 2000 CZ is at `https://www.ers.usda.gov/data-products/commuting-zones-and-labor-market-areas/`.

[8]Crosswalks: `https://www.census.gov/eos/www/naics/concordances/concordances.html`.

data. Specifically, we first convert all other versions of NAICS4 codes to the 2012 version and map each county to its associated CZ using the same procedures as before. We calculate total pay, total employment, and average pay in each industry-locale-year.[9]

We merge variables from QCEW with those from the VT database at the industry-locale-year level. If an industry-locale-year is observed to have employment in the QCEW but no violations in VT, we assign zeros as the values for violation variables because no agencies cited companies for labor-rights violations there. Our QCEW-VT sample has 102,204 unique observed local industries (NAICS4-CZ) and 1,465,807 observed local industry-years.

Our data allows for a novel description of the variation in labor-violation intensity in many dimensions. Adjusting for industry composition and times effects, the most-intense violations of labor rights in the last decade appear clustered in commuting zones of the Great Plains and the South with low intensities in the mid-Atlantic and the West (Figure 1)[10]. Figures in the appendix describe national trends in violation intensity across time (Figure A.2), the states (Figure A.3) and industries (Figure A.4) with the highest and lowest violation intensities. Construction has the highest violation intensity while management has the lowest intensity. This pattern foreshadows our main result that higher wages are associated with lower violations.

[9]One assumption we make is that the version of NAICS used in each year in the VT database is the same as the one in Quarterly Census of Employment and Wages (QCEW) program from the Bureau of Labor Statistics. Specifically, the 2002 version for the years between 2000 and 2006, the 2007 version for the years between 2007 and 2010, the 2012 version for the years between 2011 and 2016, and the 2017 version for the years since 2017. Also, when a version of NAICS4 crosswalks into multiple 2012 NAICS4 codes, we drop it from our sample because we cannot reliably map it into a specific 2012 NAICS4 for our analysis. Around 4.9% of labor-related violations are dropped from our sample for this reason. Another 1.3% of labor-related violations are further dropped because the NAICS4 codes reported in VT database do not belong to either 2002, 2007, 2012 nor 2017 version of NAICS4 codes.

[10]The Figure legend shows negative values because it plots regression residuals rather than raw violation intensities. Figure A.1 in the appendix shows the raw violation intensity by commuting zone, without adjusting for industry composition and year. The map is fairly similar to Figure 1, except that the North-East has a lower violation intensity.

2 Validation: Relationship between Labor-Violation Intensity and Worker Self-Reported Working Conditions

Before moving into the analysis of the relationship between local industry violation intensity and wages, we generate evidence on the validity of this novel labor-violation intensity measure by relating it to individual worker's self-reports of their working conditions in a nationally-representative survey. This analysis is motivated by the theory that the two kinds of measures share a common factor: underlying job quality. The survey is the 2015 American Working Conditions Survey and includes information on worker demographics and various aspects of working conditions reported by workers as well as their industry (NAICS4) (Maestas et al., 2018). Based on each surveyed worker's industry, we assign them the measured violation intensity for that industry (NAICS4) in that year.[11] Do workers in industries measured as having with more-intense labor violations tend to report worse working conditions, controlling for other differences between workers?

We define variables to capture aspects of working conditions that we would expect to be correlated with labor-rights violation citations: violations of workers' rights to earned pay, safe and healthy working conditions, and freedom from discrimination and harassment. After doing the procedures described below, we standardize each measure, except for the indicator variable for last-minute change of work schedule, to zero mean and unit standard deviation in the national population.

- Abuse index: We use 2 group of questions. One group asks, "Over the last month, during the course of your work have you been subjected to...?" where ... is "verbal abuse," "unwanted sexual attention," "threats," and "humiliating behavior." The other group asks about rarer events with a longer time window: "And over the past 12 months, during the course of your work have you been subjected to...?" where ... is "physical violence," "bullying/harassment," and "sexual harassment." These groups yield seven indicators of yes responses. For each individual, we average across them. A higher value implies more abuse at work.

[11] The survey lacks geographic detail that would enable matching more locally.

- Last-minute change of work schedule indicator: We use responses to the question, "Do changes to your work schedule occur often?" We define someone as experiencing last-minute scheduling changes if and only if they answer "Yes, the same day" or "Yes, the day before." If they get more notice or report schedule changes not often, the indicator takes the value zero.

- Physical exposure index: We use responses to a group of 9 variables asking how much the worker is exposed to the following at work in their main job: "vibrations (hand tools/machinery)," "loud noise," "high temperatures," "low temperatures," "breathe smoke/fumes/powder/dust," "breathe vapors," "handling chemical products," "breathe tobacco smoke," and "handling infectious materials." Each response is a Likert scale from 1 to 7 where higher values indicate less exposure. We standardize each variable across individuals, then take the simple average across the variables for each individual. We put a minus sign before the index so that a higher value implies more exposure to physical risks.

- Stress index: We use responses to seven questions of the form, "For each of the following statements, please select the response which best describes your work situation." The statements are: "enough time to finish work," "know expectations," "motivated to do your best," "treated fairly," "receive contradictory instructions," "experience stress in your work," "required to hide feelings." Responses range from 1 ("always") to 5 ("never"). For the first four statements, higher responses indicate more stress, with the opposite for the last three statements. We standardize each variable across the sample. We put minus signs before the last three variables so each variable's value rises in stress. We take the simple average across variables for each individual. A higher index implies more stress at work.

- Good-boss index: We use responses to seven questions, each a statement following this preamble, "Do you agree or disagree with the following statements? Your immediate boss..." The seven statements are, "trusts you," "respects you," "gives praise/recognition," "gets people to work together," "is helpful," "provides useful feedback," "encourages & supports your development." Agreement with each is captured by a indicator. We take the simple average across these variables for each individual. Higher index values imply better bosses.

- Workplace-quality index: We use responses to seven questions, each a statement following this preamble, "The next question is not about your own job but about your workplace. To what extent do you agree or disagree with the following:" The seven statements are: "employees are appreciated when done a good job," "management trusts employees to do work well," "conflicts are resolved fairly," "work is distributed fairly," "there is good cooperation between you & colleagues," "generally, employees trust management," "you like & respect your colleagues." Each response varies from 1 (strongly agree) to 5 (strongly disagree), so higher values indicate lower workplace quality. We first standardize each variable across the sample and then average across variables for each individual. We put a minus sign before the index such that a higher value implies better workplace quality.

This gives a measure of each of these aspects of working conditions for each worker in the AWCS. To estimate the correlation between labor-violation intensities and workers' reports of their working conditions, we run the following regression:

$$Working\_Condition_{ij} = \alpha + \beta \times Log(1 + Violation\_Intensity)_j + \Gamma' X_i + \varepsilon_{ij} \tag{1}$$

with i indexing an individual and j indexing an industry (4-digit NAICS). X_i is a vector of individual characteristics including gender, age, earnings, race, and ethnicity. We use two measures for *Violation Intensity*: the count of violations cited normalized by the number of employees (a prevalence measure), and the penalties levied normalized by the employee wage bill (a severity measure). We cluster the standard errors at the industry level.

Our estimates show that workers in industries where enforcement agencies issue more citations and levy more penalties against companies for labor-rights violations also tend to report worse working conditions (Table 3). A higher rate of labor violations per employee in an industry predicts a higher probability of last-minute schedule change, higher indexes for abuse- and physical exposure-related issues, and worse assessments of bosses and workplace quality (Table 3: Panel A). The relationship is most statistically significant for the index for physical exposure-related issues (Table 3: Panel A). We do not find that the industry-level violation intensity is correlated with stress in workplaces. Similarly (Table 3: Panel B), workers in industries where authorities levy greater penalties for labor violations per dollar of pay report worse working conditions of all kinds, except stress.

We then condition on worker demographics, so that rather than simply comparing across industries, we compare workers who are observably-similar in terms of gender, age, race and ethnicity, and earnings but who work in different industries. Conditional on worker characteristics, the violation penalty per dollar of pay remains a strong predictor of self-reported working conditions, except for stress (Table 3: Panel D). When the outcome is violation counts per employee, controlling for worker demographics makes the relationship between self-reported working conditions and violations insignificant, except in the case of physical exposure (Panel C), but all coefficients keep their signs.

Further, we find that, even when controlling for labor violation intensity, higher individual worker earnings ("Log (earnings)") tend to predict lower prevalence of adverse working conditions on all measures other than stress (Table 3: Panel C and D). Thus, an individual worker with higher pay has a lower chance of experiencing adverse working conditions, even after we account for the overall propensity of an industry to violate workers rights and demographic characteristics.

Next, we turn to an analysis that focuses on the relationship between wages and labor-violation intensity using a different analytic design, moving from examining a cross-section of workers to a panel of local industries across years.

3 Relationship Between Changes in Local Industry Average Pay and Labor-Violation Intensity

To estimate the relationship between changes in average wage per employee and average violation intensity in a local industry over time, we estimate the following regression:

$$Log(1+Violation\_Intensity)_{it} = \alpha + \beta \times Log(Wage)_{it} + \mu_i + \eta_t + \varepsilon_{it} \tag{2}$$

with i indexing a local industry (NAICS4×CZ) and t indexing year, respectively. We use two measures for *Violation Intensity*: the natural logarithm of one plus the count of violations cited normalized by the number of employees in thousand, and the natural logarithm of one plus penalties levied normalized by the employee wage bill in million. μ_i and η_t are sets of local industry and year fixed effects, respectively. Observations are weighted by total employment at the local industry-year level. We cluster the standard errors at the local industry level. The coefficient of primary interest is β, the elasticity of labor-violation intensity with respect to the average wage in the local industry. Giving this model a causal interpretation requires assuming that changes in unobservable determinants of violation intensity are independent of changes in the average wage at the local industry-year level.

3.1 Main results

Across local industries and controlling for year fixed effects, average pay per employee is positively correlated with labor violations counts per 1,000 employees (Table 4, panel A, col. 1) but is negatively correlated with labor violations penalty amount per million pay (Table 4, panel B, col. 1). Both estimated coefficients are statistically significant at the 1% level.

We then use a panel specification in Table 4, column (2), controlling for both local industry and year fixed effects. The average pay per employee is negatively correlated with both measures of labor violation intensity (Table 4, Panels A and B). The positive cross-sectional association between wages and violation intensity as measured by counts in column 1 of Panel A can be explained by industry heterogeneity, and in particular the fact that secondary sector industries tend to both pay higher wages and have higher violation intensity. Within the same local industry over time, labor violation intensity becomes lower when the average pay per employee becomes higher. In terms of magnitudes, the estimates from Table 4, column (2) suggest that a 10% increase in the average pay is associated with a 0.15% decrease in the number of labor-violations cited per 1,000 employee or a 4.22% decrease in the labor-violations penalty per million of wage bill. The second measure can be interpreted as a kind of regressive wage tax: when wages increase, a smaller share of wages is taken away in the form of labor violations.

The magnitude of the measured relationship between wages and labor violations is fairly small. However, if only a fraction of true violations are cited and that fraction is constant, then the magnitude of contribution of labor-rights violations to inequality scales up. Furthermore, as discussed above, higher wage workers are more likely to report violations, and this likely biases the coefficient toward zero. In general, our results imply that, as workers get higher wages, they also enjoy better working conditions in the form of more freedom from having their rights violated.

Finally, in column (3), we restrict the sample to local industry-year observations in which there are labor violations and re-estimate equation (3) with both local industry and year fixed effects. The magnitudes of the estimated effects of average pay per employee on labor violation intensity become much larger than the ones in column (2) of Panels A and B: a 10% increase in the wage is associated with a 5.5% decline in violation prevalence and a 10.2% decline in violation severity.

3.2 Heterogeneity in the Relationship

Here we replicate the analysis of the relationship between changes in wages and changes in violation intensity within local industry across years but allowing for different relationships by economic sector and then by enforcement agency.

3.2.1 Secondary sector industries versus others

Secondary sector industries (mining, utilities, construction, and manufacturing) tend to have relatively high average pay but also higher violation intensity in terms of counts. This is why the cross-sectional relationship between counts violation intensity and wages is positive in Table 4, Panel A, column (1). Here, we further investigate how the relationship between violation intensity and wages differs across sectors.

In Table 5, Panel A, the dependent variable is the count-based intensity measure. The magnitude of the estimated coefficient on $Log(Wage)$ is larger for secondary sector industries. In particular, the elasticity of violations counts per 1,000 employee with respect to average annual pay is -0.069 for industries in the secondary sector and is only -0.01 for other industries (Table 5: Columns (2) and (4) of Panel A). The difference between these two estimated coefficients is statistically significant at the 1% level. In Panel B, we use the penalty-based intensity measure as the dependent variable. The estimated effects of wages on the penalty-based violation intensity are similar across these two types of industries.

3.2.2 Enforcement Agencies

In this subsection, we examine the relation between labor violation intensity and employee wages for various agencies that enforce the violations: (1) OSHA, (2) WHD, and (3) NLRB.

Our results in Table 6 show that the effect of employee average wages on violation intensity in a local industry is heterogeneous across agencies. For violations enforced by OSHA and WHD, the estimated effect is qualitatively similar to the effect across all agencies in column (2) of Table 4: violation intensity becomes lower when employees are paid higher wages. However, for violations enforced by NLRB, we find that the estimated coefficient on $Log(Wage)$ is positive and statistically significant at 1% level in both panels. This result implies that when wages increase in a local industry, violations related to labor organizing tend to increase.

The negative association between wages and violations enforced by OSHA and WHD drives the estimates when all types of violations are lumped together in Table 4. This makes sense because these types of violations are by far the most frequent (Table 1).

Why might we see a different, positive association between wages and violations of workers' rights to organize? Organizing-rights violations can occur both in new organizing campaigns in nonunion firms and in disputes over contracts and rights in unionized firms. For new organizing, unionization efforts are more likely among workers in newer and more-productive firms Dinlersoz et al. (2017). Local industries with rising wages might be more likely to have organizing drives, to which employers may react by violating workers' rights.

3.3 Robustness to changes in enforcement regime

The choices enforcement agencies about pursuing specific cases can affect our measure of violations. For example, within the Bush administration, enforcement policies were relatively stable. However, the Wage and Hour Division (WHD), under Director David Weil during the Obama administration, shifted enforcement resources to strategically focus on priority industries defined by a high risk of violations and limited worker complaints (Weil, 2010). These industries include fast-food, hotels, and residential construction.

To understand whether changes in enforcement regime affect the relationship between wages and underlying violations as proxied by measured violations, we re-run our main analysis separately for the Bush and Obama administrations (Table A.3), and by agency. Within administration and agency, the influence of complaints and enforcement strategies on the relationship between wages and underlying violations should be relatively stable. Overall, the relationship between wages and measured violations is fairly similar across presidential administrations, though the negative relationship between wages and violations is stronger and more significant during the Bush administration.

The difference between the Bush and the Obama administrations could relate to the change in enforcement regime at WHD, with the new focus on priority industries. We thus investigate the relationship between wages and WHD violations within the Bush vs. Obama administration and in priority vs. non-priority industries (Table A.4). The relationship between wages and violations is basically always negative but is stronger in priority industries in the Obama (strategic enforcement) administration. In non-priority industries, the relationship between wages and violations is negative and of similar magnitude in both the Bush and the Obama administrations. In priority industries, the within-industry relationship between wages and violations is more negative during the Obama administration. This might be explained by the targeting of priority industries with vulnerable workers. If wages in a local industry increase, WHD might perceive workers as less vulnerable, leading to a softening of enforcement relative to the beefed up baseline enforcement in these priority industries.

3.4 Robustness Tests

In this subsection, we perform several robustness tests to our main results in Table 4.

We begin by looking at how weighting affects the results. In column (1) of Table 7, we report estimations of equation (3) without weighting by employment so each industry-CZ-year observation contributes the same to the estimation. The magnitude of the correlation between labor violations counts per 1,000 employees and average pay per employee is similar to the weighted estimates in column (2), Panel A of Table 4; however, the magnitude of the correlation between labor violations penalty amount per million pay and average pay per employee is smaller than the one in column (2), Panel B of Table 4.

Next, we assess robustness to controlling for any common shock at the industry level or CZ level in each year. In column (2) of Table 7, we report the weighted estimations and replace the year fixed effects with industry$\times$year and CZ$\times$year fixed effects. Our results suggest that, within the same local industry, labor-violation intensity falls when the average pay per employee rises even after absorbing any shock at the industry or the CZ level in a year (Table 7, column (2), Panels A and B). Compared to the results in Table 4, the magnitude of the correlation between labor violations penalty amount per million pay and average pay per employee becomes smaller but is still statistically significant at the 1% level.

In appendix Table A.2, we present more robustness tests for Table 4. We show that results are very similar when a local industry is defined at the state level rather than at the CZ level. Results are also similar when adding in MSHA mining violations[12] at the state level, though the coefficient on violation prevalence is no longer significant. Finally, dropping data from the NLRB or data after 2011 – when NLRB industry codes are missing so NLRB observations are dropped – also yields similar results.

3.5 Alternative Measures of Worker Bargaining Power

Rather than focusing on the relationship between changes in wages and changes in violation intensity, in this section we replace average wage with alternative proxies of worker bargaining power: educational attainment, labor market concentration among employers, and worker union density.

3.5.1 Education

We measure the fraction of workers in each industry-locale-year who have any college education using the Census's Quarterly Workforce Indicators (QWI). QWI derives from the Longitudinal Employer-Household Dynamics, which harmonizes linked employer-employee data based on states' unemployment insurance records. QWI provides statistics on worker demographics by industry-county-quarter. We use counts of all workers and those with at least a bachelors degree for each industry-CZ-quarter, and calculate the fraction of workers who are college-educated in each industry-CZ-quarter. For each industry-CZ-year, we take the simple average of the fraction of college-educated workers across all quarters.

In column (3) of Table 7, we use, instead of wages, the fraction of employees that have at least bachelor degrees in a local industry as a proxy for employees' human capital and bargaining power. The estimations are weighted by the total employment in the local industry and year. However, the estimated coefficients in both panels are close to be zero, suggesting that education has little impact on labor violation intensity.

[12]Charles et al. (2019) show that MSHA violations increase when mines experience a positive demand shock.

3.5.2 Labor Market Concentration

In this subsection, we use local industry employment concentration as an alternative measure of employees' bargaining power. A local industry is still defined as the interaction between a 4-digit NAICS code and a CZ. If concentration is higher in a local industry, then the local employers would have a larger monopsony power, lowering employees' outside options and bargaining power.

In each local industry, the employment concentration is defined as the Herfindahl-Hirschman Index (HHI) calculated based on the observed firm-level employment. We use the establishment-level data from InfoGroup Historical Business File to measure local industry HHI. For each covered establishment, InfoGroup provides data on the employment, sales, NAICS code, geographic information, and the linked parent company. Specifically, the formula for HHI in a local industry m and year t is as follow:

$$HHI_{m,t} = \sum_{i=1}^{n} s_{i,m,t}^2 \tag{3}$$

where $s_{i,m,t}$ is the employment share of firm i in local industry m in year t. In each local industry, we aggregate the establishment-level employment to the parent company and then calculate $s_{i,m,t}$.

To estimate the effect of local industry HHI on violation intensity, we run the same regression as in equation (3) except that we replace $Log(Wage)$ with $Log(EmploymentHHI)$. In addition to the OLS estimations, we also instrument *Log(Employment HHI)* with the average of the log(1/Number of Firms) in other CZs for the same 4-digit NAICS industry (Azar, Marinescu and Steinbaum, 2020).

Table 8 reports the results. The dependent variables in Panels A and B are the natural logarithm of one plus labor violation counts per 1,000 employees and the natural logarithm of one plus labor violation penalty per million pay, respectively. In each panel. columns (1) and (2) report the OLS estimations and column (3) reports the 2SLS estimation.

In column (1) of each panel, we control for year fixed effects. The results show that, across local industries, local industry HHI is negatively correlated with both measures of labor violation intensity. Both estimated coefficients are statistically significant at the 1% level. We control for both local industry and year fixed effects in column (2) of each panel. The estimated coefficients are still negative but the magnitudes and statistical significance of the measured relationship become much smaller.

Column (3) of each panel reports the 2SLS estimation. The estimated coefficients are positive and statistically significant at the 1% level. The IV is not weak as the Kleibergen-Paap F-stat is 353. The results show that, within the same local industry over time, labor violation intensity becomes higher when the local industry HHI becomes higher. The estimates suggest that a 10% increase in local industry HHI is associated with a 6.02% increase in the number of labor-violations cited per 1,000 employee or a 2.99% increase in the labor-violations penalty per million of wage bill. Therefore, the IV results show an increase in labor violations when workers' employment opportunities and bargaining power decrease due to an increase in labor market concentration.

3.5.3 Union coverage

To incorporate union status into our analysis of the relationship between violation intensity and average wages, we shift our analysis from changes within industry-CZ across years to changes within industry-state across years.

We perform our analysis on an alternative sample constructed from the Current Population Survey (CPS). The main advantage of CPS over QCEW is that union coverage information for individuals is available in the outgoing rotation groups (ORG) and it allows us to examine whether labor unions play a role in affecting the violations of labor rights by employers. In this sample, the unit of observation is an interaction between a census code-based industry and a state.

To measure the share of workers covered by union contracts, we draw on the Current Population Survey (CPS) from IPUMS (Flood et al., 2018). We can measure coverage share by industry and year. The finest geographic cut we use is state. To look at the relationship between union coverage and labor-violations intensity, we construct an alternative version of the labor-violations intensity measures from VT that defines locale as state, rather than commuting zone. In the matched CPS-

VT sample, the unit of observation is an interaction between a census code-based industry and a state in a year. A census code-based industry is one or a group of 1990 census industry codes in CPS. We construct the crosswalk between different versions of NAICS codes in VT and the census code-based industry code from IPUMS using the crosswalk provided by the Census.[13] To assure alignment between all predictors in our CPS sample, we construct measures of average wage, fraction of workers who have a bachelors degree, and total employment by industry-state-year as well. If an industry-state-year observation in CPS is not covered in VT, we measure the values of violation-related measures as zeros. We observe 10,334 industry-states in 167,384 industry-state-years. The average pay in the CPS-VT sample is \$42,576 and 13.1% of employees are covered by union contracts. The measured violation count is 0.4 per 100,000 and penalties average \$6.27 per million dollars in pay. Table 2, Panel B reports the summary statistics of several variables in the CPS-VT sample.

We re-estimate equation (3) using the CPS sample and the results are reported in Table 9. The estimations in column (1) are consistent with the ones in Table 4. Our estimations show that a 10% increase in the average pay per employee (\$4,258) is associated with a 0.006% decrease in the violations counts per 1,000 employees (column (1), Panel A) or a 3.0% decrease in the violations penalty amount per million pay (column (1), Panel B).

In column (2) of each panel in Table 9, we examine the relation between union coverage rate and labor violations intensity in a unit-year cell. Our estimations show that, within an industry-state, violation rates become lower when union coverage becomes greater. Specifically, a one-standard-deviation increase in union coverage rate (17.8%) is associated with a 0.04% decrease in violations counts per 1,000 employees or a 0.5% decrease in violations penalty amount per million pay, though the latter effect is not statistically significant. Finally, in column (3), we include both the wage and union coverage as dependent variables. Union coverage is associated with a lower prevalence of violations, even conditional on the wage (Panel A), but there is no effect of union coverage on the severity of violations conditional on the wage (Panel B).

[13]The crosswalk is available at `https://www.census.gov/topics/employment/industry-occupation/guidance/code-lists.html`.

This result is important because the equilibrium relationship between union coverage rate and labor violations intensity is likely to be the net effect of two opposing forces, which could lead to a positive or negative relationship between unionization and labor violations. On the one hand, unions could exercise power to provide more protections for workers and decrease violations of labor rights ("protective effect"). On the other hand, unions could force disclose of a larger share of committed violations ("reporting effect"). The estimated negative relationship between union coverage rate and labor violations intensity suggests that the "protective effect" of unions outweighs any "reporting effect."

4 Conclusion

In this paper, we investigated the prevalence and correlates of labor rights violations. First, labor rights violations predict worse self-reported job quality across industries. Second, a 10% increase in average wages in an industry and commuting zone is associated with a 0.15% decline in violations per employee and a 4% decline in fines per dollar of worker pay. Furthermore, we find that unions decrease the prevalence of labor rights violations. Our results suggest that job quality is positively correlated with the wage and is boosted by unionization. In contrast to the predictions of a simple compensating wage differentials model, labor rights violations decrease with worker pay. Thus, inequality in job quality as measured by labor-rights violations exacerbates wage inequality in the U.S.

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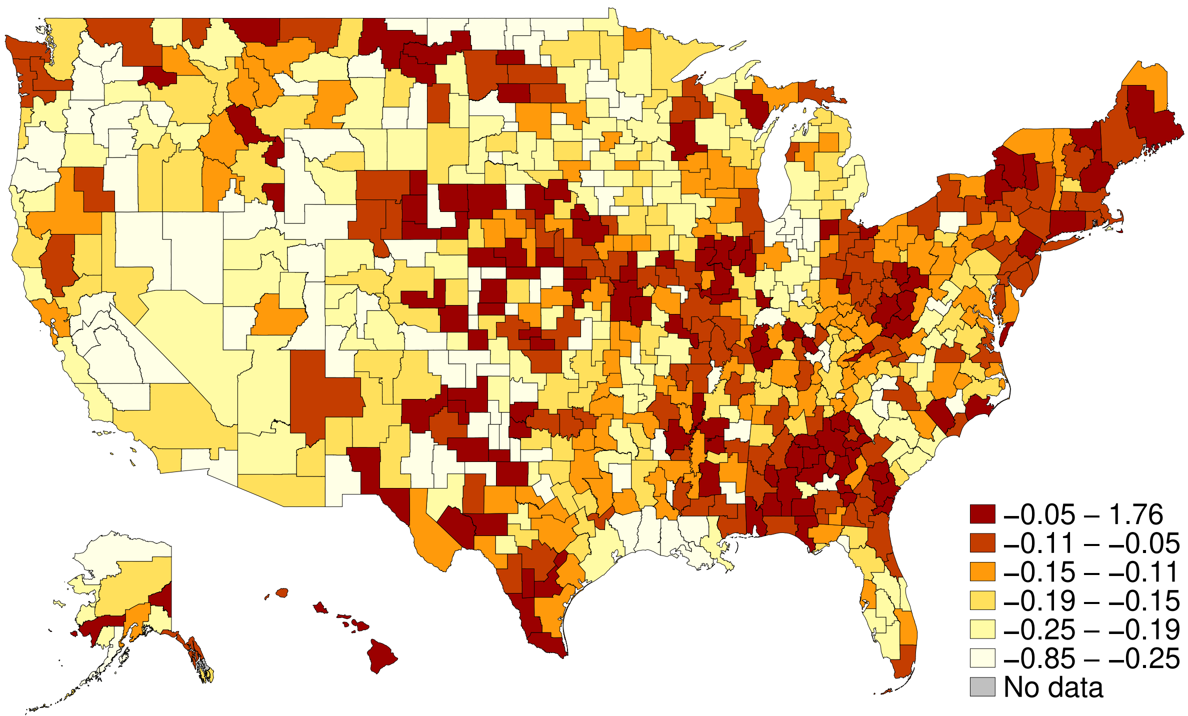
Figure 1: Labor-violation intensity by commuting zone

This figure reports violations intensities adjusted for industry composition and time effects across 2000 commuting zones (CZ). For each measure of violations intensity, we first regress the violation intensity on 4-digit NAICS industry and year fixed effects and then calculate the industry employment-weighted average of the residuals within a CZ. We finally calculate the simple average residual in a CZ over the most-recent decade, 2010-2019.

Violation Counts



Violation Penalties

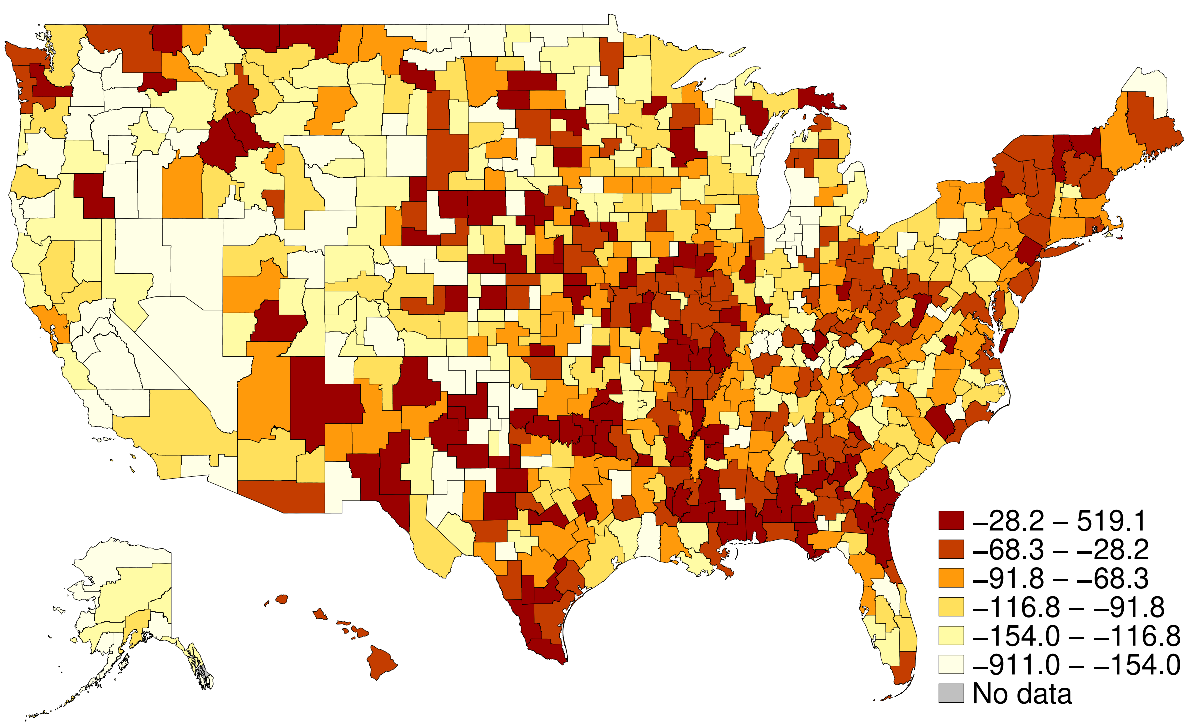


Table 1: **Summary Statistics by Agencies**

This table reports summary statistics by agencies. The statistics are based on the data in the sample for estimation. *Avg. Count* is the average of total violations counts in a year across all the years. *Avg. Penalty* is the average of the penalty per violation in a year across all the years and is expressed in thousands of dollars. *Avg. Fraction of Counts* is the average of the fraction of total labor violations counts in a year across all the years. *Avg. Fraction of Penalties* is the average of the fraction of total labor violations penalties in a year across all the years.

Agency Code	Avg. Count	Avg. Penalty ($000)	Avg. Fraction of Counts	Avg. Fraction of Penalties
	(1)	(2)	(3)	(4)
NLRB	858	141.5	0.251	0.427
OSHA	6602	20.61	0.534	0.306
WHD	3601	56.64	0.316	0.437

Table 2: **Summary Statistics**

This table reports the summary statistics of variables in the empirical analysis, weighted by the total employment. All variables are at the local industry-year level. In the QCEW-VT sample, a local industry is defined as the interaction between a 4-digit 2012 NAICS code and a 2000 CZ code. In the CPS-VT sample, a local industry is defined by the interaction between a census code-based industry and a state.

	Panel A: QCEW-VT Sample					
	N	Mean	Std.Dev.	P10	P50	P90
Labor Violation Dummy	1,465,807	0.305	0.461	0.000	0.000	1.000
Labor Violation Count per 1,000 Employees	1,465,807	0.101	0.682	0.000	0.000	0.197
OSHA Violation Count per 1,000 Employees	1,465,807	0.063	0.601	0.000	0.000	0.061
WHD Violation Count per 1,000 Employees	1,465,807	0.033	0.287	0.000	0.000	0.069
NLRB Violation Count per 1,000 Employees	1,465,807	0.005	0.109	0.000	0.000	0.000
Labor Violation Penalty per Million Pay	1,465,807	70.024	2825.002	0.000	0.000	114.616
OSHA Violation Penalty per Million Pay	1,465,807	19.690	423.222	0.000	0.000	15.637
WHD Violation Penalty per Million Pay	1,465,807	39.357	1103.714	0.000	0.000	48.042
NLRB Violation Penalty per Million Pay	1,465,807	10.977	2564.881	0.000	0.000	0.000
Average Pay per Employee ($000)	1,465,807	53.411	38.018	19.292	44.418	97.245
Fraction of College-educated Employees	1,211,616	0.273	0.141	0.131	0.236	0.479
	Panel B: CPS-VT Sample					
	N	Mean	Std.Dev.	P10	P50	P90
Labor Violation Count per 1,000 Employees	167,384	0.004	0.013	0.000	0.000	0.012
Labor Violation Penalty per Million Pay	167,384	6.784	4287.826	0.000	0.061	8.551
Average Pay per Employee ($000)	167,384	42.576	16.592	22.630	41.119	63.722
Union Coverage	167,384	0.131	0.178	0.000	0.052	0.382

Table 3: **Working Conditions and Labor Violations**

This table reports the relation between working conditions reported by workers and labor violation intensity at the 4-digit NAICS level in the year 2015. In Panels A and C, the labor violation intensity measure is the natural logarithm of one plus labor violation counts per 1,000 employees. In Panels B and D, the labor violation intensity measure is the natural logarithm of one plus labor violation penalty amount per million pay. In Panels A and B, we do not control for individual characteristics. In Panels C and D, we control for individual characteristics. Standard errors are clustered at the 4-digit NAICS level.

	Panel A: Counts per 1000 Employees					
	Abuse	Last-min. Change	Physical Exposure	Stress	Good Boss	Good Workplace
	(1)	(2)	(3)	(4)	(5)	(6))
Log(1+Count per 1,000 Employees)	0.118*	0.043*	0.357***	0.001	-0.046	-0.091
	[0.066]	[0.023]	[0.066]	[0.051]	[0.062]	[0.072]
Adjusted R^2	0.004	0.003	0.052	-0.001	-0.000	0.002
N	1103	510	1104	1103	1104	1104

	Panel B: Penalty per Million Pay					
	Abuse	Last-min. Change	Physical Exposure	Stress	Good Boss	Good Workplace
	(1)	(2)	(3)	(4)	(5)	(6))
Log(1+Penalty per One Million Pay)	0.066***	0.024**	0.150***	-0.019	-0.065***	-0.063***
	[0.023]	[0.010]	[0.024]	[0.020]	[0.023]	[0.022]
Adjusted R^2	0.009	0.009	0.065	-0.000	0.008	0.007
N	1103	510	1104	1103	1104	1104

Working Conditions and Labor Violations (Cont'd)

	Panel C: Counts per 1000 Employees					
	Abuse	Last-min. Change	Physical Exposure	Stress	Good Boss	Good Workplace
	(1)	(2)	(3)	(4)	(5)	(6))
Log(1+Count per 1,000 Employees)	0.103	0.029	0.332***	0.003	-0.059	-0.114
	[0.065]	[0.026]	[0.065]	[0.052]	[0.064]	[0.076]
Male	0.014	0.038	0.262***	-0.054	0.093	-0.017
	[0.063]	[0.032]	[0.050]	[0.060]	[0.065]	[0.059]
Log(Age)	-0.095	-0.075	-0.081	0.049	-0.257**	-0.079
	[0.117]	[0.081]	[0.084]	[0.112]	[0.105]	[0.124]
Log(Earnings)	-0.044	-0.032*	-0.095***	0.006	-0.027	-0.015
	[0.027]	[0.018]	[0.028]	[0.024]	[0.020]	[0.028]
White	0.006	0.042	0.006	0.046	-0.066	-0.139
	[0.079]	[0.045]	[0.083]	[0.102]	[0.085]	[0.094]
Black	0.270	0.046	0.347***	-0.057	0.037	-0.138
	[0.174]	[0.054]	[0.131]	[0.114]	[0.115]	[0.131]
Hispanic	0.092	-0.033	0.100	-0.002	-0.092	0.010
	[0.105]	[0.037]	[0.061]	[0.074]	[0.084]	[0.085]
Adjusted R^2	0.012	0.009	0.106	-0.004	0.004	0.001
N	1081	494	1081	1081	1081	1081

	Panel D: Penalty per Million Pay					
	Abuse	Last-min. Change	Physical Exposure	Stress	Good Boss	Good Workplace
	(1)	(2)	(3)	(4)	(5)	(6))
Log(1+Penalty per One Million Pay)	0.057**	0.020*	0.138***	-0.016	-0.072***	-0.070***
	[0.023]	[0.010]	[0.025]	[0.021]	[0.023]	[0.023]
Male	-0.001	0.032	0.229***	-0.048	0.117*	0.003
	[0.063]	[0.031]	[0.051]	[0.060]	[0.066]	[0.059]
Log(Age)	-0.096	-0.074	-0.081	0.051	-0.253**	-0.077
	[0.117]	[0.081]	[0.086]	[0.111]	[0.104]	[0.123]
Log(Earnings)	-0.040	-0.031*	-0.091***	0.002	-0.038*	-0.021
	[0.027]	[0.017]	[0.028]	[0.024]	[0.021]	[0.027]
White	0.016	0.050	0.029	0.043	-0.078	-0.151
	[0.078]	[0.046]	[0.083]	[0.102]	[0.083]	[0.092]
Black	0.273	0.057	0.354***	-0.057	0.034	-0.142
	[0.173]	[0.055]	[0.133]	[0.114]	[0.115]	[0.130]
Hispanic	0.092	-0.032	0.104*	-0.000	-0.089	0.011
	[0.104]	[0.037]	[0.060]	[0.074]	[0.084]	[0.084]
Adjusted R^2	0.015	0.014	0.115	-0.004	0.013	0.007
N	1081	494	1081	1081	1081	1081

Table 4: **Average Pay and Labor Violations**

This table reports the relation between average pay per employee and labor violation intensity. The dependent variables in Panels A and B are the natural logarithm of one plus violation counts per 1,000 employees and the natural logarithm of one plus violation penalty per million pay, respectively. A local industry is defined as the interaction between a 4-digit 2012 NAICS code and a 2000 CZ code. Estimations are weighted by the total employment in a local industry-year. In column 3, we restrict the sample to local industry-year observations in which there are labor violations. Standard errors are clustered at the local industry level.

	Panel A: Labor Violation Counts per 1000 Employees		
	(1)	(2)	(3)
Log(Average Annual Pay-QCEW)	0.008***	-0.015***	-0.055***
	[0.002]	[0.003]	[0.015]
Local Industry FEs		Y	Y
Year FEs	Y	Y	Y
Adjusted R^2	0.016	0.409	0.805
N	1,465,807	1,465,807	93,082
	Panel B: Labor Violation Penalty per Million Pay		
	(1)	(2)	(3)
Log(Average Annual Pay-QCEW)	-0.169***	-0.422***	-1.186***
	[0.030]	[0.060]	[0.203]
Local Industry FEs		Y	Y
Year FEs	Y	Y	Y
Adjusted R^2	0.036	0.359	0.466
N	1,465,807	1,465,807	93,082

Table 5: **Different Types of Industries**

This table reports the results for secondary sector industries and all other industries. Industries in the secondary sector are mining, utilities, construction, and manufacturing industries. A local industry is defined as the interaction between a 4-digit 2012 NAICS code and a 2000 CZ code. The dependent variables in Panels A and B are the natural logarithm of one plus violation counts per 1,000 employees and the natural logarithm of one plus violation penalty per million pay, respectively. Columns (1) and (2) of each panel reports the results for secondary sector industries and columns (3) and (4) of each panel reports the results for all other industries. Estimations are weighted by the total employment in a local industry-year. Standard errors are clustered at the local industry level.

	Panel A: Labor Violation Counts per 1000 Employees			
	Secondary Sector Ind.		Other Ind.	
	(1)	(2)	(3)	(4)
Log(Average Annual Pay-QCEW)	-0.135***	-0.069***	-0.009***	-0.010***
	[0.011]	[0.013]	[0.001]	[0.003]
Local Industry FEs		Y		Y
Year FEs	Y	Y	Y	Y
Adjusted R^2	0.089	0.479	0.017	0.144
N	280,195	280,195	1,185,612	1,185,612
	Panel B: Labor Violation Penalty per Million Pay			
	Secondary Sector Ind.		Other Ind.	
	(1)	(2)	(3)	(4)
Log(Average Annual Pay-QCEW)	-0.537***	-0.340***	-0.331***	-0.456***
	[0.108]	[0.103]	[0.030]	[0.068]
Local Industry FEs		Y		Y
Year FEs	Y	Y	Y	Y
Adjusted R^2	0.086	0.430	0.047	0.310
N	280,195	280,195	1,185,612	1,185,612

Table 6: **Different Agencies**

This table reports the relation between average pay per employee and labor violation intensity by agencies. The dependent variables in Panels A and B are the natural logarithm of one plus violation counts per 1,000 employees and the natural logarithm of one plus violation penalty per million pay, respectively. A local industry is defined as the interaction between a 4-digit 2012 NAICS code and a 2000 CZ code. Estimations are weighted by the total employment in a local industry-year. Standard errors are clustered at the local industry level.

	Panel A: Counts per 1000 Employees		
	OSHA	WHD	NLRB
	(1)	(2)	(3)
Log(Average Annual Pay-QCEW)	-0.010***	-0.009***	0.003***
	[0.003]	[0.002]	[0.001]
Local Industry FEs	Y	Y	Y
Year FEs	Y	Y	Y
Adjusted R^2	0.484	0.134	0.046
N	1,465,807	1,465,807	1,465,807
	Panel B: Penalty per Million Pay		
	OSHA	WHD	NLRB
	(1)	(2)	(3)
Log(Average Annual Pay-QCEW)	-0.210***	-0.326***	0.077**
	[0.041]	[0.056]	[0.031]
Local Industry FEs	Y	Y	Y
Year FEs	Y	Y	Y
Adjusted R^2	0.436	0.286	0.147
N	1,465,807	1,465,807	1,465,807

Table 7: **Robustness Tests**

This table reports the robustness tests to our main results. The dependent variables in Panels A and B are the natural logarithm of one plus violation counts per 1,000 employees and the natural logarithm of one plus violation penalty per million pay, respectively. A local industry is defined as the interaction between a 4-digit 2012 NAICS code and a 2000 CZ code. Except for column (1), all estimations are weighted by the total employment in a local industry-year. Standard errors are clustered at the local industry level.

	Panel A: Counts per 1000 Employees		
	No weights	Flexible FE	Education
	(1)	(2)	(3)
Log(Average Annual Pay-QCEW)	-0.011***	-0.008***	
	[0.002]	[0.002]	
Fraction of College-educated Employees			0.000
			[0.003]
Local Industry FE	Y	Y	Y
Year FE	Y		Y
Industry×Year FE		Y	
CZ×Year FE		Y	
Adjusted R^2	0.148	0.457	0.422
N	1,465,807	1,465,807	1,211,616
	Panel B: Penalty per Million Pay		
	No weights	Flexible FE	Education
	(1)	(2)	(3)
Log(Average Annual Pay-QCEW)	-0.048***	-0.146***	
	[0.006]	[0.046]	
Fraction of College-educated Employees			0.007
			[0.061]
Local Industry FE	Y	Y	Y
Year FE	Y		Y
Industry×Year FE		Y	
CZ×Year FE		Y	
Adjusted R^2	0.211	0.460	0.401
N	1,465,807	1,465,807	1,211,616

Table 8: **Concentration and Labor Violations**

This table reports the relation between labor market concentration and labor violation intensity. The dependent variables in Panels A and B are the natural logarithm of one plus violation counts per 1,000 employees and the natural logarithm of one plus violation penalty per million pay, respectively. A local industry is defined as the interaction between a 4-digit 2012 NAICS code and a 2000 CZ code. Log(Employment HHI) is the logarithm of the Herfindahl Hirschman Index, using shares of employment in the local industry. The instrument for Log(Employment HHI) in a local industry is the average of the log(1/Number of Firms) in other CZs for the same industry. Estimations are weighted by the total employment in a local industry-year. Standard errors are clustered at the local industry level.

	Panel A: Labor Violation Counts per 1000 Employees			
	OLS	OLS	2SLS	First Stage
	(1)	(2)	(3)	(4)
Log(Employment HHI)	-0.007***	-0.001	0.036***	
	[0.001]	[0.001]	[0.003]	
IV				0.602***
				[0.032]
Local Industry FEs		Y	Y	Y
Year FEs	Y	Y	Y	Y
Adjusted R^2	0.018	0.409		0.862
N	1,343,176	1,343,176	1,343,176	1,343,176
Kleibergen-Paap F-stat				353.73

	Panel B: Labor Violation Penalty per Million Pay		
	OLS	OLS	2SLS
	(1)	(2)	(3)
Log(Employment HHI)	-0.216***	-0.018*	0.299***
	[0.014]	[0.010]	[0.052]
Local Industry FEs		Y	Y
Year FEs	Y	Y	Y
Adjusted R^2	0.051	0.390	
N	1,343,176	1,343,176	1,343,176

Table 9: **CPS Sample**

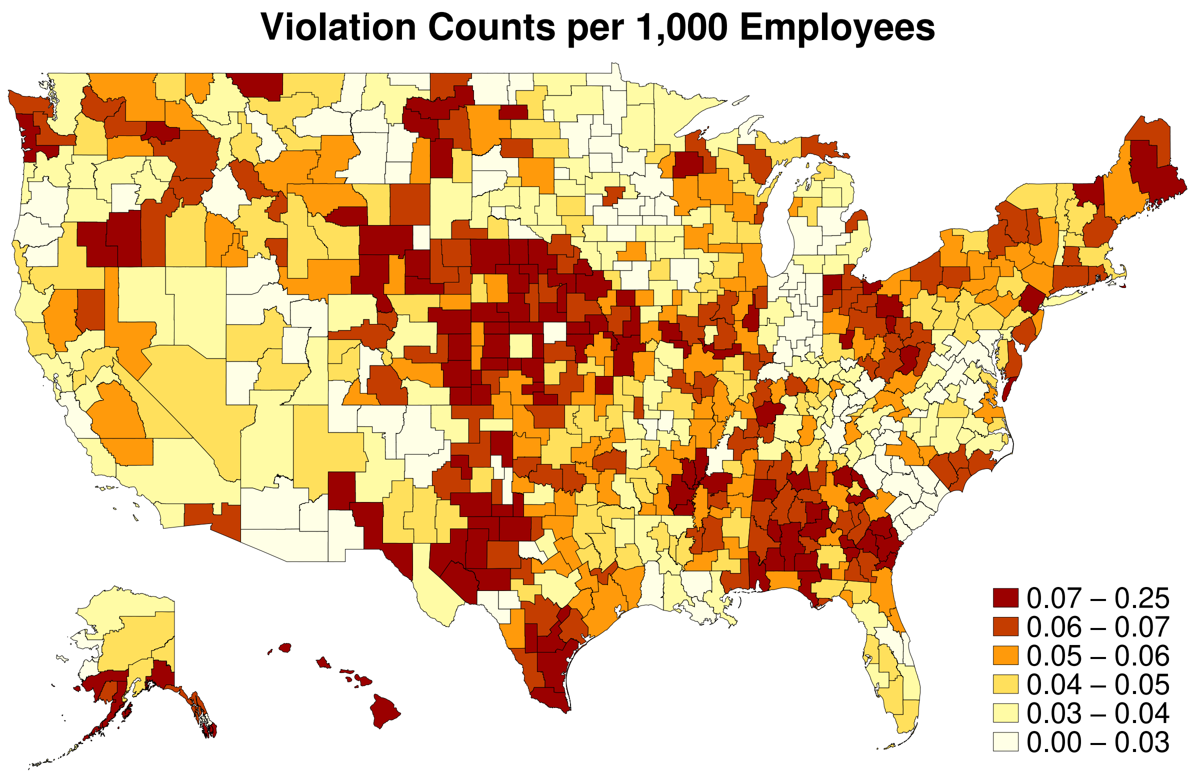
This table reports the relations between average pay per employee or union coverage rate and labor violation intensity using the merged sample between CPS and Violation Tracker database. The dependent variables in Panels A and B are the natural logarithm of one plus violation counts per 1,000 employees and the natural logarithm of one plus violation penalty per million pay, respectively. "Average Pay-CPS" is calculated as the average weekly earnings in a labor market times 52. A local industry is defined as an interaction between a census code-based industry and a state in a year. A census code-based industry is one or a group of 1990 census industry codes in CPS. The estimations are weighted by the total employment in a local industry. Standard errors are clustered at the local industry level.

	Panel A: Violation Counts per 1000 Employees		
	(1)	(2)	(3)
Log(Average Pay-CPS)	-0.00057***		-0.00054***
	[0.000]		[0.000]
Union Coverage Rate		-0.00239***	-0.00233***
		[0.001]	[0.001]
Local Industry FE	Y	Y	Y
Year FE	Y	Y	Y
Adjusted R^2	0.366	0.366	0.366
N	167,384	167,384	167,384
	Panel B: Violation Penalty per Million Pay		
	(1)	(2)	(3)
Log(Average Pay-CPS)	-0.299***		-0.300***
	[0.015]		[0.015]
Union Coverage Rate		-0.028	0.005
		[0.045]	[0.045]
Local Industry FE	Y	Y	Y
Year FE	Y	Y	Y
Adjusted R^2	0.517	0.514	0.517
N	167,384	167,384	167,384

Appendix A Additional Results

Figure A.1: Raw labor-violation intensity by commuting zone

This figure reports the raw violations intensities across 2000 commuting zones (CZ). For each measure of violations intensity, we calculate the average value in a CZ pooling over the most-recent decade, 2010-2019.



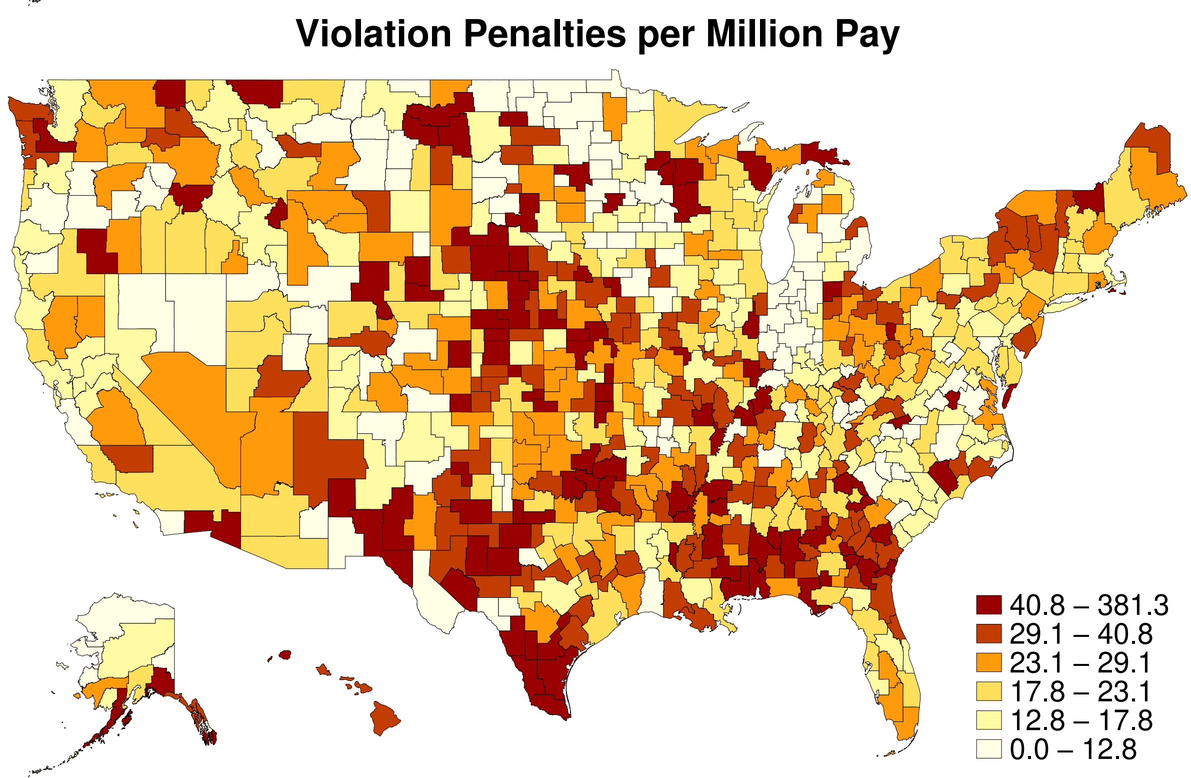


Table A.1: **List of Agencies that Enforce Labor Violations**

This table reports the list of agencies that enforce labor violations in the Violation Tracker database. For each agency, *Share of Violation Counts* and *Share of Penalties* are the shares of total violations and penalties across all years in the Violations Tracker database, respectively. The list is sorted in a descending order by *Share of Violation Counts*. There are 290,696 violations and 12.66 million (expressed in 2019 dollar) penalties across the years.

Agency Code	Agency	Share of Violation Counts (%)	Share of Penalties (%)
OSHA	OCCUPATIONAL SAFETY & HEALTH ADMINISTRATION	53.138	20.603
WHD	LABOR DEPARTMENT WAGE AND HOUR DIVISION	26.760	30.322
MSHA	MINE SAFETY & HEALTH ADMINISTRATION	9.485	5.377
NLRB	NATIONAL LABOR RELATIONS BOARD	4.340	15.269
CA-LCO	CALIFORNIA LABOR COMMISSIONER'S OFFICE	2.588	2.331
EBSA	EMPLOYEE BENEFITS SECURITY ADMINISTRATION	0.950	4.068
EEOC	EQUAL EMPLOYMENT OPPORTUNITY COMMISSION	0.680	14.374
WA-DLI	WASHINGTON STATE DEPARTMENT OF LABOR & INDUSTRIES	0.577	0.208
PA-DLI	PENNSYLVANIA DEPARTMENT OF LABOR & INDUSTRY	0.390	0.298
MA-AG	MASSACHUSETTS ATTORNEY GENERAL	0.361	0.718
KY-DWS	KENTUCKY DEPARTMENT OF WORKPLACE STANDARDS	0.226	0.168
IL-DOL	ILLINOIS DEPARTMENT OF LABOR	0.146	0.051
OFCCP	OFFICE OF FEDERAL CONTRACT COMPLIANCE PROGRAMS	0.131	1.366
NY-AG	NEW YORK ATTORNEY GENERAL	0.041	1.101
MO-DLIR	MISSOURI DEPARTMENT OF LABOR & INDUSTRIAL RELATIONS	0.039	0.013
DOJ_RIGHTS	JUSTICE DEPARTMENT CIVIL RIGHTS DIVISION	0.031	0.083
MN-DLI	MINNESOTA DEPARTMENT OF LABOR & INDUSTRY	0.024	0.006
USAO	THE U.S. ATTORNEY'S OFFICE	0.022	1.780
CA-SFCA	SAN FRANCISCO (CA) CITY ATTORNEY	0.015	0.103
WI-AG	WISCONSIN ATTORNEY GENERAL	0.008	0.091
NJ-AG	NEW JERSEY ATTORNEY GENERAL	0.007	0.010
IL-AG	ILLINOIS ATTORNEY GENERAL	0.004	0.010
WA-AG	WASHINGTON ATTORNEY GENERAL	0.003	0.015
NY-BKLYNDA	BROOKLYN (NY) DISTRICT ATTORNEY	0.002	0.045
NY-NYCCO	NEW YORK CITY COMPTROLLER'S OFFICE	0.002	0.064
MO-AG	MISSOURI ATTORNEY GENERAL	0.002	0.002
NY-MANDA	MANHATTAN (NY) DISTRICT ATTORNEY	0.002	0.061
CA-AG	CALIFORNIA ATTORNEY GENERAL	0.002	0.065
HI-AG	HAWAII ATTORNEY GENERAL	0.002	0.725
CA-MULTI	CALIFORNIA MULTI-JURISDICTION CASE	0.001	0.027
DC-AG	DISTRICT OF COLUMBIA ATTORNEY GENERAL	0.001	0.001
ME-AG	MAINE ATTORNEY GENERAL	0.001	0.036
PA-AG	PENNSYLVANIA ATTORNEY GENERAL	0.001	0.007
AZ-AG	ARIZONA ATTORNEY GENERAL	0.001	0.027
CA-LACA	LOS ANGELES (CA) CITY ATTORNEY	0.001	0.018
CT-AG	CONNECTICUT ATTORNEY GENERAL	0.001	0.006
DOJ_CIVIL	JUSTICE DEPARTMENT CIVIL DIVISION	0.001	0.053
CA-CCCDA	CONTRA COSTA COUNTY (CA) DISTRICT ATTORNEY	0.001	0.002
CA-LACDA	LOS ANGELES COUNTY (CA) DISTRICT ATTORNEY	0.001	0.059
CA-OCDA	ORANGE COUNTY (CA) DISTRICT ATTORNEY	0.001	0.021
CA-SCCDA	SANTA CLARA COUNTY (CA) DISTRICT ATTORNEY	0.001	0.015
CFPB	CONSUMER FINANCIAL PROTECTION BUREAU	0.001	0.178
FTC	FEDERAL TRADE COMMISSION	0.001	0.001
MI-AG	MICHIGAN ATTORNEY GENERAL	0.001	0.001
CA-LACDCBA	LOS ANGELES (CA) COUNTY DEPARTMENT OF CONSUMER AND BUSINESS AFFAIRS	0.000	0.001
CA-OCA	OAKLAND (CA) CITY ATTORNEY	0.000	0.000
CA-SFDA	CITY AND COUNTY OF SAN FRANCISCO (CA) DISTRICT ATTORNEY	0.000	0.000
CA-SONDA	SONOMA COUNTY (CA) DISTRICT ATTORNEY	0.000	0.003
DE-AG	DELAWARE ATTORNEY GENERAL	0.000	0.003
DOE	ENERGY DEPARTMENT OFFICE OF ENFORCEMENT	0.000	0.003
EPA	JUSTICE DEPARTMENT ENVIRONMENT AND NATURAL RESOURCES DIVISION	0.000	0.017
FL-AG	FLORIDA ATTORNEY GENERAL	0.000	0.004
FL-MDSA	MIAMI-DADE (FL) STATE ATTORNEY	0.000	0.001
MT-AG	MONTANA ATTORNEY GENERAL	0.000	0.021
NM-AG	NEW MEXICO ATTORNEY GENERAL	0.000	0.002
NY-DFS	NEW YORK DEPARTMENT OF FINANCIAL SERVICES	0.000	0.121
NY-NCDA	NASSAU COUNTY (NY) DISTRICT ATTORNEY	0.000	0.003
NY-NYCDCWP	NEW YORK CITY DEPARTMENT OF CONSUMER AND WORKER PROTECTION	0.000	0.001
NY-QCDA	QUEENS COUNTY (NY) DISTRICT ATTORNEY	0.000	0.010
NY-SCDA	SUFFOLK COUNTY (NY) DISTRICT ATTORNEY	0.000	0.010
OH-AG	OHIO ATTORNEY GENERAL	0.000	0.011
OWCP	DEPARTMENT OF LABOR OFFICE OF WORKERS' COMPENSATION PROGRAMS	0.000	0.001
TX-TRAVISDA	TRAVIS COUNTY (TX) DISTRICT ATTORNEY	0.000	0.004

Table A.2: **More Robustness Tests**

This table reports the robustness tests to our main results. The dependent variables in Panels A and B are the natural logarithm of one plus violation counts per 1,000 employees and the natural logarithm of one plus violation penalty per million pay, respectively. In column (1), we define a local labor market as the interaction between a 4-digit 2012 NAICS code and a state code. In column (2), we still use a state as the definition of a geographic area but we further fill in the industry code as 21, the mining sector, if violations are enforced by MSHA. In columns (3) and (4), we define a local industry as the interaction between a 4-digit 2012 NAICS code and a 2000 CZ code. We drop violations enforced by NLRB in column (3) and drop observations after 2011 in column (4). Estimations are weighted by the total employment in a local industry-year. Standard errors are clustered at the local industry level.

	Panel A: Labor Violation Counts per 1000 Employees			
	State-level	State-level With MSHA	CZ-level No NLRB	CZ-level Before 2011
	(1)	(2)	(3)	(4)
Log(Average Annual Pay-QCEW)	-0.020***	-0.012	-0.017***	-0.015***
	[0.007]	[0.008]	[0.003]	[0.003]
Local Industry FEs	Y	Y	Y	Y
Year FEs	Y	Y	Y	Y
Adjusted R^2	0.610	0.644	0.415	0.409
N	264,324	255,849	1,465,807	1,465,807
	Panel B: Labor Violation Penalty per Million Pay			
	State-level	State-level With MSHA	CZ-level No NLRB	CZ-level Before 2011
	(1)	(2)	(3)	(4)
Log(Average Annual Pay-QCEW)	-0.888***	-0.906***	-0.479***	-0.422***
	[0.134]	[0.135]	[0.059]	[0.060]
Local Industry FEs	Y	Y	Y	Y
Year FEs	Y	Y	Y	Y
Adjusted R^2	0.449	0.451	0.359	0.359
N	264,324	255,849	1,465,807	1,465,807

Table A.3: **Subsamples under Bush and Obama Administrations**

This table reports the results for subsamples under Bush (2001-2008) and Obama (2009-2016) administrations. Panel A reports the results for total labor violations intensity. The dependent variable in columns (1) and (3) is the natural logarithm of one plus violation counts per 1,000 employees and the dependent variable in columns (2) and (4) is the natural logarithm of one plus violation penalty per million pay. Panels B and C report the results for labor violations intensity by enforcement agencies. Estimations are weighted by the total employment in a local industry-year. Standard errors are clustered at the local industry level.

	Panel A: Total Labor Violations Intensity			
	Bush		Obama	
	Counts per 1000 Employees	Penalty per Million Pay	Counts per 1000 Employees	Penalty per Million Pay
	(1)	(2)	(3)	(4)
Log(Average Annual Pay-QCEW)	-0.014***	-0.521***	-0.006	-0.224
	[0.005]	[0.099]	[0.005]	[0.144]
Local Industry FEs	Y	Y	Y	Y
Year FEs	Y	Y	Y	Y
Adjusted R^2	0.237	0.394	0.478	0.402
N	575,423	575,423	597,880	597,880

	Panel B: Counts per 1000 Employees By Agency					
	Bush			Obama		
	OSHA	WHD	NLRB	OSHA	WHD	NLRB
	(1)	(2)	(3)	(4)	(5)	(6)
Log(Average Annual Pay-QCEW)	-0.001	-0.011***	-0.002	-0.001	-0.009***	0.002*
	[0.003]	[0.004]	[0.001]	[0.003]	[0.003]	[0.001]
Local Industry FEs	Y	Y	Y	Y	Y	Y
Year FEs	Y	Y	Y	Y	Y	Y
Adjusted R^2	0.273	0.138	0.085	0.548	0.191	0.020
N	575,423	575,423	575,423	597,880	597,880	597,880

	Panel C: Penalty per Million Pay By Agency					
	Bush			Obama		
	OSHA	WHD	NLRB	OSHA	WHD	NLRB
	(1)	(2)	(3)	(4)	(5)	(6)
Log(Average Annual Pay-QCEW)	-0.094*	-0.471***	-0.015	-0.092	-0.252*	0.109***
	[0.048]	[0.098]	[0.054]	[0.066]	[0.136]	[0.036]
Local Industry FEs	Y	Y	Y	Y	Y	Y
Year FEs	Y	Y	Y	Y	Y	Y
Adjusted R^2	0.383	0.381	0.264	0.490	0.329	0.056
N	575,423	575,423	575,423	597,880	597,880	597,880

Table A.4: **Wage & Hour Division Violations: Priority vs. Non-priority Industries**

This table reports the results for wage & hour division violations intensity by priority and non-priority industries. The classification of priority and non-priority industries is from Weil (2010). The dependent variables in Panels A and B are the natural logarithm of one plus violation counts per 1,000 employees and the natural logarithm of one plus violation penalty per million pay, respectively. In each panel, we report results for the full sample (2000-2019) in columns (1) and (2), subsample under Bush administration (2001-2008) in columns (3) and (4), and subsample under Obama administration (2009-2016) in columns (5) and (6). Estimations are weighted by the total employment in a local industry-year. Standard errors are clustered at the local industry level.

	Panel A: Violation Counts per 1,000 Employees					
	Full Sample		Bush		Obama	
	Priority	Non-priority	Priority	Non-priority	Priority	Non-priority
	(1)	(2)	(3)	(4)	(5)	(6)
Log(Average Annual Pay-QCEW)	-0.054***	-0.005***	0.014	-0.007*	-0.120***	-0.006**
	[0.009]	[0.001]	[0.015]	[0.004]	[0.021]	[0.003]
Local Industry FEs	Y	Y	Y	Y	Y	Y
Year FEs	Y	Y	Y	Y	Y	Y
Adjusted R^2	0.164	0.130	0.222	0.117	0.218	0.184
N	107,160	1,220,668	43,815	481,095	43,725	498,988

	Panel B: Violation Penalty per One Million Pay					
	Full Sample		Bush		Obama	
	Priority	Non-priority	Priority	Non-priority	Priority	Non-priority
	(1)	(2)	(3)	(4)	(5)	(6)
Log(Average Annual Pay-QCEW)	-2.676***	-0.163***	-0.525	-0.149*	-4.787***	-0.215
	[0.400]	[0.045]	[0.476]	[0.080]	[0.715]	[0.136]
Local Industry FEs	Y	Y	Y	Y	Y	Y
Year FEs	Y	Y	Y	Y	Y	Y
Adjusted R^2	0.354	0.281	0.502	0.263	0.387	0.347
N	107,160	1,220,668	43,815	481,095	43,725	498,988

Figure A.2: Trends of Violations Intensity Nationally

This figure reports the trend of violation intensity between 2000 and 2019. *Total Penalties/Payroll* is the total violations penalties in a year per Million pay. *Total Counts/Emp* is the total violations counts in a year per 1,000 employees.

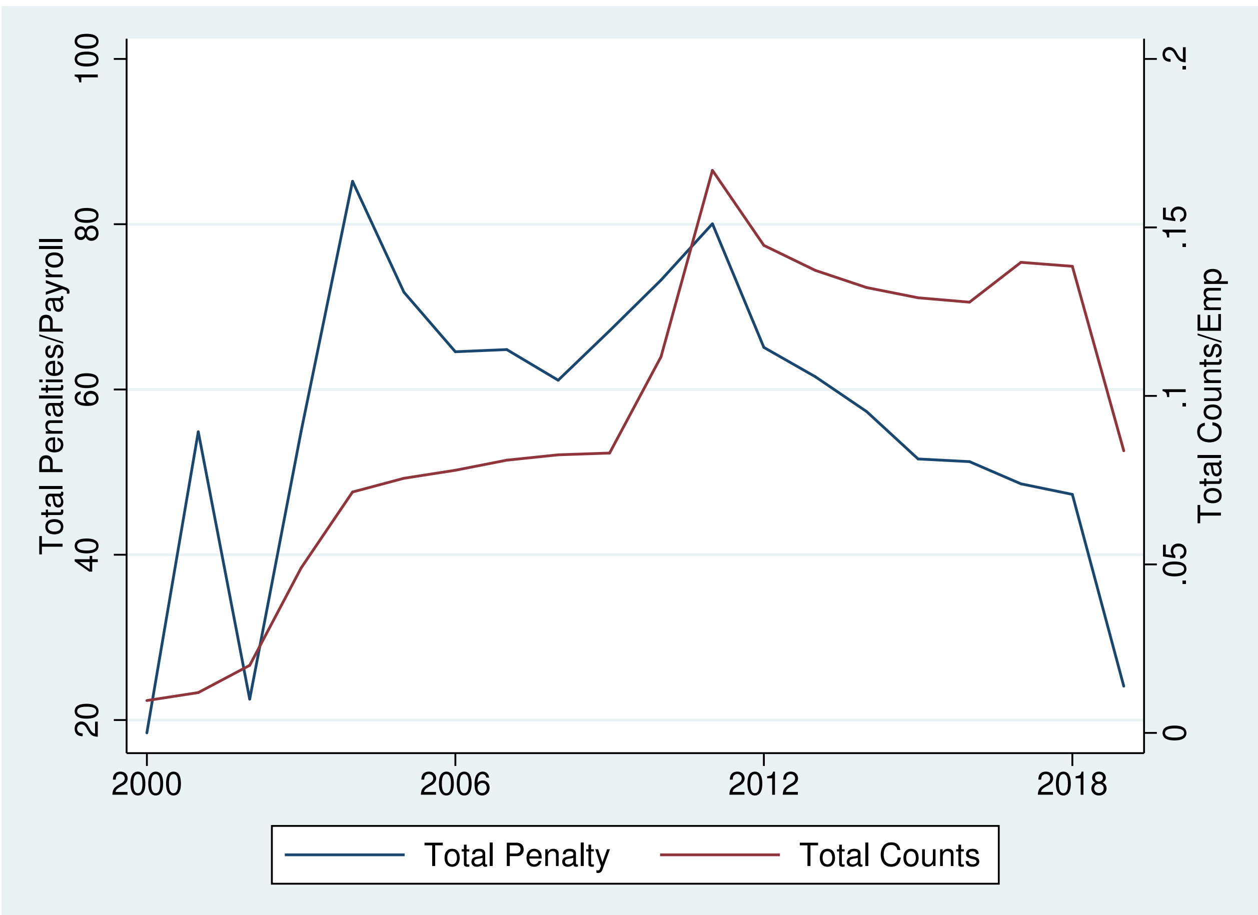


Figure A.3: States with highest and lowest labor-violation intensities in total and by agency

This figure reports the top and bottom ten states in terms of violations intensities in total and for each agency. For each measure of violations intensity, we calculate the average value in a state across the most recent ten years, i.e., 2010-2019.

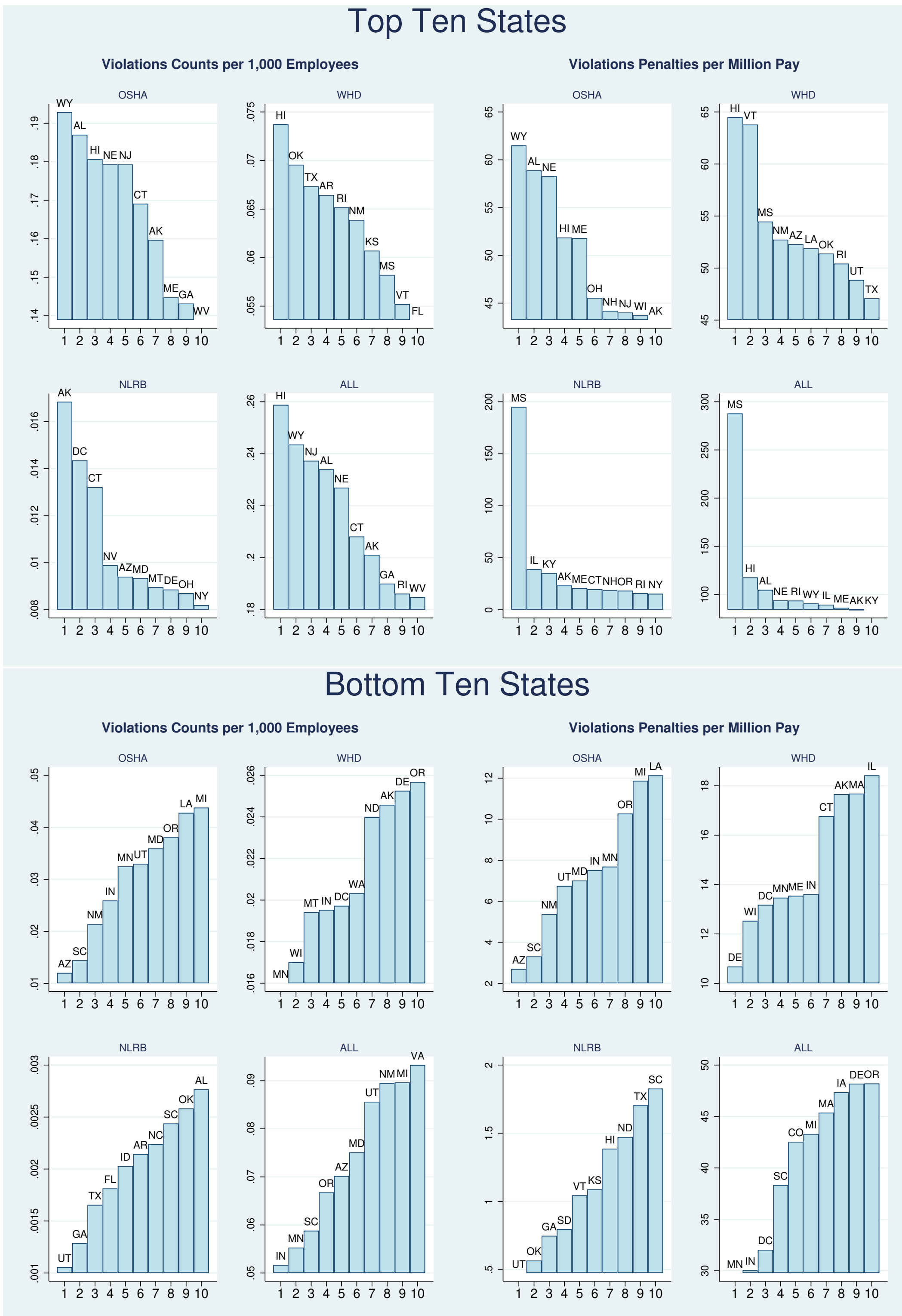


Figure A.4: Industries with highest and lowest labor-violation intensities in total and by agency

This figure reports the top and bottom five NAICS sectors in terms of violations intensities in total and for each agency. For each measure of violations intensity, we calculate the average value in a NAICS sector across the most recent ten years, i.e., 2010-2019.