On the Distributional Effects of Regulated Overtime Standards

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Preliminary, please do not cite.
Version: October 31, 2024

Abstract

Hired farm workers are among the most socially and socioeconomically disadvantaged members of the U.S. agri-food system. Solving this systemic inequity has gained public and political traction in recent years, leading to a variety of policy changes. This paper presents the first causal evidence on the viability of one such policy – standards for overtime pay – as a mechanism to improve farm worker well-being. The paper focuses on the short-run effects of the policies in California, the first of several states to enact new overtime standards for agricultural workers in recent years. Results suggest that employers responded to the legislation by reducing worker hours to avoid incurring the new costs associated with long working hours – I find statistically significant increases in the proportions of workers working at or just below the new overtime thresholds, and reductions in the proportions working above the thresholds. On average, workers worked 5 fewer hours and earned roughly $160 less each week.

Keywords: US Farmworkers; Labor Policy; Agricultural Business Management

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This paper uses confidential data from the National Agricultural Workers Survey which can be obtained by submitting a request to the U.S. DOL. The author is willing to assist with procedures for accessing the data.

1 Introduction

Overtime regulations are intended to improve worker welfare by mandating extra compensation for extended working hours. These laws exist in nearly all OECD countries, but there is limited empirical evidence on their impact (OECD, 2021). One reason for this dearth of information is the widespread and established nature of these laws, which makes it challenging for researchers to leverage new policy interventions for causal analysis.[1] Additionally, overtime policies are less mutable compared with other well-studied labor market policies, such as minimum wages, which lessens opportunities to study marginal policy changes.[2] Even in instances of regulatory changes to overtime standards, researchers confront challenges in identifying effects due to inadequate or imprecise measures of working hours.[3]

This paper exploits a recent policy change and a unique dataset to offer novel empirical evidence on the implications of regulated overtime standards for the workers they aim to protect. The U.S. Fair Labor Standards Act of 1938 establishes standards for many terms of employment at the federal level, including minimum wages and overtime pay standards. The law categorically exempts certain workers, employers, and industries from aspects of the law, but as with most federal regulations, enables states to set more stringent standards. Among those federally exempt are farm workers and the agricultural operations employing them, arguably due to historical discrimination (Dixon, 2021; Linder, 1987; Perea, 2011). This exemption for agricultural workers has received growing attention from worker advocacy groups, media, and most recently, policymakers, leading multiple states to pass legislation removing it. These policies create a rare opportunity to evaluate the effects of overtime regulations.

This study focuses on California, the first state to remove farm worker overtime exemptions in recent years through a gradual phase-in of reduced overtime hours thresholds

[1] See, for example, the discussions in Brown and Hamermesh, 2019; Hart, 2004; and Quach, 2022

[2] See Neumark and Shirley (2022) for a recent review of this literature.

[3] Overtime laws typically restrict working hours at the daily, weekly, or monthly levels, but few employer-, employee-, or household-based surveys collect precise measures of hours at these levels for individual workers. For example, the ACS and CPS ask respondents for their "usual hours worked per week", which can suffer from recall or recency bias, and have generally been found to produce inconsistent estimates of working hours (Bick et al., 2022; Neal and Baum-Snow, 2009). See Giattino and Ortiz-Ospina (2021) for a discussion of the different sources of data on working hours available internationally and associated limitations of each.

beginning in 2019.[4] The analysis leverages a survey dataset, specifically designed for and administered to U.S. crop workers, that is uniquely suited to study worker-related outcomes from the policy change. Data come from the National Agricultural Workers Survey (NAWS), the only nationally-representative survey of U.S. farm workers, which collects a relatively uncommon level of detail on terms of employment for field workers on crop-growing operations. Data are currently available through 2022, so the analysis focuses on the short-run and immediate effects of the legislation while controlling for trends in the prior years, ultimately spanning 2009 to 2022. In this context, this research evaluates the effects of overtime regulations on the hours and earnings of currently employed workers.

One common motivation for mandating overtime standards is that they will reduce long workweeks and increase employment, thereby promoting work sharing and increasing social welfare. However, both theoretical and empirical evidence evaluating these claims is mixed. Economic theory has shown how overtime regulations can lead to increases, decreases, or no changes in working hours, wages, employment, and a variety of other firm- and worker-related outcomes, depending on the underlying preferences of the firms and workers (Brechling, 1965; Ehrenberg, 1971; Hart, 2004; Rosen, 1968).

Empirical applications study an equally wide array of outcomes and yield a range of, sometimes conflicting, findings (Brown and Hamermesh, 2019; Hart, 2004). Some studies find that government mandated overtime standards cause individual working hours to decrease (Buchmueller and Senesky, 2003; Chemin and Wasmer, 2009; Costa, 2000; Hamermesh and Trejo, 2000; Kuroda and Yamamoto, 2012; Skuterud, 2007). Others find null effects (Johnson, 2003; Trejo, 2003) or that effects are concentrated among specific worker types (Bhattacharya et al., 2000; Golden and Wiens-Tuers, 2005; Kuroda and Yamamoto, 2012).

[4]Throughout the manuscript I use "overtime hours threshold" to refer to the number of weekly working hours beyond which employers are required (by law) to compensate workers with a higher pay rate. This hours threshold is also referred to as the weekly overtime standard, the straight-time hours threshold, or the maximum standard hours. I will refer to the higher overtime pay rate as overtime pay. In the U.S. this is set at one and a half times regular pay; that is, pay for hours below the overtime threshold, also referred to as base wages, straight-time wages, or standard wages. Prior to the legislation, all California farm workers were subject to overtime pay after 10 hours in one day or 60 in one week (Martin, 2020). These initial standards were already more stringent than federal standards and those in nearly every other U.S. state, which do not require agricultural employers to provide any compensation for overtime work. Assembly Bill 1066 (AB-1066 Agricultural workers: wages, hours, and working conditions), set a phase-in schedule that lowers the daily and weekly overtime thresholds by 0.5 and 5 hours, respectively, until reaching the standards for other industries of 8 hours per day and 40 hours per week (California State Legislature 2016).

One study even presents evidence that hours increase for higher waged workers (Cahuc and Carcillo, 2014). Findings are equally mixed for other employment-related outcomes, ranging from positive to negative effects for employment, wages, and earnings, depending on the context (Chen and Wang, 2011; Friesen, 2001; Goff, 2022; Kuroda and Yamamoto, 2012; Oaxaca and Sagyndykova, 2020; Quach, 2022; Raposo and van Ours, 2010). Overtime standards have also been linked with increases in the prevalence of multiple job holdings (Renna, 2006), strategic changes in job titles that take advantage of categorical exemptions from overtime standards (Cohen et al., 2023), and improvements in worker health and safety (Ichihara et al., 2019; Pega et al., 2021). In sum, despite the long and widespread history of overtime regulations, there is not consensus on their implications for the workers they aim to protect.

This study makes three contributions to the literature on overtime regulations. To the best of my knowledge, I am the first to study effects from reductions in the weekly overtime hours threshold in the U.S. This is important given recent public and political interest in extending overtime to multiple categorically exempt workers and industries — for example, gig workers (Helper, 2020) — and potentially reducing the overtime threshold for all workers (Takano, 2023). A small number of studies leverage state-level changes to other aspects of overtime regulations. For example, Buchmueller and Senesky (2003) and Hamermesh and Trejo (2000) examine California's policy requiring overtime pay for daily working hours (8 hours a day) in addition to weekly. Quach (2022) studies preemptive responses to a policy that changing the salary level to qualify for overtime pay. Some studies perform more descriptive analyses in lieu of policy changes. Goff (2022) uses a structural model and evidence on bunching in the hours distribution to show how longstanding overtime regulations are shaping worker hours and employment. Barkume (2010) and Golden and Wiens-Tuers (2005) conduct cross-sectional comparative analyses of U.S. industries and workers to demonstrate where and for whom overtime hours are most common. By comparison to prior studies in the U.S. context, this paper presents novel causal evidence on the effects from a substantive reduction in the weekly overtime hours threshold; moving from requiring overtime pay for working more than 60 hours a week to requiring the pay after 40 hours a week.

The second contribution is to document distributional impacts from the law. For the

most part, prior empirical work has focused on average effects of overtime laws, though some test for effects at specific hours thresholds. For example, Hamermesh and Trejo (2000) tests for changes in the probability of employees working hours beyond the new threshold and Goff (2022) and Quach (2022) test for bunching at overtime thresholds. My analysis goes beyond these and, to the best of my knowledge, presents the first full distributional analysis of the effects of the overtime regulation on hours and earnings. Understanding these effects is important for multiple reasons. First, the analysis gives credence to the average effects by showing that how hours change are consistent with theoretical predictions based on optimal firm behavior (Hart, 2004; Quach, 2022). In particular, fewer employees work hours above overtime thresholds while more work hours below the thresholds. I also find evidence of increased hours bunching precisely at the newly mandated hours thresholds. To this end, results from the distributional analyses provide additional support for the effects at the mean.

Beyond robustness, the distributional analyses are useful for exploring heterogeneity in the policy's effects. For example, it is plausible that a reduction in average working hours captures increases in hours for some workers and decreases for others. My analysis unveils that the average effects are largely driven by hours reductions. After the law was enacted, California farm employees became significantly less likely to work 51-60 hours per week and more likely to work 36-45 hours. Accompanying these reductions in working hours are corresponding reductions in real weekly earnings for much of the workforce. The law results in relative reductions in the share of workers with weekly earnings in the upper tail of the distribution (more than $800 per week) and increases in the share with earnings toward the middle and lower end of the distribution ($400 to $700 per week). Ultimately, these income effects indicate that the law reduced income inequality among farmworkers, but because incomes among workers in this sample are low in general, this also indicates that the workforce as a whole became worse-off relative to other industries. However, because these hours reductions facilitate more leisure time for workers, these results do not rule out that the law is welfare enhancing for these currently employed workers.

Finally, I explore whether the effects of the law are heterogeneous across worker characteristics. Prior work has explored heterogeneous effects across wages and gender (Chen and

Wang, 2011) and I add to this by exploring other characteristics that are made possible only by the detail collected in the NAWS. In particular, I test for differential outcomes across worker age, gender, documentation status[5], experience, education, and the type of task they are performing (for example, those related to harvest).

The paper proceeds as follows. In the next section I provide key institutional details on U.S. federal overtime policy and California's recent changes to overtime standards and minimum wages. In section 3 I summarize theoretical work on overtime laws and highlight predictions related to worker hours, earnings, and overall employment. In section 4 I introduce the dataset and present graphical evidence from the raw data on how hours and earnings changed following the implementation of new overtime standards. In section 5 I present a series of empirical specifications for identifying mean and distributional effects of the legislation. Section 6 presents and discuss findings related to worker hours, wages, and earnings, and section **??** presents findings for other outcomes. Finally, section 8 summarizes findings and discusses their transferability to other contexts and their limitations, and concludes with policy recommendations.

2 California's New Overtime Law

At the federal level, the Fair Labor Standards Act (FLSA) has set requirements related to overtime pay, minimum wages, and other worker protections since 1938. However, some workers – including certain agricultural employees – are categorically exempt from FLSA requirements (DOL, 2016a).[6] Under the FLSA, states can set rules that are more stringent in these terms of employment, but must meet federal standards as a minimum.[7]

California has more stringent standards for many terms of employment in the FLSA. For

[5]The NAWS variable on legal immigration status categorizes workers as citizens, legal permanent residents, other work authorized, and undocumented. This measure is generally considered one of the most reputable available in U.S. survey data. See Bachmeier et al. (2014) and Castillo et al. (2024) for details on how the measure is constructed and validated, and a demonstration of its validity. For the purpose of this study I simplify these four possible immigration statuses to and indictor variable for undocumented status.

[6]These categorical exemptions are most often specific to different aspects of the FLSA. For example, salaried workers are exempt from overtime laws under the FLSA, but are not exempt from standards for the minimum wage, youth employment, or employer record-keeping.

[7]This is most common for minimum wages – the majority of U.S. states have minimum wages set above federal levels (DOL, 2023).

example, non-exempt employees in California are entitled to higher minimum wages[8] and overtime pay based on both weekly and daily hours of work.[9] In addition, some federally-exempt workers are covered under California overtime standards (DIR, 2019). Most relevant to this study, California has historically required overtime pay for farm workers for working more than 10 hours in a day or 60 in a week. Overtime pay for farm workers is 1.5 times the normal compensation rate, which is the standard across all industries and federally. For workers who are paid a piece rate, that is, per unit of output, the hourly overtime rate is the higher of 1.5 times their piece rate times hourly output or 1.5 times their hourly base wage (which must equal or exceed the state minimum wage).

In 2016 California passed Assembly Bill 1066 (AB-1066) which mandated a gradual phase-in of reduced overtime hours thresholds, among other stipulations aimed at protecting farm workers (California State Legislature, 2016). Table 1 shows the schedule of the overtime threshold phase-in under AB-1066. The phase-in began in 2019 for employers with more than 25 employees and in 2022 for employers with 25 or fewer employees. The phase-in consists of annual reductions in the weekly and daily overtime thresholds of 5 and 0.5 hours, respectively, until reaching the standards for non-exempt workers— 40 hours a week and 8 hours a day— which occurs in 2022 for larger employers and in 2025 for smaller employers.

In the remainder of the paper I treat the standards as implemented for employers with more than 25 employees as the effective policy. I do this because my data do not include information on employer size and, based on the characteristics of California crop producers, there is a higher probability that surveyed workers are employed on larger farms.[10] However, because the data include some employees on smaller operations, my estimates should be considered lower bounds on the true effects of the legislation. I revisit this limitation in my concluding remarks.

[8] In 2022, California hourly minimum wage rates were $15 for employers with more than 25 employees and $14 otherwise, whereas the federal minimum was $7.25

[9] Non-exempt workers in California receive overtime pay for working more than 40 hours in a week or 8 hours in a day.

[10] California crop production has historically been characterized by large farms producing labor-intensive crops (ERS, 2000). According to more recent data this characterization remains true today; the author's own analysis of data from the 2020 QCEW unveils that California employers in crop production employed an average of 17 workers across the year. And according to data from the USDA Farm Labor Survey, the bulk of California farm workers are employed on operations with more than 10 employees, increasing the likelihood that workers on these larger operations are interviewed in the NAWS.

Table 1: California Agricultural Overtime Change Schedule

Effective Date for Employers with 26 or More Employees	Effective Date for Employers with 25 or Fewer Employees	Overtime Pay Required After (Hours per Day/Hours per Week)
Pre 2019	Pre 2022	10/60
Jan. 1 2019	Jan. 1 2022	9.5/55
Jan. 1 2020	Jan. 1 2023	9/50
Jan. 1 2021	Jan. 1 2024	8.5/45
Jan. 1 2022	Jan. 1 2025	8/40

Notes: Table adapted from the California Labor Commissioner's Office FAQs on Minimum Wage `https://www.dir.ca.gov/dlse/faq_minimumwage.htm` and Overtime for Agricultural Workers `https://www.dir.ca.gov/dlse/Overtime-for-Agricultural-Workers.html`.

One additional legislative change occurring concurrently with AB-1066 are California's minimum wage increases. Under the FLSA, small farm employers[11] are exempt from minimum wage and youth employment standards in addition to overtime. However, California and several other states have had long-standing policies that remove these minimum wage exemptions (Justice, 2023; Martin, 2020). This means that in addition to the changing overtime requirements, workers and employers are simultaneously impacted by California's rising minimum wages. Table A.1 in the appendix shows this schedule over the study period. While I attempt to account for the minimum wage increases in multiple ways in the analysis, I do not think it is feasible to fully disentangle their effects, particularly on wages and earnings. I discuss the potential role of minimum wages at detail in appendix D and caveat my findings accordingly.

3 Theoretical Background

Economic theory offers support and intuition for a wide range of effects from overtime legislation. Here I summarize theoretical predictions related to effects from legislation that set or lower the hours threshold beyond which employers are required to pay a higher overtime

[11]Defined as operations that "used no more than 500 "man days" of farm labor in any calendar quarter of the preceding calendar year". This translates to roughly 2 full time equivalent employees.

rate on working hours, number of workers, wages, and earnings.[12] The aim is to motivate and guide the empirical analysis that follows.

Two main branches of economic theory models inform the debate on the hours, employment, and earnings effects of mandated overtime pay (Hart, 2004). The first focusses on firm demand for working hours. These models explore optimal outcomes from the perspective of cost-minimizing employers facing mandated reductions in the overtime hours threshold. The earliest of these models differentiates between three equilibrium outcomes, acknowledging that firm heterogeneity can result in preferences for employing workers at hours below, at, or above the overtime threshold (Brechling, 1965). Distinguishing between these potential equilibria yields three alternative predictions on the effects of overtime regulation on hours and employment. Average hours and employment will remain unchanged for firms that employ workers below the overtime threshold; average hours will fall and employment will rise for firms that employ workers at the overtime threshold; and, somewhat counterintuitively, average hours will rise and employment will fall for firms that employ workers above the threshold (Brechling, 1965; Ehrenberg, 1971; Hamermesh and Trejo, 2000; Hart, 2004; Rosen, 1968; Trejo, 2003). While informative, these predictions are limited by the omission of important labor market dynamics. In particular, worker preferences and non-employment strategies of the firm, such as adjusting capital investments, production technology, output levels, or the base wage rate.

The second branch of theory models address some of these limitations by incorporating the hours preferences of workers, considering implications for individual, rather than average, working hours, and treating the base wage rate as endogenous. This work started with Lewis (1969)[13] which treats daily earnings and workday length as job attributes that both employers and employees have preferences over. This model unveils the critical role of endogenously determined wages in moderating effects: the model predicts that working hours will remain fixed, but base (or standard-time) wages will fall to precisely offset the income increase

[12]For brevity, I limit the discussion of prior work to the theory most relevant to this study, but it is important to note that there is an array of theoretical and empirical work on the impacts of overtime laws that go beyond these topics. Some work studies effects from changes in the overtime rate; for an overview see chapter 4 of Hart (2004). Yet other work has focused on the implications for firms, like changes in output, technology, or capital investments (Nadiri and Rosen, 1969; Topel, 1982).

[13]And is nicely summarized in Hamermesh (2020), Hart (2004), and Trejo (2003).

from more hours being paid the overtime rate. This result arises assuming that prior to the legislation, working arrangements consisting of hours and earnings were agreed upon between employers and workers, so that both parties are happy to accept reductions in the base wage to maintain this equilibrium.[14] Later work built on these predictions to show how mandated reductions in overtime thresholds can lead to reductions in hours coupled with increases in base wages, with changes in wages precisely offsetting overall utility effects (Ehrenberg and Schuhman, 1984; Filer et al., 1996; Hart, 2004; Trejo, 1991). Some recent work has married these two literatures to generate testable predictions for whether data are consistent with the firm labor demand model or employer-employee matching model. In particular, showing that working hours precisely at the overtime hours threshold is never utility-maximizing for the worker, implying that observing bunching, or large mass points, at overtime thresholds is consistent with firm demand models, in other words, contexts in which firms set hours (ao et al., 2008; Goff, 2022; Quach, 2022).

In sum, there is no consensus among economic theorists as to how mandated reductions in overtime hours thresholds will impact terms of employment. Instead, existing theory offers guidance as to alternative combinations of terms of employment, namely hours, total employment, and wages, that are consistent with economic theory. This might suggest that overtime laws can have heterogeneous impacts, reducing hours for some workers while maintaining or increasing hours for others, potentially leading to bunching at the new hours thresholds if firms dictate scheduling. If firms continue employing workers for hours that now require overtime pay, employers may lower base wages to mitigate heightened payroll costs.[15] On the other hand, for workers who had their hours reduced to be willing to take the job, base wages might increase to offset income effects from shorter workweeks. Accordingly, earnings might increase, decrease, or remain the same depending on the joint changes in

[14]To my knowledge, this literature largely ignores the role of regulated minimum wages, which would prevent this result from fully realizing for low-wage workers. It also ignores other real world limitations, such as the ability of a firm to adjust base wages for some workers and not for others without evoking concerns among employees around pay inequities (Hart, 2004).

[15]Because employers in this setting are required to pay at least the state minimum wage, they might be less able to employ this strategy. Further, reductions in nominal wage rates is uncommon because most workers would be unwilling to accept a pay decrease. However, reductions in real wages, or wages relative to prior trends may arise if employers employ similar strategies with more real world feasibility. These might include offering smaller or no annual raises, and might result in more workers earning the legal minimum wage.

hours and wages. Finally, if mean hours are reduced, employers may hire additional workers to maintain current levels of production. Employers may hire these workers from the current pool of workers, with individual workers engaging in multiple employment positions, or employers may hire new workers altogether. I explore these possibilities in the remainder of the paper.

4 Data

The data for this analysis come from the National Agricultural Workers Survey (NAWS), an employment-based repeated cross-sectional survey of U.S. crop workers administered annually by the U.S. Department of Labor.[16] The survey began in 1989 and data are currently available through 2022. Workers are interviewed at their workplace rather than their home and employers are selected through a stratified multi-stage sampling technique that accounts for location-specific seasonality in farm employment (DOL, 2016b). The survey includes questions on household and worker demographics, characteristics of their current farm and non-farm jobs, and an array of other outcomes.

This paper uses the restricted access NAWS files which include more precise geographic and temporal information than what is available in the public access files.[17] I analyze data in two-fiscal year increments and apply the NAWS-provided sampling weights to account for the survey's complex sampling design when producing summary statistics and in regression analyses.[18] I use data from 2009 through 2022 which enables me to document the evolution of worker outcomes in the 10 years prior to and the 4 years following the overtime legislation.

[16]Information on the NAWS, the public access files, and details on how to request access to the restricted files (used in this paper) are available on the NAWS website: `https://www.doleta.gov/naws/`.

[17]The NAWS public access files make analysis possible at the region-cycle level. NAWS regions reflect the underlying populations of crop workers and divide the U.S. into six distinct areas: the East, Southeast, Midwest, Southwest, Northwest, and California. The public access files also report the two fiscal years (October through September) of the interview cycle during which interviews were conducted, rather than the interview year. This analysis requires the state-year level information included only in the restricted access version of the NAWS because this information is necessary for constructing control groups of workers from other states and for matching workers to accurate state-year level minimum wage rate.

[18]For details on the sampling methodology see the *Statistical Methods of the National Agricultural Workers Survey*, available at: `https://www.doleta.gov/naws/pages/public-data/docs/NAWS_Statistical_Methods_AKA_Supporting_Statement_Part_B.pdf`. For additional information on best practices for analyzing the NAWS data see *An Introduction to Analyzing the NAWS Public Access Data*, available at `https://www.doleta.gov/naws/pages/public-data/docs/Intro_Analyzing_NAWSPAD.pdf`.

The NAWS are the best available data for this analysis for several reasons. First, the NAWS collects detailed and recent information on worker hours, wages, and earnings. NAWS enumerators ask employees for the number of hours they worked for their current farm employer in the week prior to the interview. This measure of hours should be more precise and subject to less recall bias than those collected from asking workers for their "usual" hours worked per week, as in the American Community Survey (ACS) and Current Population Survey (CPS). Figure C.1 in appendix C emphasizes this and shows the distributions of California crop worker hours in the pre-treatment period (2009-2018) using the NAWS (figure C.1a) and ACS (figure C.1b) measures.[19] Although average hours are similar in the two datasets in the pre-treatment period (45 in the NAWS and 42 in the ACS), the distribution of hours in the ACS are more concentrated around 40 hours a week. Data from the ACS suggest that more than half of the workforce reported working 40-44 hours a week, and 45% indicated working precisely 40 hours a week, whereas data from the NAWS suggest roughly 20% of the workforce has hours in this range, and 16% reported working precisely 40 hours a week. There are multiple plausible explanations for the differences between the distributions of working hours between these surveys, but one obvious contributing factor is the difference in the questionnaires; the ACS measure involves recalling and averaging for the last year, whereas the NAWS references the prior work week.

The NAWS also collects detailed information on worker pay. Survey enumerators first ask workers how they are paid — by the hour, a piece rate, a combination of piece rate and hourly, or salaried. Respondents who are paid by the hour are then asked for their normal hourly wage rate and those paid a piece rate or combination are then asked a series of questions to impute a typical hourly wage equivalent, including their piece rate and typical output per hour. In primary specifications, I explore wage implications for all non-salaried workers[20], but demonstrate the robustness of results to restricting the sample to hourly-paid workers only. This distinction is potentially important because the hourly wage of piece rate-

[19] Appendix C replicates several analyses in this paper using the ACS data. Generally results at the average are similar to those in the NAWS, but distributional effects differ. I present these results as secondary due to issues with accurately identifying farm workers, potential for recall bias in the measure of hours, and other factors detailed in the appendix.

[20] I remove salaried workers from the analysis because they comprise a small portion of the overall sample — 236 workers, or three percent, of the California sample in the pre-policy period (2009-2018), and 34 workers, or two percent, of the California sample in the post-policy period (2018-2022).

and combination-paid workers reflects heterogeneity in productivity in addition to the wage rate.

The NAWS also asks workers for earnings in their most recent pay period for their current farm employer, and values are reported down to the cent. This is more granular than the earnings data in other surveys, which is typically reported annually, binned in wide ranges, and aggregated across all jobs. For the primary specifications related to worker earnings, I use workers' reported before tax earnings, restrict the sample to include all workers who receive weekly or biweekly paychecks, and construct a measure of weekly pay.[21] I deflate all measures of wages and earnings to 2022 equivalent dollars using the annual (nationwide) CPI.

Table 2 panel A summarizes the main hours, wages, and earnings variables from 2009-2022. Over this period, California workers have, on average, worked longer hours and earned more in hourly and weekly wages, compared with workers in control states. In both California and the control states the majority of workers receive weekly or biweekly paychecks (97 percent in CA and 95 percent in control states). Figure B.1 in the appendix shows the evolution of these variables in California. Before the overtime law went into effect, workers' hours were increasing slightly and wages and earnings were rising in tandem. After the law went into effect, hours dropped dramatically, the hourly wages continued to rise, and weekly earnings stagnated. The post-policy growth in hourly wages was lower than in prior years, but the majority of the decrease in weekly earnings is likely attributable to the reduction in working hours.

Table 2 also summarizes variables on key demographic and job characteristics for farmworkers in the NAWS. Compared with workers in control states, the average California farmworker is slightly older (39 versus 38), has more years of experience working on US farms (16 versus 13), and has fewer years of formal education (7 versus 9). A higher share of California farmworkers are undocumented (56 percent versus 39 percent) and have children (51 percent versus 39 percent), while a lower share are female (27 percent versus 31 percent) and speak English at least "somewhat" (26 percent versus 53 percent).

Not surprisingly given the novelties of California agriculture compared with other states,

[21] For workers receiving biweekly paychecks, I divide earnings by two to estimate weekly earnings.

the jobs of California farmworkers in terms of the tasks performed, crops worked with, and payment type differ from those in other states. Most California farmworkers are performing "semi-skilled tasks" (34 percent) and the fewest are engaged in "post-harvest" activities (15 percent), whereas most workers in control states are engaged in "pre-harvest" activities (32 percent), and the fewest are engaged in "harvest" activities (18 percent). Most California workers are employed in fruit and nut production (58 percent) and the fewest in field crops (3 percent) or multiple/miscellaneous (1 percent), whereas most workers in control states work in horticulture (37 percent) and the fewest work in fruit and nut production (15 percent) or multiple/miscellaneous (4 percent). Finally, most farmworkers in both California and control states are paid by the hour (86 and 94 percent, respectively), but in California 11 percent are paid a piece rate, whereas only 5 percent in control states are paid by the piece.

The NAWS offers considerable advantage over other data sets in terms of detail on hours, earnings, and farm job characteristics, but there are also limitations. The survey is only administered to crop workers, which limits extrapolating findings to workers employed on ranches and other animal operations that were also impacted by the law. Relying on the NAWS also means that I cannot use workers in other industries within California as control groups in a triple differences design. In the remainder of the paper, I use crop workers in other states as control groups, but this approach is somewhat limited due to the uniqueness of California: California is by far the largest agricultural employer and it produces a wider array of farm commodities, and California's minimum wages have increased faster than those in other states, which challenges identification due to differential pre-trends. Cross-industry comparisons within California would better control for California-specifics, like minimum wage, but would be similar challenged due to the uniqueness of employment in the agricultural sector compared with others, for example due to seasonality and the importance of climate. Despite these pitfalls, the NAWS is the best available data for assessing the implications of California's overtime laws. I detail these and other identification concerns in the empirical framework and results section, and caveat findings and their external validity in the concluding section.

Table 2: Summary Statistics

	California		Control States	
	mean	sd	mean	sd
Panel A: Main Employment Variables				
Hours last week	45.01	11.797	43.28	13.743
Wage $/hour	13.34	3.406	12.48	3.255
Earnings $/week	526.48	177.758	469.31	185.361
Panel B: Worker Demographics				
Age	39.17	13.396	38.00	13.815
Education (years)	7.45	3.816	9.04	3.971
Farm experience (years)	16.41	12.551	13.60	12.430
Female (prop.)	0.27	0.452	0.31	0.455
Undocumented (prop.)	0.56	0.508	0.39	0.479
Has kid (prop.)	0.51	0.512	0.39	0.478
Speaks English (prop.)	0.26	0.448	0.53	0.490
Panel C: Job Characteristics				
Task (prop.):				
Pre-harvest	0.28	0.459	0.32	0.456
Harvest	0.23	0.429	0.18	0.379
Post-harvest	0.15	0.367	0.24	0.418
Semi-skilled	0.34	0.486	0.26	0.432
Supervisor	0.00	0.005	0.00	0.024
Crop type (prop.):				
Field crops	0.03	0.179	0.18	0.377
Fruits & Nuts	0.58	0.505	0.15	0.353
Horticulture	0.09	0.291	0.37	0.473
Vegetables	0.28	0.462	0.26	0.430
Misc/Mult	0.01	0.112	0.04	0.197
Pay type (prop.):				
Hourly	0.86	0.359	0.94	0.241
Piece Rate	0.11	0.327	0.05	0.219
Combination	0.03	0.171	0.01	0.107
Observations (full sample)	8,717		10,198	
# Paid weekly or biweekly (earnings sample)	8,444		9,705	

Notes: Table shows means and standard deviations for key variables for workers in California and control states (all non-overtime states; that is, all states except New York and Washington, which changed their overtime standards in 2020 and 2022, respectively) from fiscal year 2009 through 2022. The data are restricted to workers with non-missing information for outcome and predictors variables and omit salaried workers. Wages and earnings are adjusted to 2022 dollars using the annual CPI. All estimates are produced applying the NAWS sampling weights and linearized standard errors.

5 Empirical Framework

The aim of this paper is to identify the effects of California's agricultural overtime legislation for agricultural employees. To accomplish this I employ two estimation strategies. The first strategy consists of a standard dynamic differences-in-differences (DiD) design that estimates the average treatment effect by comparing changes in outcomes for crop workers in California to those in other (never treated) states. The second strategy applies a distribution regression (DR) approach within the DiD framework to uncover heterogeneous treatment effects across the distributions of hours and earnings (Almond et al., 2011). I present these results as a comparison of observed and counterfactual distributions (Biewen et al., 2022; Chernozhukov et al., 2013).

5.1 Differences-in-Differences Estimators

Changes in outcomes among California workers in the periods following the overtime law implementation are potentially influenced by a multitude of factors. There are two factors of particular concern over this time period. First, is that the post-implementation period includes the onset of COVID-19, which may have impacted both labor supply and demand, particularly in the 2020 harvest season, leading to changes in hours and earnings that should not be attributed to the overtime legislation. Second, California minimum wages rose over this period (table A.1), which might influence both hours and earnings.

To address these concerns and control for other potentially confounding factors, I use a standard DiD model to isolate the effects of the policy change. I begin by estimating the two-way fixed effects model in an event study specification that can be written as:

$$Y_i = \gamma_s + \gamma_t + \sum_{t=-10}^{2} \beta_t d_i^t + \varepsilon_i \tag{1}$$

where Y_i is the outcome of interest for employee i, $\boldsymbol{X_i}$ is a vector of control variables for that worker's demographic and job characteristics that might influence outcomes, γ_s is a state-specific fixed effect, γ_t is a time fixed effect, and d_i^t is a time to treatment indicator equal to 1 if worker i was working in California while interviewed at time t, with time to

treatments defined in two-year windows. The coefficients of interest are β_0 and β_2, which give the changes in outcomes in the years following the implementation of the overtime legislation, compared with those in 2017/18. I further explore average treatment effects in the post-policy period by replacing the time to treatment indicator with an indicator variable equal to 1 if worker i was interviewed in 2019 or later and equal to 0 otherwise.

The necessary identifying assumption for equation 1 to recover unbiased treatment effects is that absent the overtime policy, worker outcomes would have changed in parallel for workers in California and in the control states. As is standard in the literature, I test for differences in pre-trends between treatment and control groups (using β_{-10} through β_{-2}) as supporting evidence for this assumption.

I also explore the sensitivity of results to controlling for worker and job attributes of California workers that might change over time, unrelated to the overtime legislation, and might influence working hours or income. In a series of stepped-in regressions, I control for worker demographics (age, gender, education, number of children, years of farmwork experience, legal immigration status, and english speaking ability), job characteristics (indicators for performing a harvest task, being paid by the hour, and working in vegetable or fruit and nut production), and the annual state minimum wage.[22] I estimate these regressions using the extended two-way fixed effects (ETWFE) regressor from Wooldridge (2021) and Wooldridge (2023). The ETWFE estimator incorporates covariates as a set of saturated interaction effects to overcome the potential bias introduced by controlling for time-varying covariates (without interactions) in the standard two-way fixed effect model (Caetano and Callaway, 2024).

Control Groups I consider three alternative delineations of control groups for these analyses. In all delineations, the treatment group consists of all agricultural workers in California and the control groups consist of workers in other states. The first control group consists of all workers in the NAWS in non-overtime states. This excludes workers interviewed in New York and Washington, which implemented overtime standards during the study period

[22] I match each worker interview to the maximum state-level minimum wage in the year they were interviewed using state minimum wage data from Vaghul and Zipperer (2022).

(in 2020 and 2022, respectively)[23]. The second further restricts the sample to workers in states with similar types of agricultural production, defined as states within the "Fruitful Rim" USDA Farm Resource Region (Oregon, Idaho, Arizona, Texas, and Florida)[24]. The third restricts the sample to workers in Western states (excluding Washington): Arizona, Colorado, Idaho, Montana, New Mexico, Nevada, Oregon, Utah, and Wyoming.

Outcomes I focus on two outcome variables in this analysis. To estimate the average hours effects, I estimate equation 1 with the outcome variable defined as weekly working hours.[25] I next explore implications for worker incomes using pre-tax weekly earnings for each worker's most recent pay period, and I restrict the analysis to workers who are paid in one or two week periods, roughly 97 percent of the California sample (table 2. I adjust earnings to 2022 real $ using the annual CPI. Results from these specifications consistently reveal strong pre-treatment trends, except in the specifications that control for the annual state minimum wage. To further explore the robustness of the earnings effects, I follow Bhuller et al. (2013); Goodman-Bacon (2021b,a) and estimate linear pre-trends for workers in the treatment and control groups, extract through all time periods, and subtract the fitted trend from the hourly wage rate for all observations. This reduces the magnitude of differences in pre-treatment trends between California and control states, but statistically significant differences in the trends remain (see figure B.5in the appendix). These linear trends are potentially less correlated with earnings than state minimum wages, which increased more in California compared with most US states.[26] Figure D.1 in the appendix shows that

[23]There are two primary reasons for excluding these states rather than using a staggered adoption differences-in-differences model and including them in the treatment group. First, both states implemented different overtime policies (for example, New York's phase in was substantially slower) making assumptions of homogeneous treatment effects implausible. Second, Washington implemented their policy in the last year of data, making isolating the effects challenging. As more data become available, further research should explore the impacts of alternative state policies in isolation.

[24]The "Fruitful Rim" USDA Farm Resource Region is characterized by large and very large non-family farms producing fruits, vegetables, and cotton. See ERS (2000) for more detail on Farm Resource Regions.

[25]This variable captures hours worked in the week prior to the interview for the worker's current farm employer. The current employer is specified as the farm where the interview is taking place. If the worker currently has multiple farm employers, hours for the other employers are not included in this measure. In the primary specifications I present results using this variable in levels, but include analogous specifications for logged working hours in the appendix.

[26]Interestingly, the two other states with most similar minimum wage increases over this period are Washington and New York, the two states omitted because they instituted overtime standards during the study period. This introduces an interesting question of the characteristics of states more likely to adopt these

earnings track closely with the California state minimum wage, particularly in the pre-policy period. To isolate earnings effects from the overtime policy from those due to rising minimum wages, I follow a similar procedure as for adjusting for region-specific pre-treatment trends. I estimate a linear regression of earnings on state minimum wages[27] in the pre-treatment period separately for workers the treatment and control groups, extract through all time periods, and subtract the fitted trend from the hourly wage rate for all observations. This procedure effectively eliminates pre-treatment differences in earnings trends across all specifications. Results from these specifications are in figure B.6 in the appendix.

In a final series of regressions, I explore whether changes in earnings are driven by changes in wages. Here, the wage-hours compensating theoretical literature would predict that hourly wages would decrease following the overtime regulations. I test this by restricting the sample to workers paid by the hour and defining the outcome variable as the "usual" hourly wage rate.[28] These specifications suggest that the policy did not impact hourly wages and are included in the Online Appendix. XX

5.2 Distributional Effects Specification

Second-order questions of interest relate to whether and to what extent the legislation impacted the distributions of hours and earnings. These analyses are important because it is possible that the overtime legislation had little or no impact on mean outcomes, but that aggregate effects mask important distributional shifts. For example, one possibility is that employers reduce hours for some workers while raising hours for others, leading to null effects at the mean, but with important welfare implications for workers. In addition, these specifications offer additional robustness to the average effects. Over the study period, the hours threshold for overtime pay reduced four times – beginning at 60 hours per week prior to the legislation, lowering to 55 hours, and reducing in 5 hour increments in each of the following years until reaching the standard 40 hour a week threshold in 2022. If the hours

legislation and whether the effects of the law would have been different without concurrent hikes in the minimum wage.

[27] I match each worker interview to the maximum state-level minimum wage in the year they were interviewed using state minimum wage data from Vaghul and Zipperer (2022).

[28] I use variable D12, which asks hourly paid workers "how much [they are paid] per hour to the nearest cent".

for some workers were reduced in response to the legislation, we would expect to see the reductions concentrated in these ranges.

Hours of work in the NAWS, as in most survey data, are reported as integers and often have high mass points at various hourly thresholds.[29] Both of these issues introduce interesting empirical challenges for studying distributional effects; common empirical approaches, for example, quantile treatment effects (QTE) or recentered inference functions (RIF), assume an underlying continuous distribution and are not appropriate for analyzing variables that are discrete, have large mass points, or have many ties (Bitler et al., 2006; Firpo et al., 2009, 2018; Lehrer et al., 2022).

To overcome this challenge I employ a distribution regression (DR) approach (Chernozhukov et al., 2013; Foresi and Peracchi, 1995). The DR approach consists of estimating a series of regressions of the form of equation 1, but with the outcome defined as a binary transformation of the CDF of the variable of interest. For example, to examine effects across the distribution of hours, I estimate a series of logistic regressions where the outcome is an indicator variable equal to 1 if hours are less than or equal to a continuum of hourly thresholds and zero otherwise. The intuition behind these regressions is to estimate the effect of the overtime legislation on the distribution of the outcome variable using a DiD identification approach (Biewen et al., 2022; Dube, 2019; Duflo, 2001; Fernandez-Val et al., 2024). These regressions can be written generally as:

$$\mathbb{1}\left[Y_i \leq z\right] = \gamma_s + \gamma_t + \sum_{t=-5}^{1} \beta_t^z d_i^t + \varepsilon_i \tag{2}$$

where $\mathbb{1}\left[Y_i \leq z\right]$ is an indicator variable equal to 1 if outcome Y, observed for worker i, is less than or equal to some threshold z and 0 otherwise. All other variables are defined as in equation 1. For a given threshold z, the coefficient estimates of the treatment effects, β_0^z and β_2^z, give the estimated effect of the overtime policy on the probability of observing a worker

[29] The location of these mass points can be driven by overtime regulations or by social norms around standard working hours; even in industries like agriculture where workers are not subject to overtime pay after 40 hours a week, bunching around this threshold is common. This is less prevalent in the NAWS compared with the ACS, most likely because the NAWS asks workers to report hours in the prior workweek whereas the ACS asks for the usual hours worked per week. See figure C.1 in the appendix for a comparison of the NAWS and ACS California farmworker hours distributions.

with an outcome at or below level z.

I estimate equation 2 over a fixed number of thresholds and present the estimated coefficients of interest as evidence on the differences in differences effects at specific points in the conditional distributions Almond et al. (2011); Duflo (2001); Foresi and Peracchi (1995). When estimating these equations over the distribution of weekly working hours, I set thresholds in 5-hour increments beginning at 35 and ending at 65 reflecting the structure of the phase-in of the overtime legislation. When estimating these equations over the distribution of weekly earnings, I set thresholds in $100 increments over the range spanning the top and bottom 5% of the earnings distribution (from $300 to $1000 per week). For both hours and earnings, I estimate the equations using a logistic regression model and using the preferred specifications from the average effect models. I then use the parameter estimates from each estimating equation to construct a counterfactual distribution (absent the change in overtime policy), and present inference from comparing the observed and counterfactual distributions Biewen et al. (2022); Cengiz et al. (2019); Chernozhukov et al. (2013); Dube (2019).

Estimating distribution regressions in the DiD framework requires more restrictive assumptions on parallel trends. In particular, the parallel trends assumption must hold for the cumulative distribution function (Roth and Sant'Anna, 2023). Accordingly, I show the event study coefficients for each of the logistic regressions before discussing results from the construction of counterfactuals.

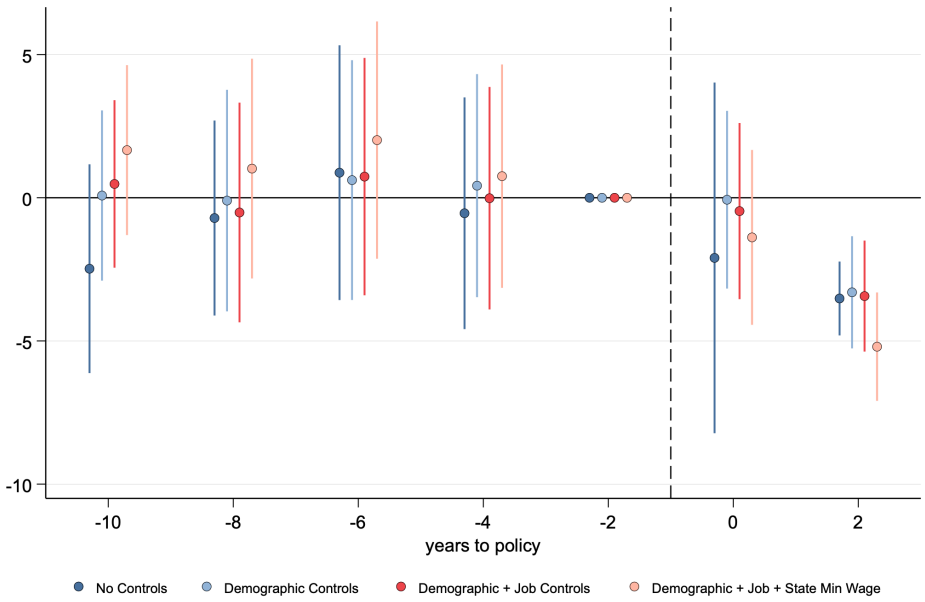
6 Results

Figure 1 shows the event study plots for the preferred DiD specifications (using all non-overtime states as the control group) with the outcome variables defined as weekly working hours (panel a) and weekly earnings (panel b). Table 3 shows the coefficient estimates of the treatment effects, sample sizes, and χ^2 tests of the joint statistical significance of the coefficients for the pre-treatment differences indicators. Across all specifications, results suggest that both hours and earnings decreased as a result of the overtime law, mostly in 2021/22, the last two years of the phase-in. Estimates suggest that, on average, California farmworkers worked 3.3 to 5.2 fewer hours per week and earned $80 to $163 less per week

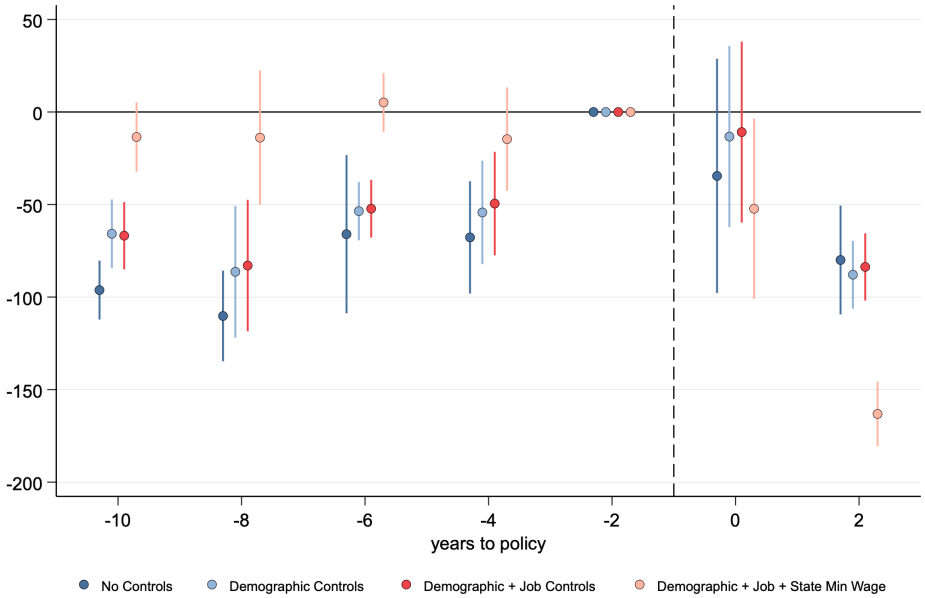
in 2021 and 22 as a result of the law. Across specifications, estimates of hours and earnings effects in the first two years of implementation (2019/20) are negative, but vary in magnitude and precision, suggesting reductions in hours ranging from 0.07 to 2.1 and reductions in pay ranging from \$10.9 to \$52.3. χ^2 tests of the joint statistical significance of the pre-treatment time indicators yield p-values ranging from 0.30 (in the specification with no controls) to 0.99 (worker controls) in the hours specifications. In the regressions with earnings as the outcome variable, only the specification that controls for the minimum wage fails to reject the null hypothesis of no pre-treatment trends. Figures B.5 and B.6 in the appendix show results from the alternative specifications for the earnings variable described in the methods section. These specifications generally exhibit less obvious pre-treatment differences in trends between California and control states and suggest decreases in earnings in 2021 and 22 ranging from \$120 to \$182. Figures B.4 and B.3 in the appendix show results from the primary specifications, but considering alternative control groups, as described in the methods section. Results across all considered control groups are consistent with those in the primary specifications. Overall, these estimates provide robust evidence that both hours and earnings fell as a result of California's overtime policy. The evidence also suggests a delayed response to the policy, with the largest effects for both hours and earnings occurring in the last two years of its phase-in.

Figure 1: Average Weekly Hours and Earnings Effects

(a) Hours



(b) Earnings



Notes: Figure shows coefficient estimates of the dynamic DiD pre-treatment and treatment effects in two-fiscal year groups (using all non-overtime states as the control group) and associated 95% uniform confidence bounds for specifications with alternative sets of control variables. The omitted time period is 2017/18, the years immediately proceeding the overtime implementation. Panel A shows results where the outcome variable is the number of hours worked for their current farm employer in the week prior to the interview. Panel B shows results where the outcome variable is weekly (pre-tax) earnings in the most recent pay period, restricting the sample to workers who receive weekly or bi-weekly paychecks. Demographic controls include age, gender, education, farm experience, and indicators for having children, legal documentation status and english speaking ability. Job controls include indicators for the crop, payment, and task types. Standard errors are clustered at the NAWS region-level.

Table 3: Estimates of Overtime Policy Effects on Hours and Earnings from Preferred Specifications

	(1) no controls	(2) worker controls	(3) worker + job controls	(4) worker + job + min wage
Primary Hours Effects				
2019/20	-2.100	-0.069	-0.466	-1.384
	(3.12385)	(1.58304)	(1.56915)	(1.55737)
2021/22	-3.518***	-3.302***	-3.434***	-5.200***
	(0.65788)	(0.99920)	(0.98859)	(0.96543)
Avg. Post Effect	-2.913**	-1.924*	-2.169**	-3.573***
	(1.41091)	(1.01376)	(0.99839)	(0.97599)
Observations	19,374	19,374	19,374	19,374
χ^2 pre-trend test p-value	0.30	0.99	0.82	0.66
Primary Earnings Effects				
2019/20	-34.546	-13.272	-10.875	-52.264**
	(32.29352)	(24.93300)	(24.94506)	(24.86091)
2021/22	-79.974***	-87.902***	-83.708***	-163.151***
	(14.99996)	(9.34019)	(9.27483)	(8.94372)
Avg. Post Effect	-60.491***	-55.894***	-52.471***	-115.593***
	(14.52313)	(15.52288)	(15.51361)	(15.34424)
Observations	18,736	18,736	18,736	18,736
χ^2 pre-trend test p-value	0.00	0.00	0.00	0.18

Notes: Table shows results from the preferred differences-in-differences specifications for hours and earnings, which use all non-overtime states as the control group. The outcome variable in the hours regressions is defined as hours worked last week. The outcome variable in the earnings regressions is defined as weekly earnings in the most recent pay period. Control variables include worker covariates – age, education, farm experience, gender, number of children, legal documentation status, and english speaking ability – and attributes of the job – indicators for crop, task, and payment types. All specifications are estimated using survey sampling probability weights and standard errors are clustered at the state-level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

7 Distributional Effects

This section presents results from the distributional regressions. Figure 4 shows the coefficient estimates from estimating a logistic model where the outcome variable is an indicator variable equal to 1 if hours (panel a) or earnings (panel b) are less than or equal to a continuum of thresholds and zero otherwise. In each figure, each color corresponds to coefficient estimates on the interaction term between California and the time period indicator variables from a single regression. Positive estimates indicate that relatively more California workers were working (earning) at or below the indicated hours (earnings) thresholds compared with workers in the control group and in the period before the overtime law went into effect. For both the hours and earnings specifications, the coefficients in the pre-policy period are small in magnitude by comparison to the those in the post-policy period, and most are not statistically significantly different from zero.

I use the coefficient estimates from these regressions to estimate counterfactual distributions of hours and earnings. That is, I subtract the policy effect in the post-treatment period and predict the likelihood that each worker in the California sample would have worked or earned within each increment between thresholds if the policy had no effect. Figure 2 shows the difference between the counterfactual (predicted, removing effects from the law) and factual (observed, with effects from the law) distributions of working hours in 2020 and 2022.[30] The results for the distribution of working hours suggest that California farmworker hours reduced fairly consistently with how the overtime law was phased-in. In 2019/2020, relatively more workers were working 41-50 hours and fewer were working 51-60 hours; in 2021/2022 relatively more workers were working 36-45 hours and fewer were working 51-60. This aligns with the mandated hours thresholds as phased-in by the California legislation (55 hours in 2019, 50 in 2020, 45 in 2021, and 40 in 2022).

Figure 3 shows the difference between the counterfactual (predicted, removing effects from the law) and factual (observed, with effects from the law) distributions of weekly earnings in 2020 and 2022.[31] These results are remarkably similar to the changes in the distributions

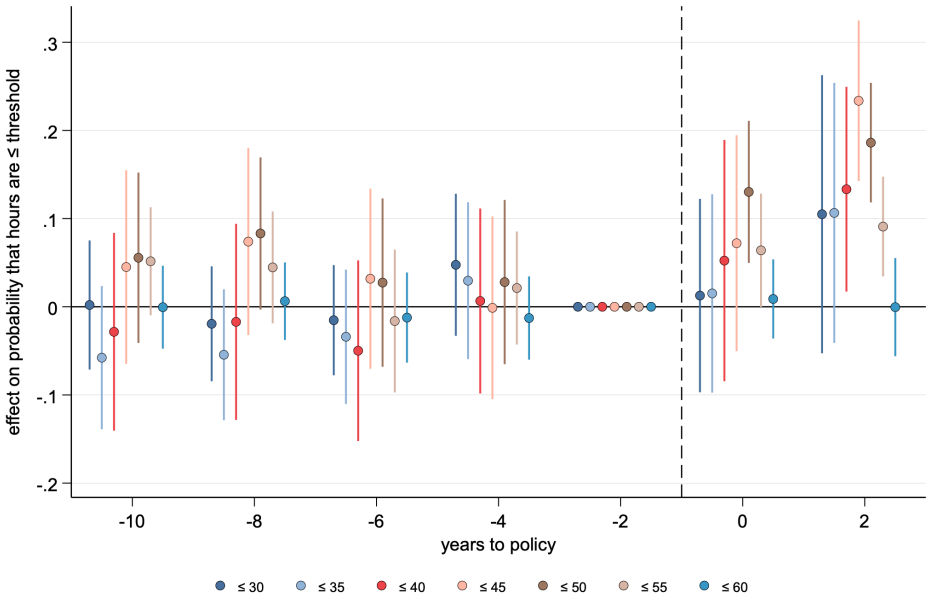
[30] Figure B.7 in the appendix shows these distributions separately, without confidence bands.
[31] Figure B.8 in the appendix shows these distributions separately, without confidence bands.

of hours. In 2019/20, relatively more workers earned $401-$700 per week and fewer earned $701 or more. In 2021/22, again relatively more workers earned $401-$700, and fewer earned $801 or more.

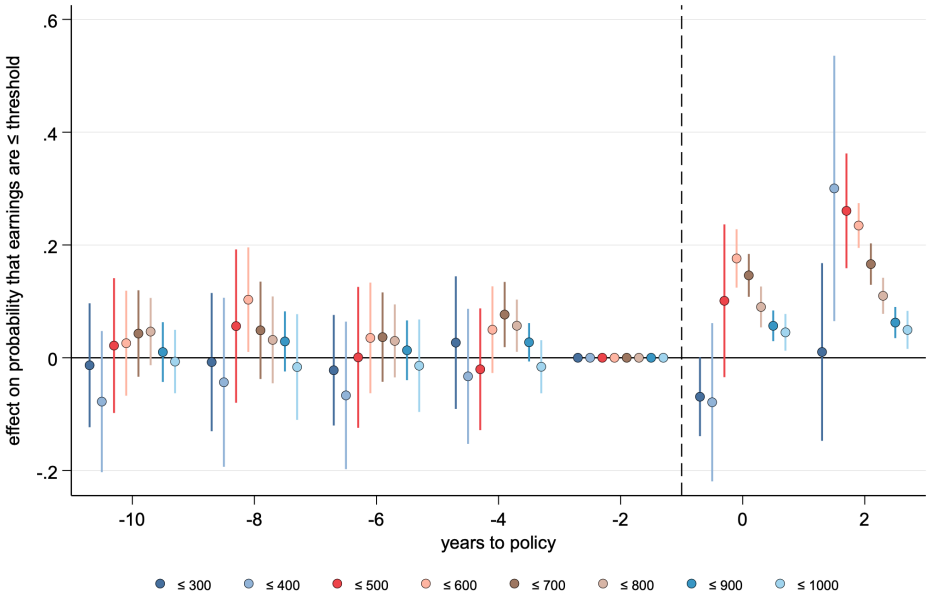
In sum, the distributional effects suggest a downward shift in both hours and earnings and are consistent with employers reducing hours to avoid paying the higher overtime rates.

Figure 2: Coefficient Estimates from DR-DiD Specifications

(a) Hours



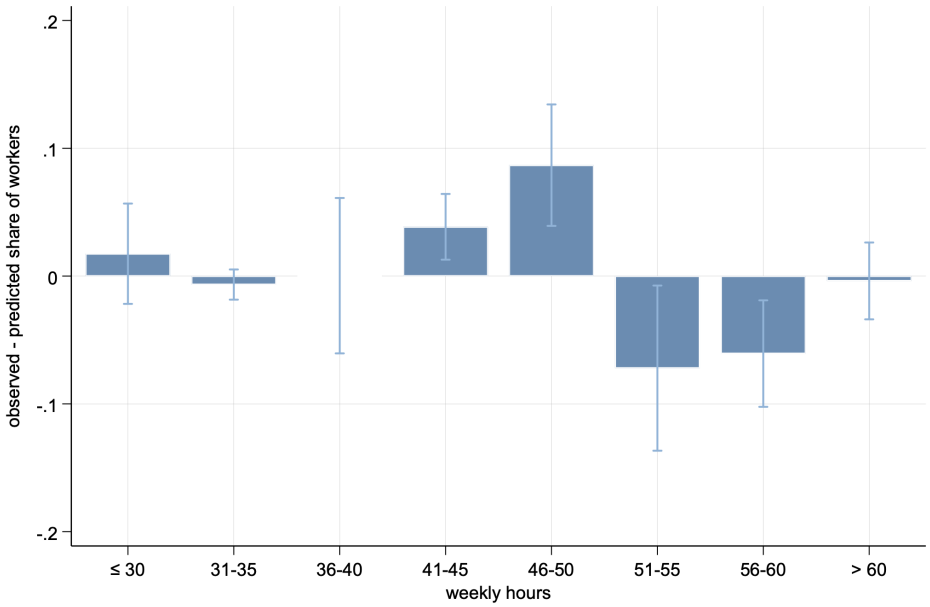
(b) Earnings



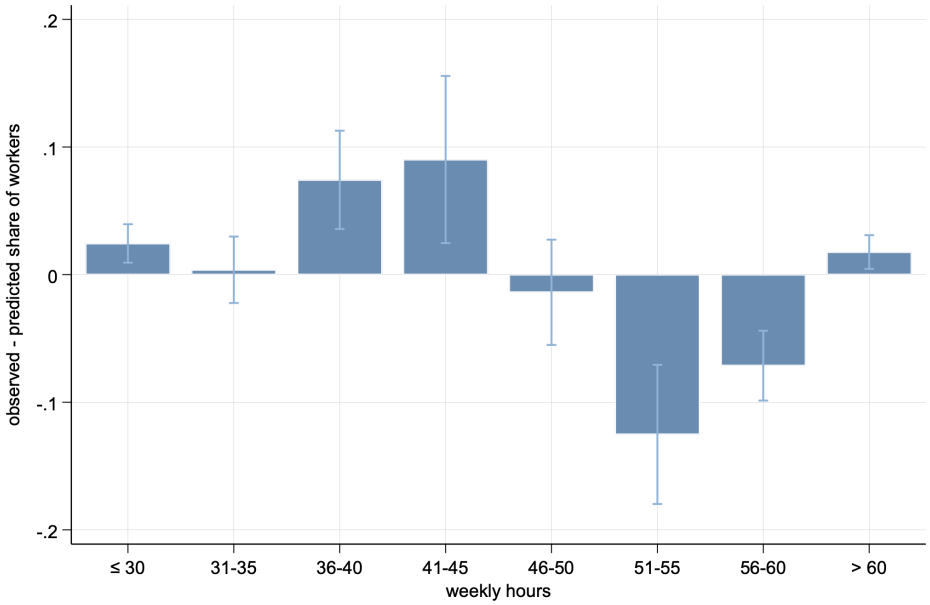
Notes: Figure shows coefficient estimates of the DR-DiD pre-treatment and treatment effects in two-fiscal year groups (using all non-overtime states as the control group) and associated 95% uniform confidence bounds. For the regressions with indicators for hours as the outcome, the controls include all worker and job covariates. The regressions with the indicators for earnings as the outcome additionally include the state minimum wage. The omitted time period is 2017/18, the years immediately proceeding the overtime implementation. Standard errors are clustered at the NAWS region-level.

Figure 3: Effects Across the Hours Distribution

(a) 2020



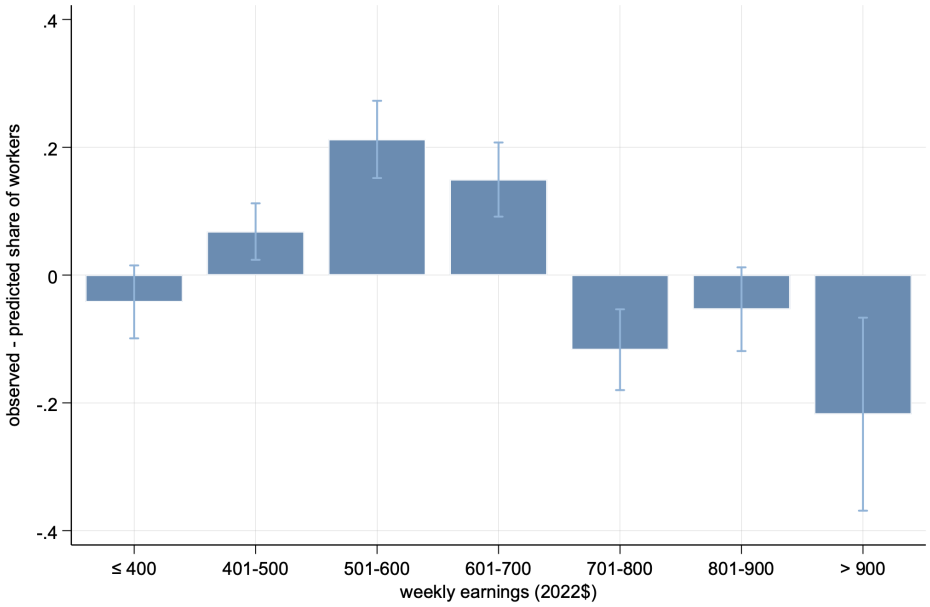
(b) 2022



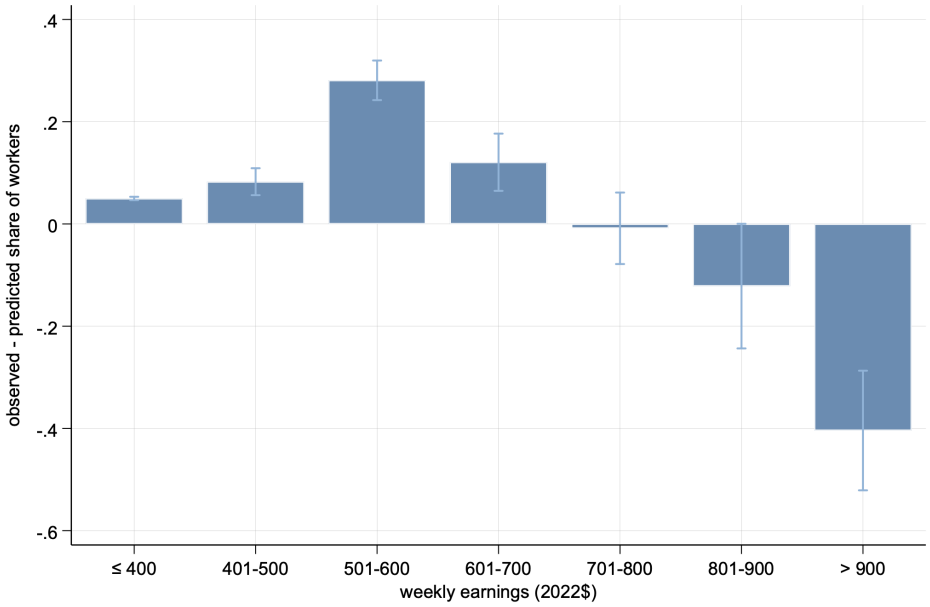
Notes: Figure shows the difference between the factual (observed) minus the counterfactual (estimated, removing effects of the overtime law) shares of California workers with hours in the indicated ranges. The capped lines on each bar indicate the 95 percent confidence intervals, estimated by clustered bootstrapping at the NAWS region-level with 100 samples. Positive values indicate that a higher share of workers worked within the hours range than would have if the law were not in place. Bars below the 0 line indicate that fewer workers worked those hours than would have without the law in place.

Figure 4: Effects Across the Earnings Distribution

(a) 2020



(b) 2022



Notes: Figure shows the difference between the factual (observed) minus the counterfactual (estimated, removing effects of the overtime law) shares of California workers with earnings in the indicated ranges. The capped lines on each bar indicate the 95 percent confidence intervals, estimated by clustered bootstrapping at the NAWS region-level with 100 samples. Positive values indicate that a higher share of workers earned within the range than would have if the law were not in place. Bars below the 0 line indicate that fewer workers had weekly earnings within the indicated range than would have without the law in place.

7.1 Heterogeneous Effects

- For effects on hours repeat the average and dr methods separately across:
  - Legal documentation status
  - Gender
  - Age
  - Experience
  - Task

8 Discussion and Conclusion

This paper offers novel evidence on the effects of regulated overtime standards for the workers they aim to protect. My analysis suggests that in the short-run, the first four years of the phase-in of California's overtime regulation for farmworkers, worker hours and earnings decreased. While reductions in earnings suggest that the law may not be benefiting the workers it aims to protect, reductions in hours work in the opposite direction. It is possible that despite these outcomes, workers are better off from the law; they may be happy to accept the lower pay in exchange for fewer working hours and having more leisure time. Or, workers may benefit from safer working environments, since research suggests longer hours can increase workplace injuries. On the other hand, workers and their families who were depending on this lost income to cover living expenses may now need to seek out second employment opportunities, negating these other benefits and adding the inconvenience of traveling between jobs.

Additional work is needed to fully understand the effects of this law on California's farm workforce, farm employers, and U.S. and international consumers. Additional research is also needed to contrast the effects in California with those in other states to understand whether there are more successful versions of the policy. For example, New York and Oregon's laws include a refundable tax credit for overtime hours paid by farm employers. Such a model is likely to reduce the financial burden on employers of paying workers for overtime hours and

may mitigate the hours and earnings reductions highlighted here.

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Table A.1: California Minimum Wage Change Schedule

Effective Date	Hourly Minimum Wage for Employers with...	
	>25 Employees	≤25 Employees
Jan. 1 2022	$15.00	$14.00
Jan. 1 2021	$14.00	$13.00
Jan. 1 2020	$13.00	$12.00
Jan. 1 2019	$12.00	$11.00
Jan. 1 2018	$11.00	$11.00
Jan. 1 2017	$10.50	$10.00
Jan. 1 2016	$10.00	$10.00
Jul. 1 2014	$9.00	$9.00
Jan. 1 2008	$8.00	$8.00

Notes: Table adapted from the California Labor Commissioner's Office FAQs on Minimum Wage `https://www.dir.ca.gov/dlse/faq_minimumwage.htm` and Overtime for Agricultural Workers `https://www.dir.ca.gov/dlse/Overtime-for-Agricultural-Workers.html`.

Online Appendix

A Extra Tables

Table A.2: Summary Statistics for California Sample, Comparison of Alternative Outcome Variables

	Pre: 2011-2014		Pre: 2015-2018		Post: 2019-2022	
	mean	sd	mean	sd	mean	sd
Alternative Measures of Hours						
Main: Hours last week (full sample)	44.61	12.18	46.21	11.86	43.57	11.53
Hours last week (weekly paycheck)	44.09	11.37	45.61	11.45	42.16	9.89
Hours last week (hourly paid)	45.02	12.53	46.42	12.03	43.97	10.97
Hours last paycheck (weekly paycheck)	45.42	10.95	46.82	10.52	41.92	9.91
Alternative Measures of Wages						
Main: Wage $/hour (full sample)	11.98	3.08	13.58	3.30	15.72	2.61
Wage $/hour (hourly paid)	11.51	2.30	13.17	2.33	15.74	2.12
Wage $/minimum wage (full sample)	1.11	0.22	1.13	0.19	1.09	0.14
Alternative Measures of Earnings						
Main: Earnings $/week (weekly or biweekly paycheck)	470.92	152.36	555.00	187.74	604.45	195.05
Earnings $/week (weekly paycheck)	464.90	146.69	550.62	185.93	589.08	179.12
Earnings $/week (weekly/biweekly, hourly paid)	465.40	154.90	537.67	165.69	601.98	179.83
Earnings $/week/minimum wage × $16 (weekly/biweekly)	725.14	232.47	760.92	253.89	668.16	217.56
Observations (full sample)	2709		2951		1868	
# Weekly or biweekly paycheck	2633		2864		1812	
# Weekly paycheck	1931		1810		1205	
# Hourly paid	2395		2684		1650	

Table shows means and standard deviations for key outcome variables for workers in California in the NAWS data during indicated sample periods. Table compares alternative outcome variables for hours (hours last week versus hours last paycheck) and alternative sample restrictions (that is, those paid by the hour, receiving weekly paychecks, or receiving weekly or biweekly paychecks). The data are restricted to workers with non-missing information for outcome and predictors variables and omit salaried workers and supervisors. Wages and earnings are adjusted to 2022 dollars using the annual CPI. Estimates are produced applying the NAWS sampling weights.

Table A.3: Hours Results, Alternative Control Groups Doubly Robust DiD

	(1) no controls	(2) worker controls	(3) job controls	(4) worker + job
RDiT: California Sample Only				
2019/20	-0.985	-0.817	-1.360	-1.267
	(0.87569)	(0.90841)	(0.88575)	(0.91650)
2021/22	-4.218***	-4.411***	-4.319***	-4.562***
	(0.92733)	(0.90835)	(0.94939)	(0.92280)
Avg. Post Effect	-3.270***	-3.295***	-3.269***	-3.193***
	(0.70518)	(0.65113)	(0.71608)	(0.64874)
Observations	8,926	8,926	8,926	8,926
R^2	0.012	0.056	0.034	0.079
DiD: All Non-OT States				
2019/20	-2.121	-0.017	-3.363*	-0.842
	(2.16569)	(1.65554)	(1.84828)	(1.65717)
2021/22	-3.620*	-3.188***	-3.824***	-3.909**
	(2.03971)	(1.19991)	(1.47257)	(1.77015)
Avg. Post Effect	-2.871	-1.603	-3.593**	-2.376
	(1.82069)	(1.17887)	(1.50832)	(1.52795)
Observations	19,374	19,374	19,374	19,374
χ^2 pre-trend test p-value	0.30	0.76	0.61	0.50
DiD: All Non-OT Fruitful Rim States				
2019/20	-0.449	-1.311	-3.294*	-3.650**
	(2.90462)	(2.33295)	(1.84000)	(1.63475)
2021/22	-2.651***	-3.237***	-5.901***	-5.536***
	(0.85463)	(0.99104)	(1.40254)	(1.42859)
Avg. Post Effect	-1.550	-2.274	-4.598***	-4.593***
	(1.86013)	(1.63651)	(1.59628)	(1.51076)
Observations	13,194	13,194	13,194	13,194
χ^2 pre-trend test p-value	0.52	0.01	0.25	0.06
DiD: All Non-OT Western States				
2019/20	-4.464*	-3.436	-3.884***	-4.245***
	(2.68613)	(2.87696)	(0.91892)	(0.65605)
2021/22	-3.269*	-4.243***	-6.726***	-6.837***
	(1.67801)	(1.28743)	(1.62472)	(1.95431)
Avg. Post Effect	-3.866*	-3.839**	-5.305***	-5.541***
	(1.99979)	(1.89276)	(1.08312)	(1.19033)
Observations	11,406	11,406	11,406	11,406
χ^2 pre-trend test p-value	0.00	0.03	0.00	0.00

Table shows results from estimating equation 1 with the outcome defined as hours worked last week. Control variables include worker covariates – age, education, farm experience, and indicators for gender, having children, and legal documentation status – attributes of the job – indicators for categories of crop, task, and payment – and year and state fixed effects. All specifications are estimated using survey sampling probability weights and standard errors are clustered at the state-level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.4: Earnings Results, Alternative Control Groups Doubly Robust DiD

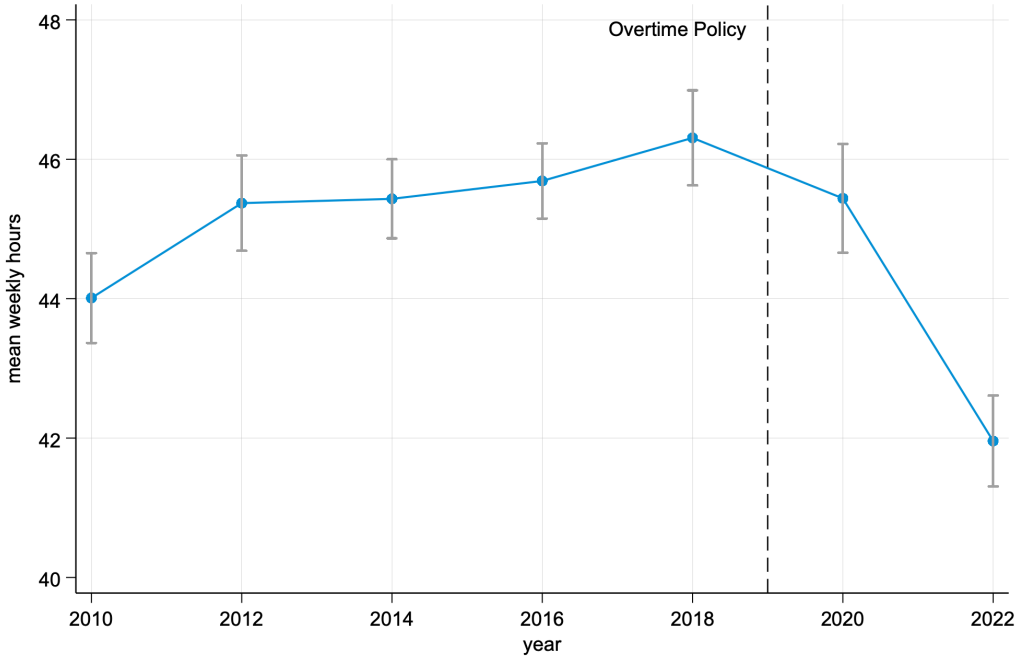
	(1) no controls	(2) worker controls	(3) job controls	(4) worker + job
RDiT: California Sample Only				
2019/20	-55.483**	-38.840*	-35.076	-12.829
	(25.86239)	(21.47571)	(26.62929)	(21.19494)
2021/22	-124.506***	-125.130***	-120.982***	-121.463***
	(16.80100)	(16.64191)	(16.69864)	(16.49773)
Avg. Post Effect	-87.276***	-91.897***	-85.230***	-90.155***
	(12.73508)	(12.03944)	(12.90732)	(12.21439)
Observations	8798	8798	8798	8798
R^2	0.028	0.092	0.037	0.101
DiD: All Non-OT States				
2019/20	-91.637***	-74.341***	-72.326***	-55.326***
	(26.04428)	(21.15829)	(27.45985)	(21.30427)
2021/22	-186.427***	-181.228***	-171.242***	-183.369***
	(31.38559)	(15.85107)	(18.78475)	(16.93120)
Avg. Post Effect	-139.032***	-127.784***	-121.784***	-119.348***
	(23.77496)	(15.19448)	(18.77497)	(15.90062)
Observations	18,736	18,736	18,736	18,736
χ^2 pre-trend test p-value	0.06	0.02	0.47	0.26
DiD: All Non-OT Fruitful Rim States				
2019/20	-88.402***	-97.194***	-90.919***	-82.355***
	(32.36427)	(26.63584)	(16.72790)	(13.70673)
2021/22	-224.404***	-226.995***	-229.098***	-224.923***
	(23.40301)	(10.04333)	(19.94073)	(9.76284)
Avg. Post Effect	-156.403***	-162.095***	-160.009***	-153.639***
	(11.42164)	(8.77542)	(13.09509)	(3.04348)
Observations	12,866	12,866	12,866	12,866
χ^2 pre-trend test p-value	0.00	0.00	0.00	0.00
DiD: All Non-OT Western States				
2019/20	-100.489***	-78.191***	-110.143***	-76.379***
	(24.18065)	(24.99531)	(13.40022)	(15.99937)
2021/22	-190.515***	-182.450***	-214.760***	-187.448***
	(39.73203)	(24.35071)	(25.62204)	(15.59799)
Avg. Post Effect	-145.502***	-130.321***	-162.452***	-131.913***
	(27.30391)	(16.04001)	(17.03350)	(13.03842)
Observations	11,168	11,168	11,168	11,168
χ^2 pre-trend test p-value	0.00	0.03	0.00	0.00

Table shows results from estimating equation 1 with the outcome defined as weekly earnings in the most recent pay period, adjusted using the pre-treatment minimum wage. Control variables include worker covariates – indicators for categories of age, education, farm experience, gender, number of children, and legal documentation status – attributes of the job – indicators for categories of crop, task, and payment – the state minimum wage, and county-by-quarter fixed effects. All specifications are estimated using survey sampling probability weights and standard errors are clustered at the state-level. The sample is restricted to workers who receive weekly or bi-weekly paychecks. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

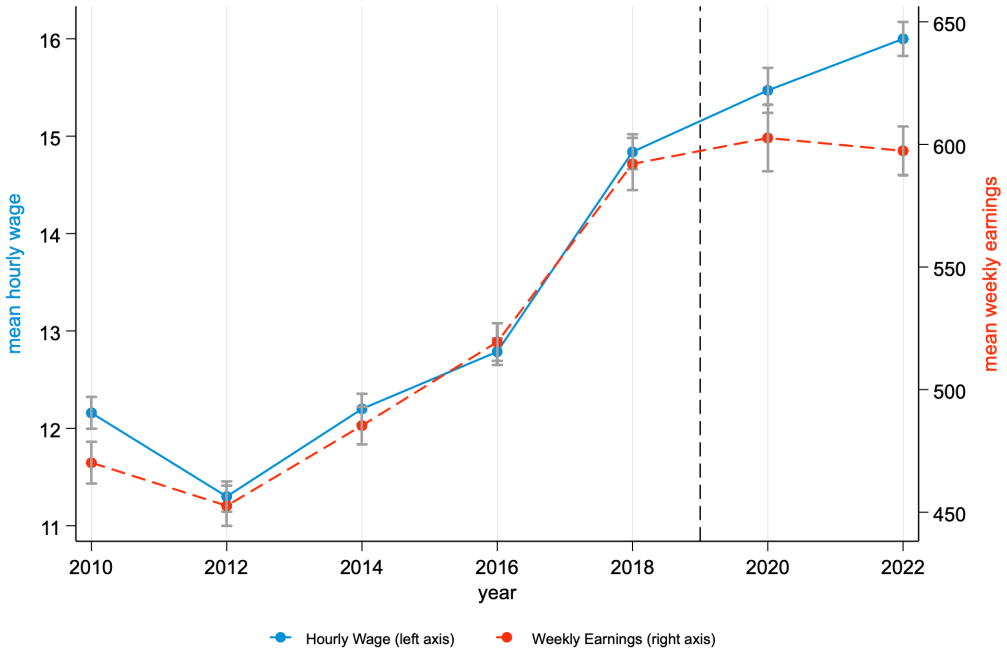
B Extra Figures

Figure B.1: California Changes in Mean Hours, Wages, and Earnings

(a) Hours

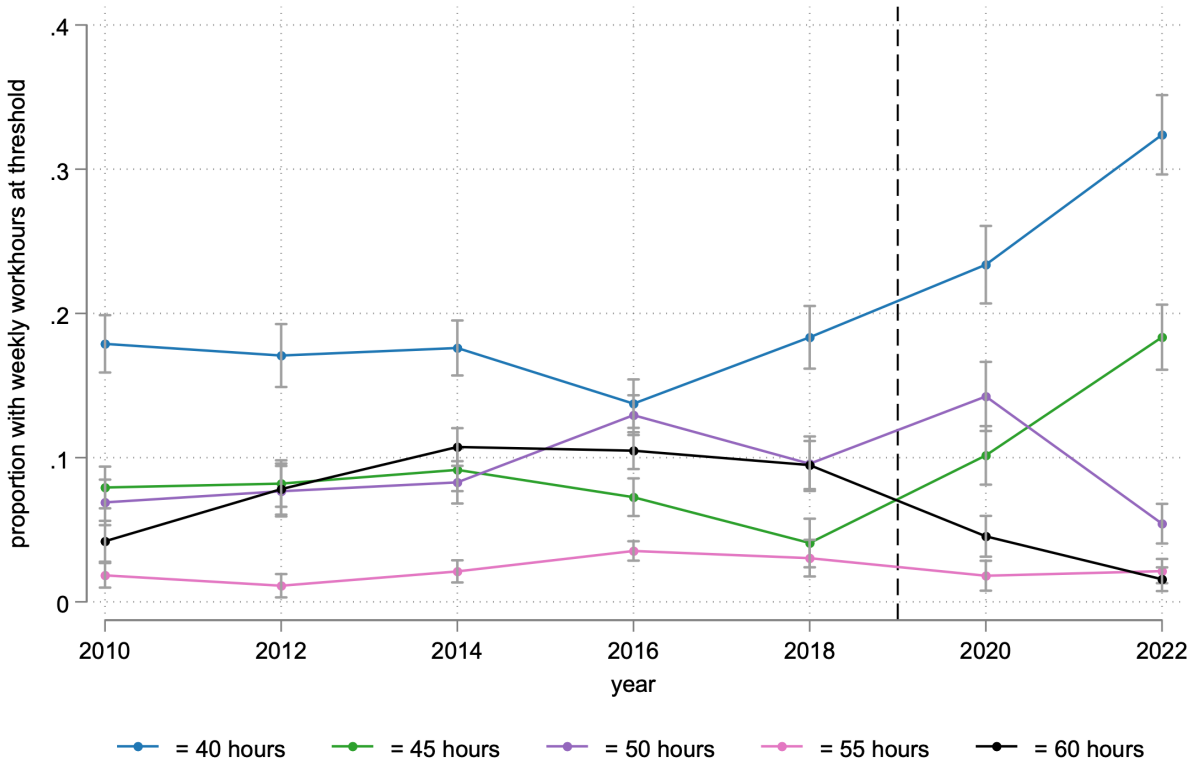


(b) Wages and Earnings



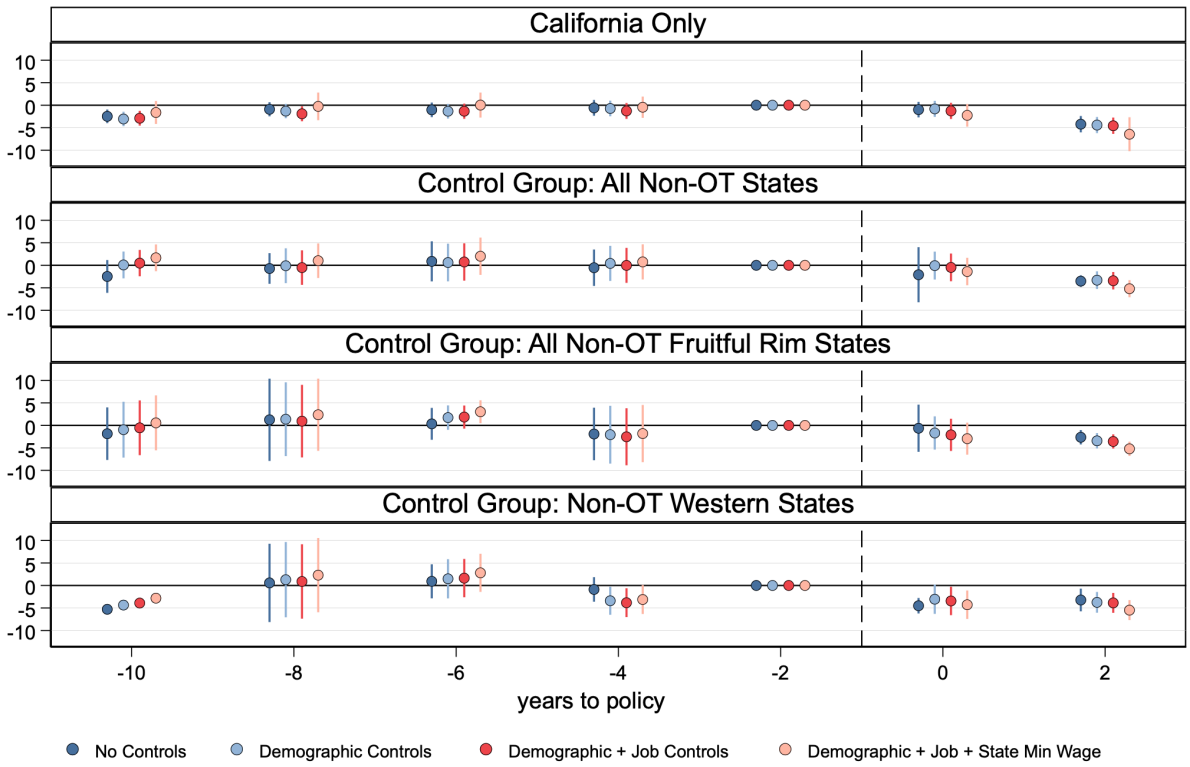
Notes: Figure shows weighted means and associated 95% confidence bounds for the hours (panel a) and hourly and weekly earnings (panel b) of California farmworkers in two-fiscal year groups.

Figure B.2: Trends in Bunching at Weekly Hours Thresholds



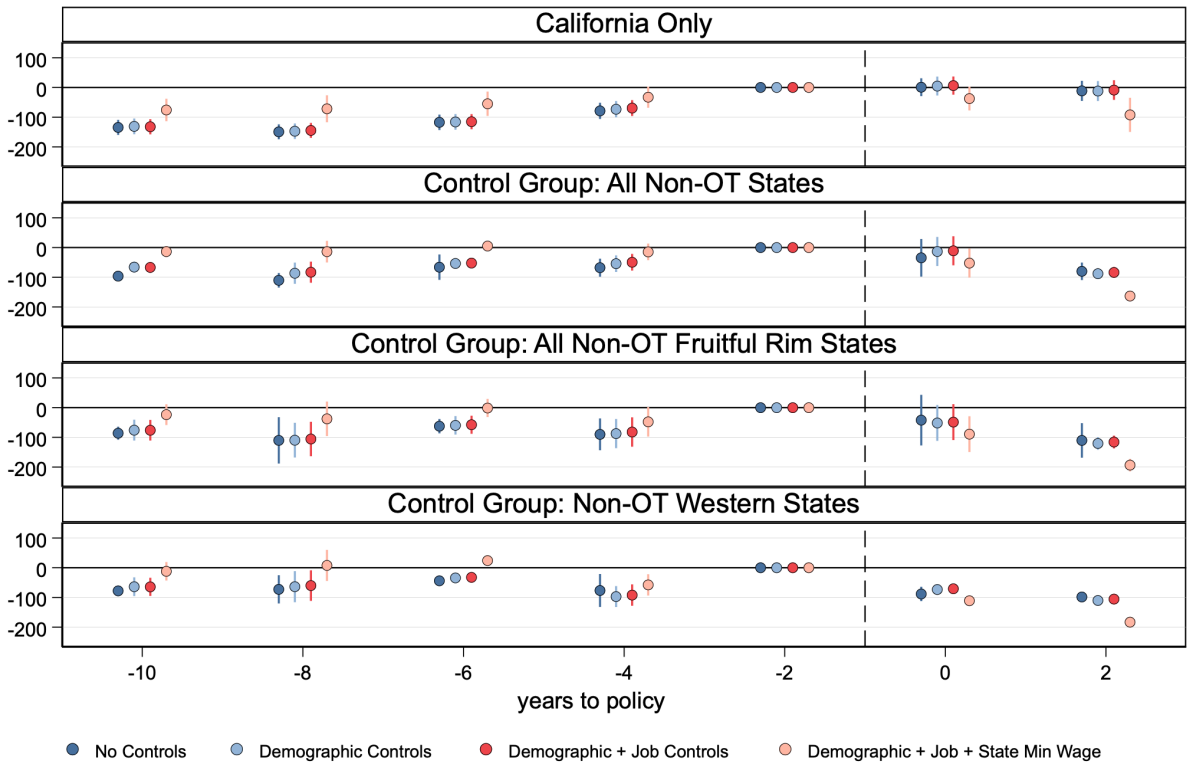
Notes: Figure shows proportion of workers who reported working (precisely) 40, 45, 50, 55, and 60 hours in the prior work week. Proportions and associated 95% confidence intervals are estimated for two-fiscal year groups using NAWS sampling weights. The vertical dashed line indicates the start of California's overtime phase-in in 2019.

Figure B.3: Average Effects Results for Hours, Alternative Control Groups



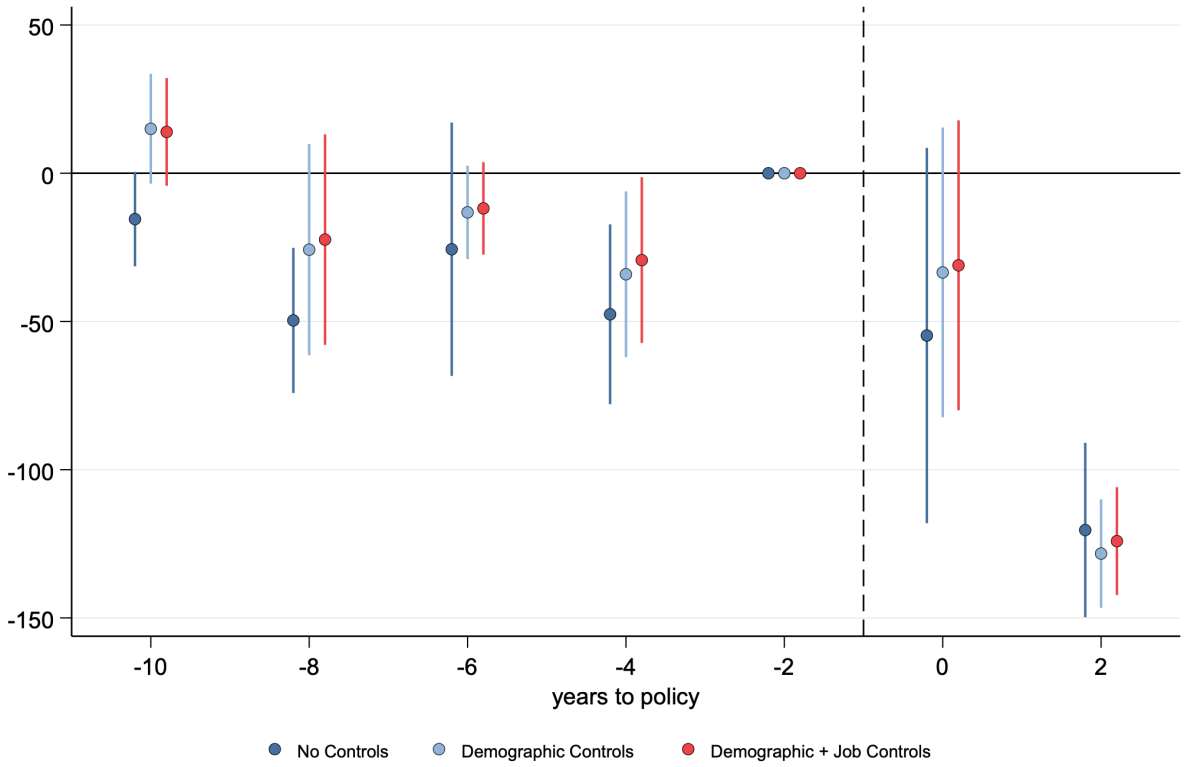
Notes: Figure shows coefficient estimates of the treatment effect coefficients with hours worked last week as the outcome variable. Coefficients are estimated for two-fiscal year groups for each set of control groups and associated 95% uniform confidence bounds for specifications with alternative sets of control variables. The omitted time period is 2017/18, the two year period immediately proceeding the overtime implementation. Demographic controls include age, gender, education, farm experience, number of children, and indicators for legal documentation status and english speaking ability. Job controls include indicators for the crop, payment, and task types. Standard errors and associated confidence intervals are clustered at the region-level.

Figure B.4: Average Effects Results for Earnings, Alternative Control Groups



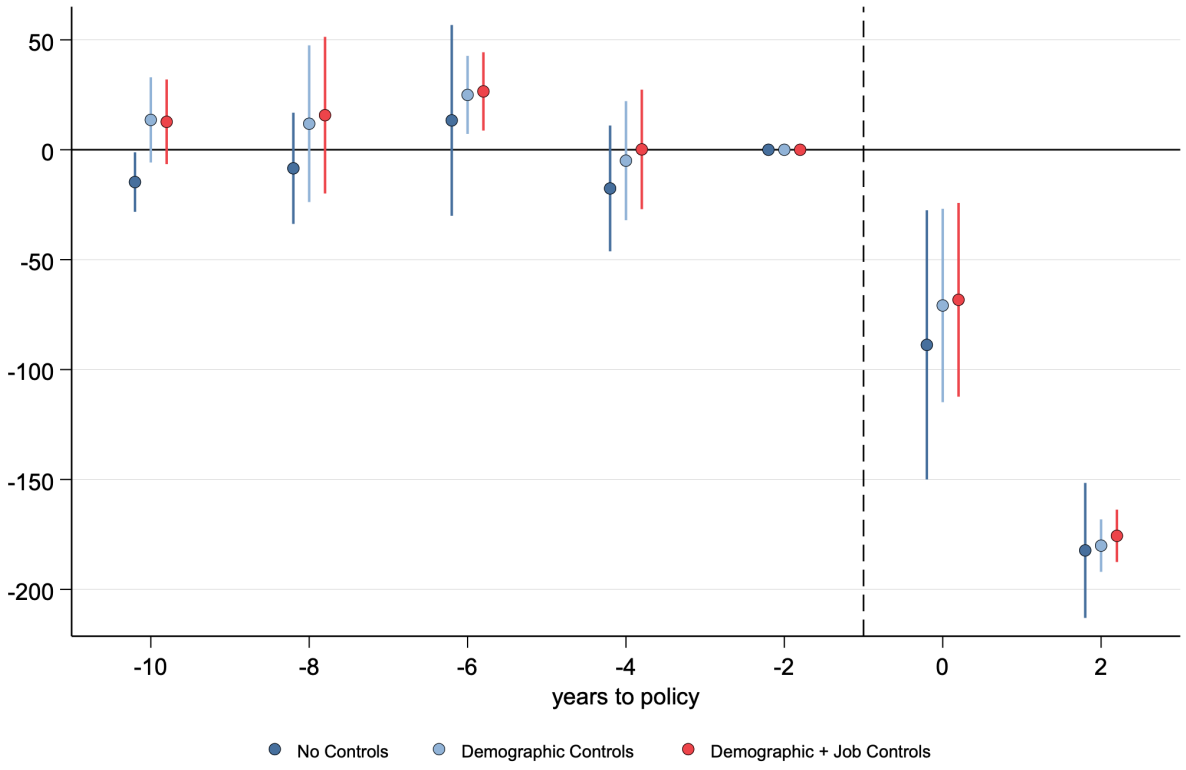
Notes: Figure shows coefficient estimates of the treatment effect coefficients with earnings as the outcome variable. Earnings are adjusted to 2022 real dollars,. Coefficients are estimated for two-fiscal year groups for each set of control groups and associated 95% uniform confidence bounds for specifications with alternative sets of control variables. The omitted time period is 2017/18, the two year period immediately proceeding the overtime implementation. Demographic controls include age, gender, education, farm experience, number of children, and indicators for legal documentation status and english speaking ability. Job controls include indicators for the crop, payment, and task types. Standard errors and associated confidence intervals are clustered at the region-level.

Figure B.5: Average Effects Results for Earnings Adjusted with Linear Pre-treatment Trends



Notes: Figure shows

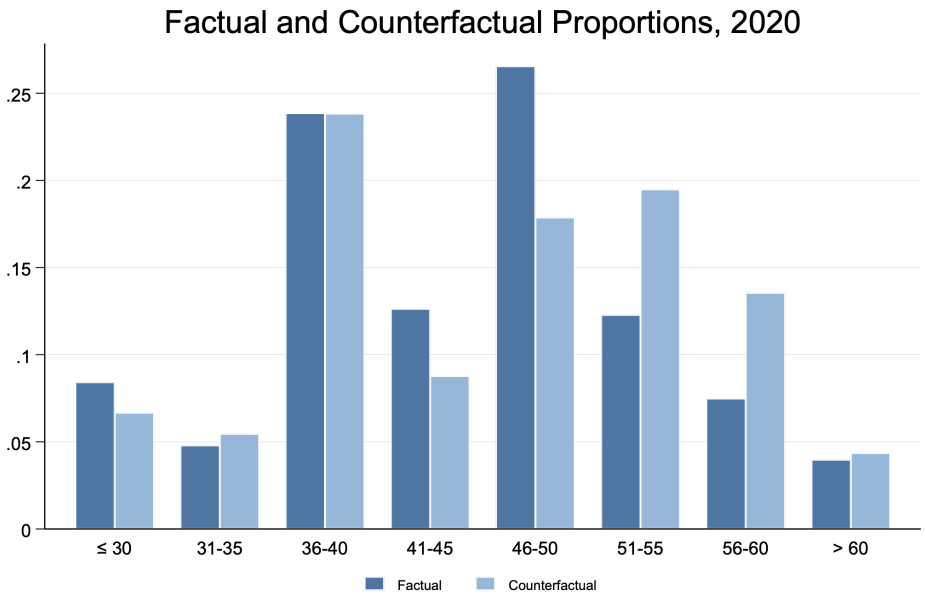
Figure B.6: Average Effects Results for Earnings Adjusted with Pre-treatment Minimum Wage



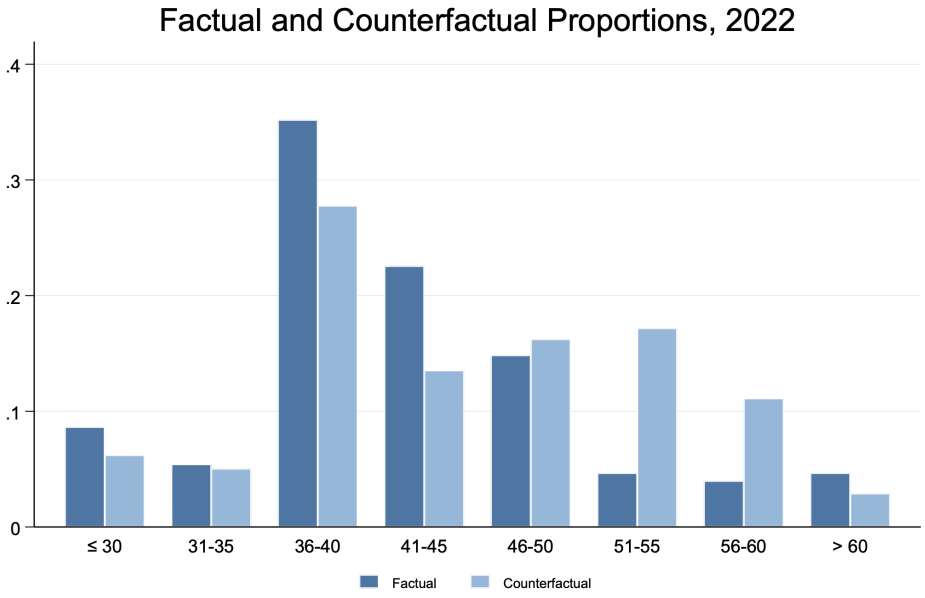
Notes: Figure shows

Figure B.7: Effects Across the Hours Distribution

(a) Effect of the Overtime Law on the Distribution of Working Hours



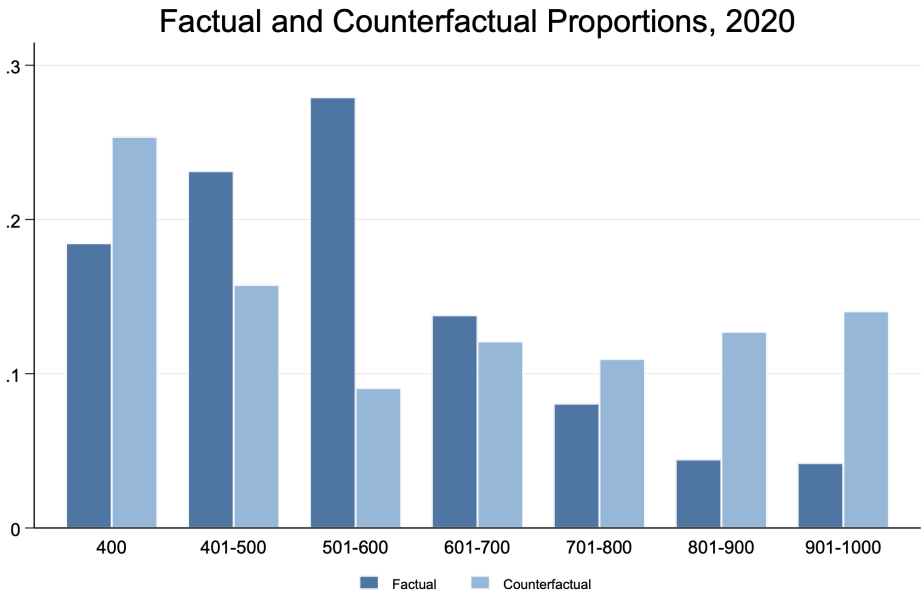
(b) Earnings



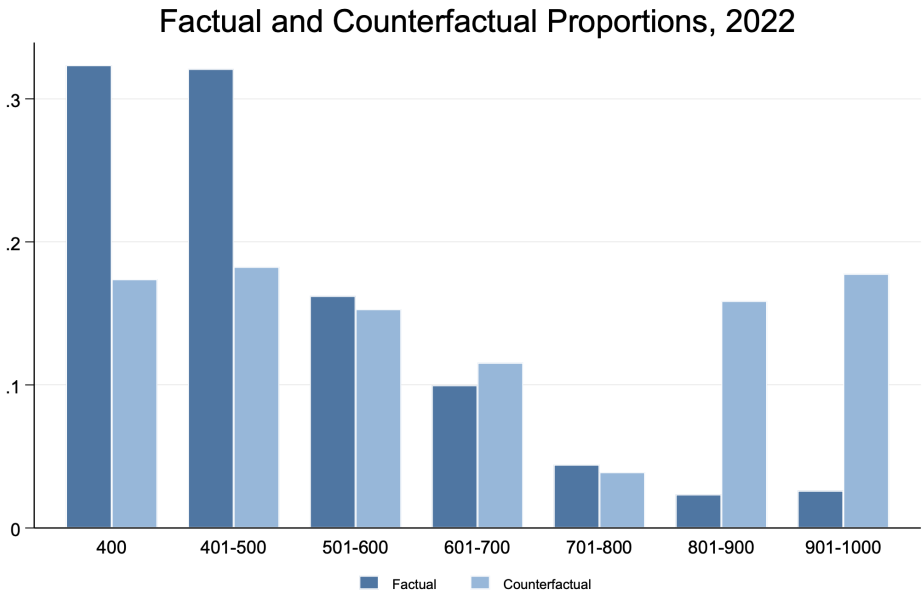
Notes: Figure shows the factual (observed) and the counterfactual (estimated, removing effects of the overtime law) shares of California workers with hours in the indicated ranges. Positive values indicate that a higher share of workers worked within the hours range than would have if the law were not in place. Bars below the 0 line indicate that fewer workers worked those hours than would have without the law in place.

Figure B.8: Effects Across the Hours Distribution

(a) Effect of the Overtime Law on the Distribution of Earnings

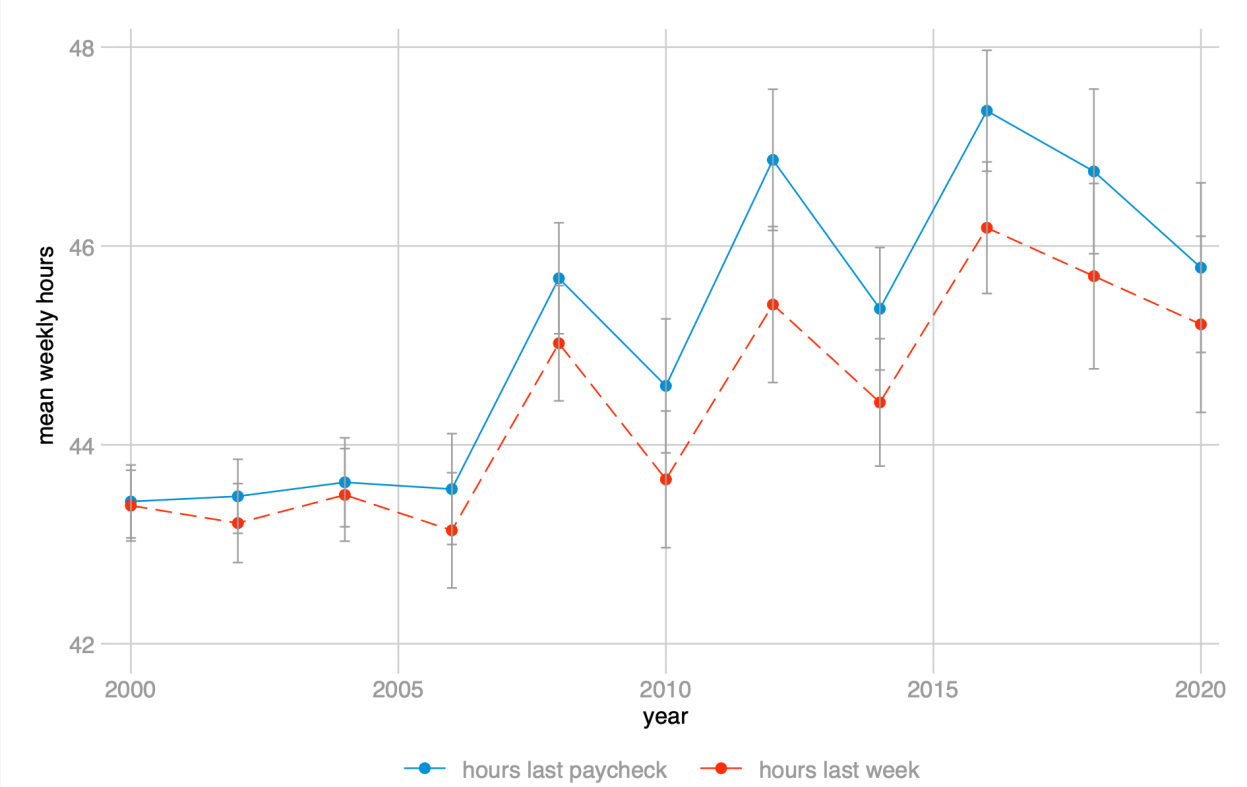


(b) Earnings



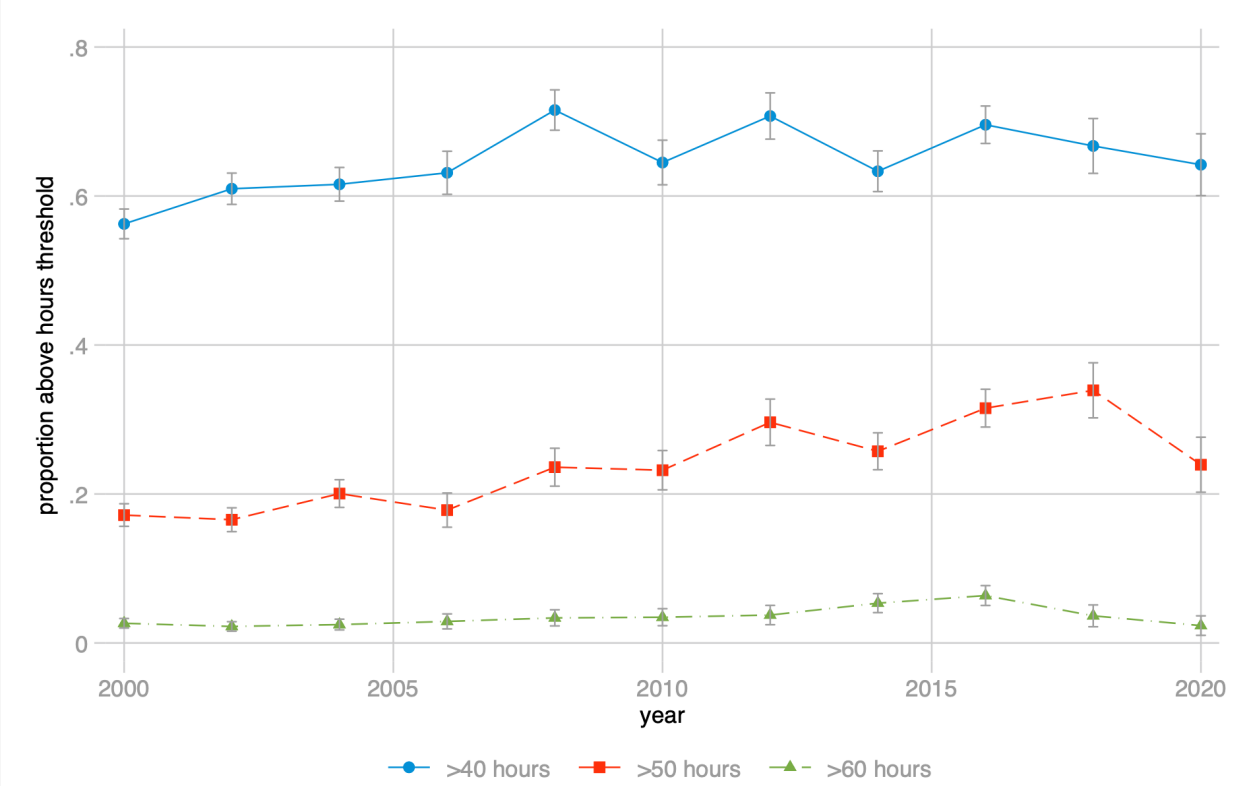
Notes: Figure shows the factual (observed) and the counterfactual (estimated, removing effects of the overtime law) shares of California workers with earnings in the indicated ranges. Positive values indicate that a higher share of workers earned within the range than would have if the law were not in place. Bars below the 0 line indicate that fewer workers had weekly earnings within the indicated range than would have without the law in place.

Figure B.9: Trends in Weekly Hours for California Crop Workers, Restricted Sample



Notes: Figure shows proportion of workers who reported working than 40 (blue, solid line), 50 (red, dashed line), and 60 hours (green, dashed line) on their last weekly pay check. Proportions and associated 95% confidence intervals are constructed for two-year groups of interview years. The sample includes all California crop workers in the NAWS sample who are compensated with a weekly paycheck (XX% of the CA sample over this time period) and interviewed from 2000 to 2020.

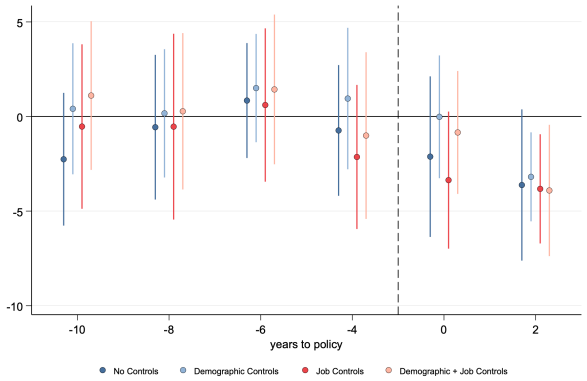
Figure B.10: Trends in Proportion of Workers Working above Weekly Hours Thresholds on Most Recent Paycheck



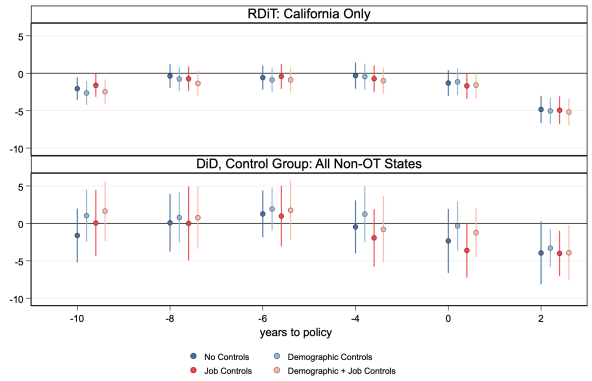
Notes: Figure shows mean hours of work and associated 95% confidence intervals for two-year bins across interview years. Each line shows values from two distinct questions in the NAWS survey on hours of work – hours worked last week (question D04, red dashed line) and hours worked during last pay period (question D08, blue solid line). This figure shows mean hours from both questions after restricting the sample to California workers who are paid weekly (weekly-paid workers account for XX% of the CA sample from 2000-2020).

Figure B.11: Average Hours and Earnings Effects with Alternative Pre-Treatment Trend Adjustments

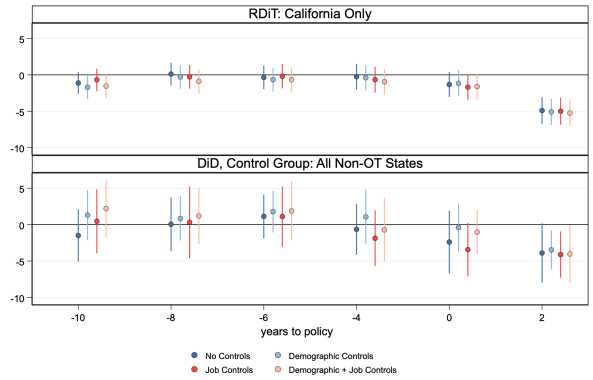
(a) Hours: No Trend Adjustment



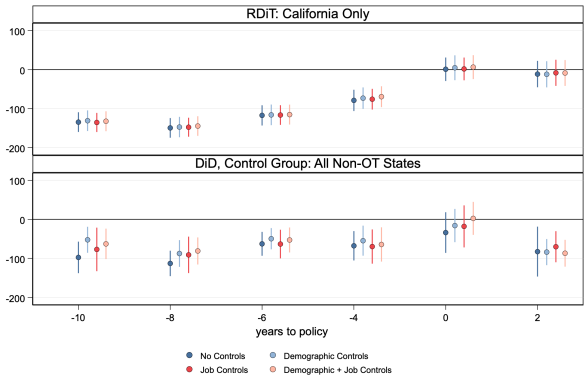
(b) Hours: Minimum Wage Adjustment



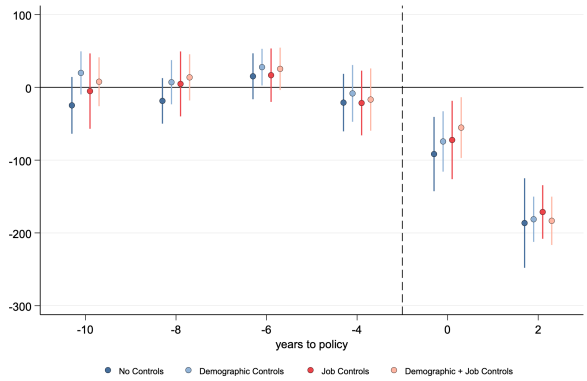
(c) Hours: Linear Trend Adjustment



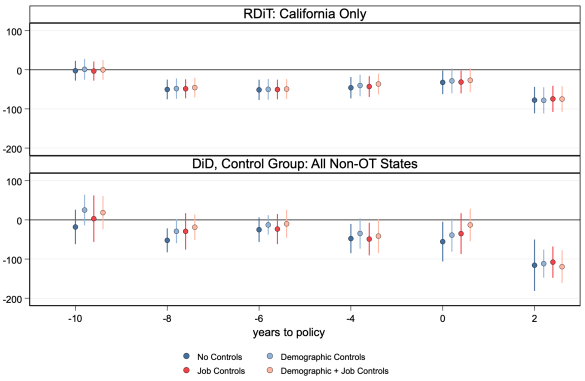
(d) Earnings: No Trend Adjustment



(e) Earnings: Minimum Wage Adjustment

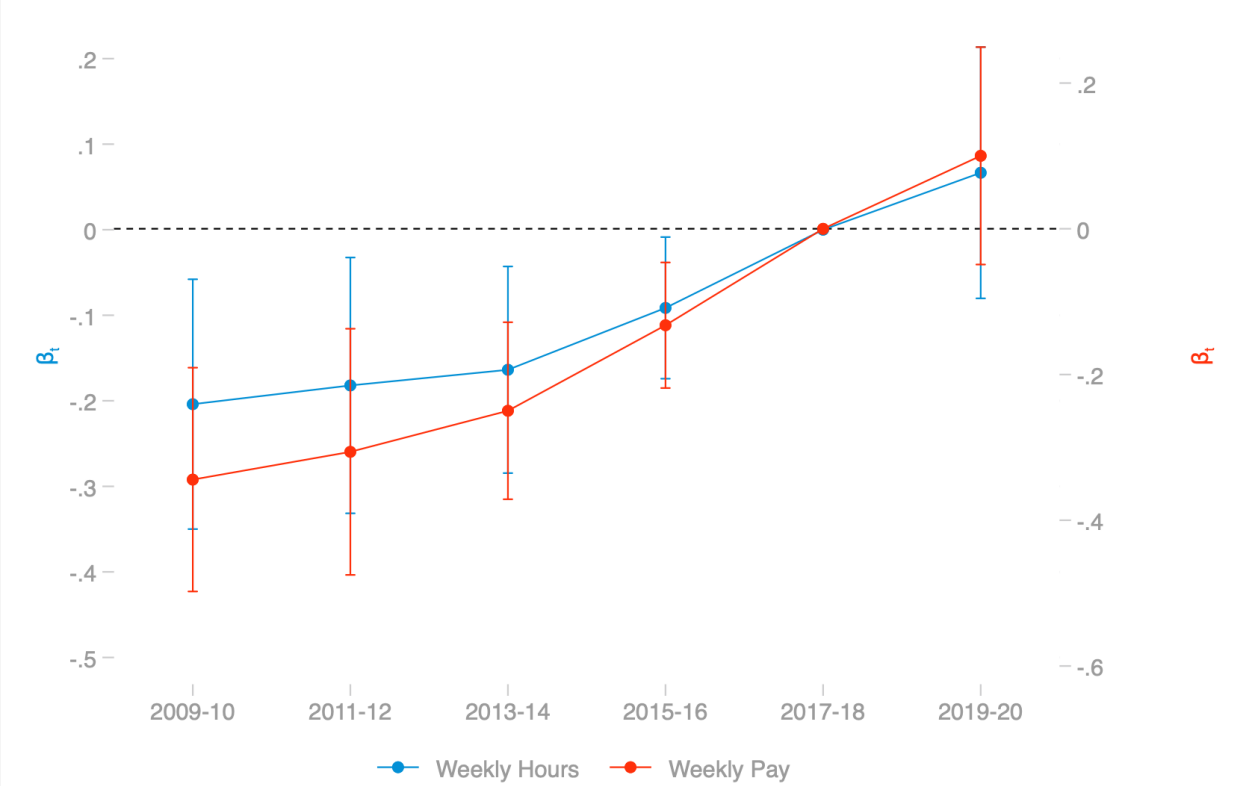


(f) Earnings: Linear Trend Adjustment



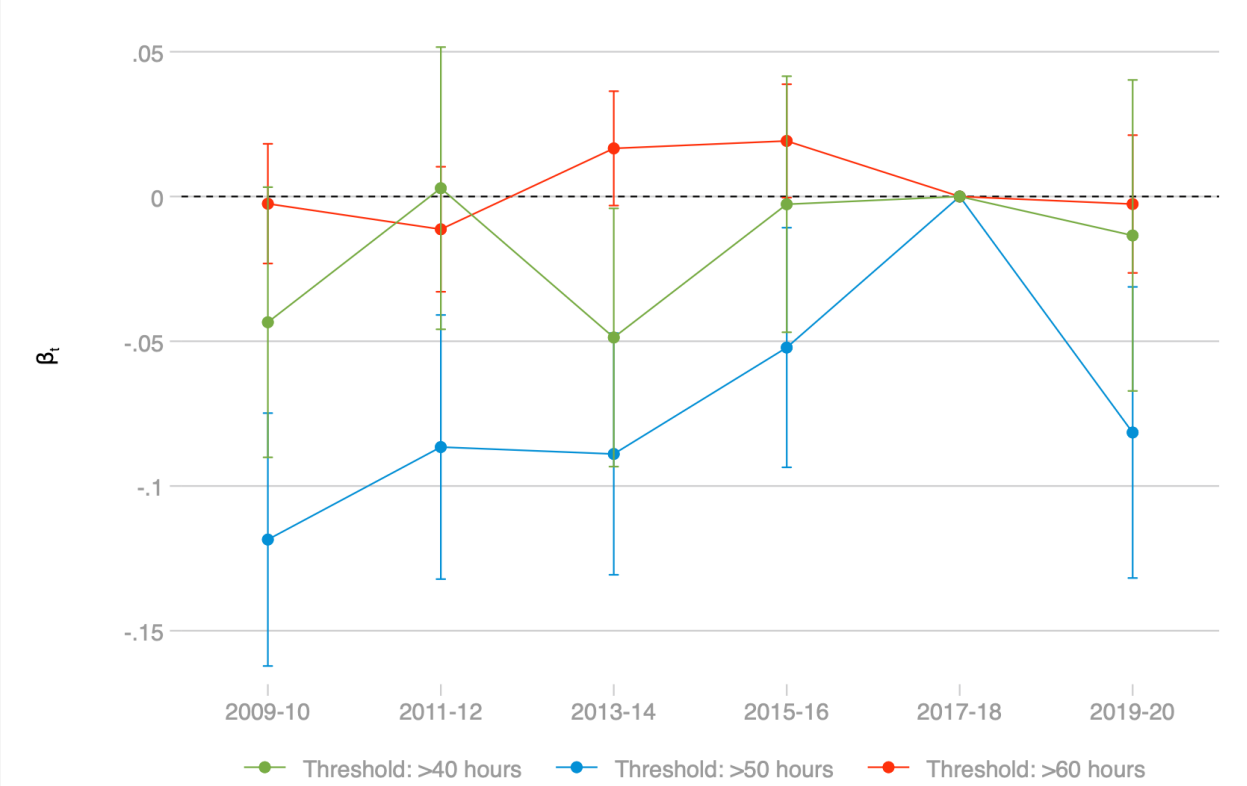
Notes: Figure shows coefficient estimates of the difference in differences treatment effect and associated confidence intervals from estimating XX

Figure B.12: Changes in Weekly Hours on Last Paycheck for California Crop Workers



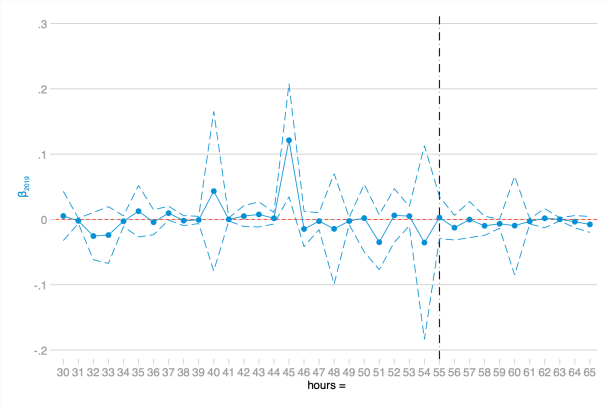
Notes: Figure shows coefficient estimates and associated 95% confidence intervals from estimating **??** with logged hours worked in the prior pay period (left axis, blue line) and logged weekly before tax earnings (right axis, red line) as the outcome variables. Control variables include worker covariates – indicators for age, gender, education, and legal documentation status – attributes of the job – indicators for the crop and task type – and county fixed effects. The sample for both regression specifications is restricted to all California crop workers interviewed from 2009 through 2020 who receive a weekly paycheck.

Figure B.13: Changes in Probability of Working Above Hours Thresholds on Last Paycheck for California Crop Workers

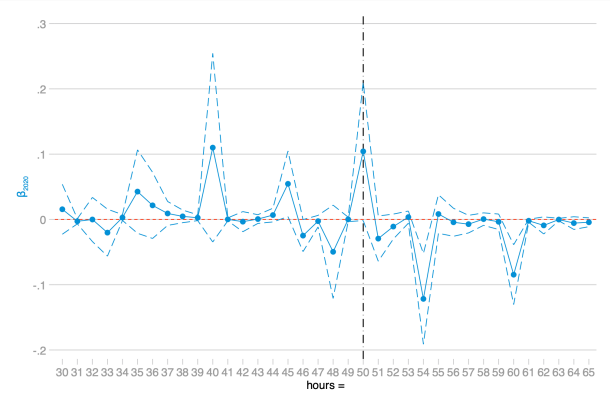


Notes: Figure shows coefficient estimates and associated 95% confidence intervals from three separate regressions estimating equation **??**. The outcome variable in each regression is an indicator variable equal to one if the worker reported hours on their most recent weekly paycheck above the indicated threshold and zero otherwise. All regressions include the same set of control variables: age, gender, education, indicators for legal documentation status, and indicators for the crop and task type. The sample includes all California crop workers interviewed from 2009 through 2020 who receive a weekly paycheck.

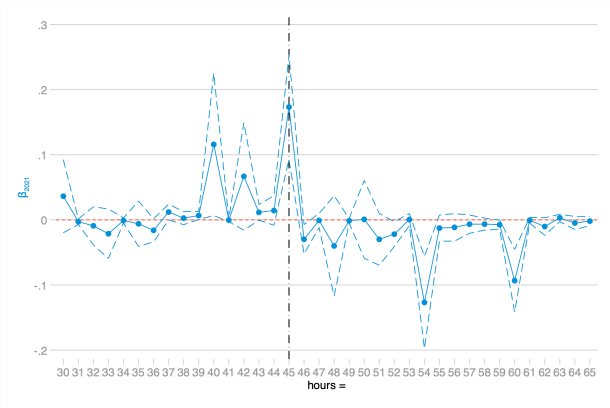
Figure B.14: Additional Evidence on Hours Bunching



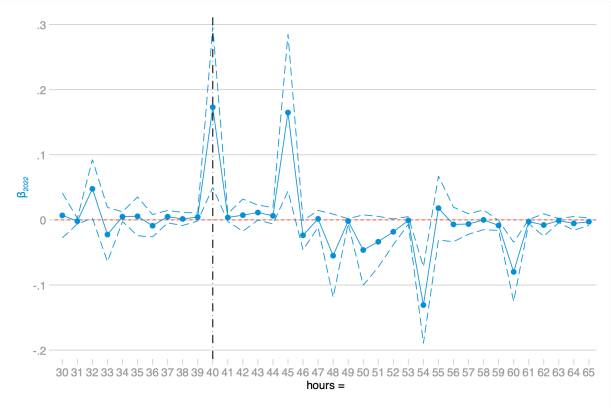
(a) 2019



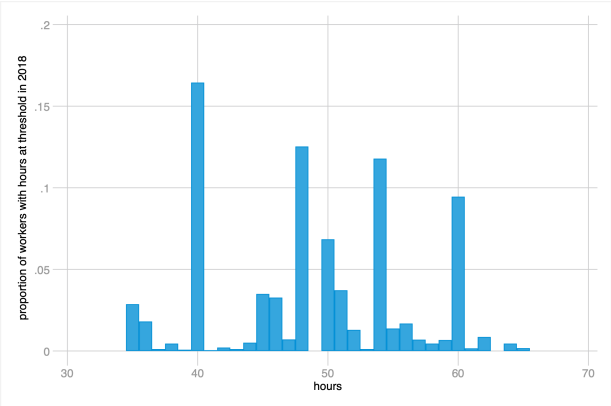
(b) 2020



(c) 2021



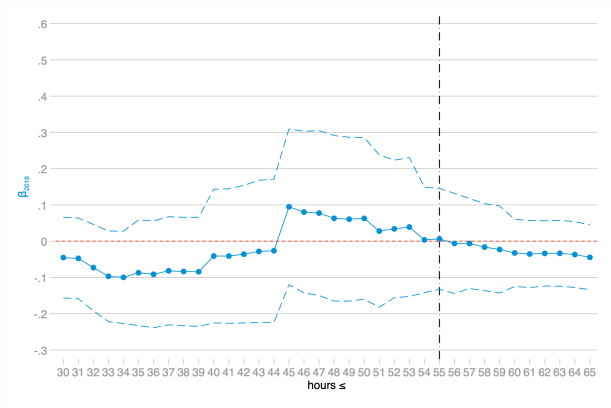
(d) 2022



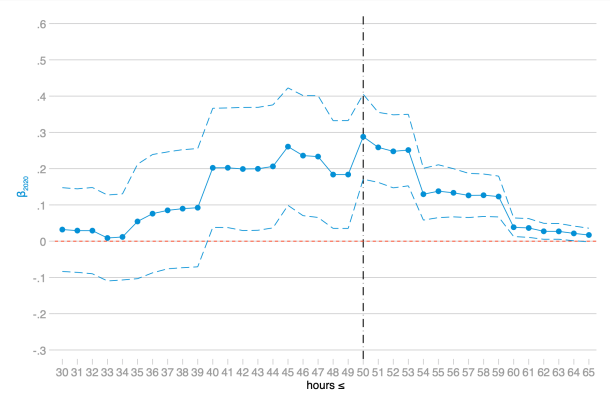
(e) 2018 Means

Notes: All estimates relative to the proportion of the workforce with hours at those levels in 2018.

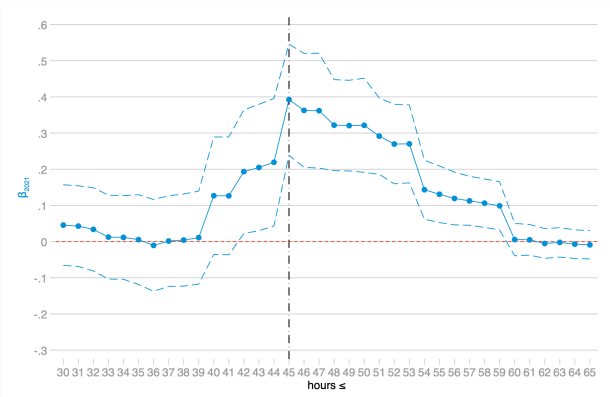
Figure B.15: Additional Evidence on Avoiding Overtime Pay



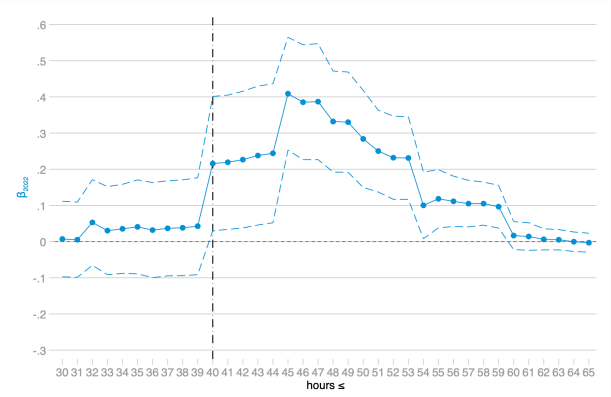
(a) 2019



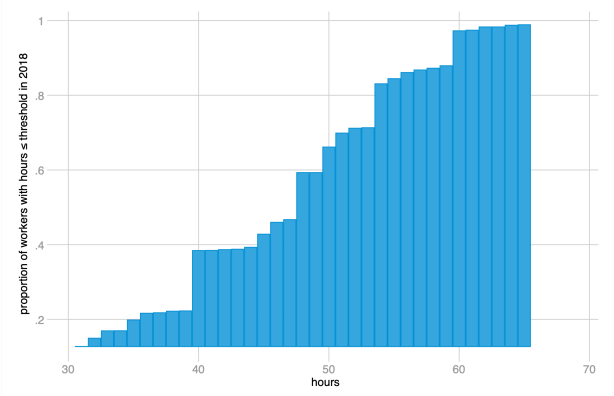
(b) 2020



(c) 2021



(d) 2022



(e) 2018 Means

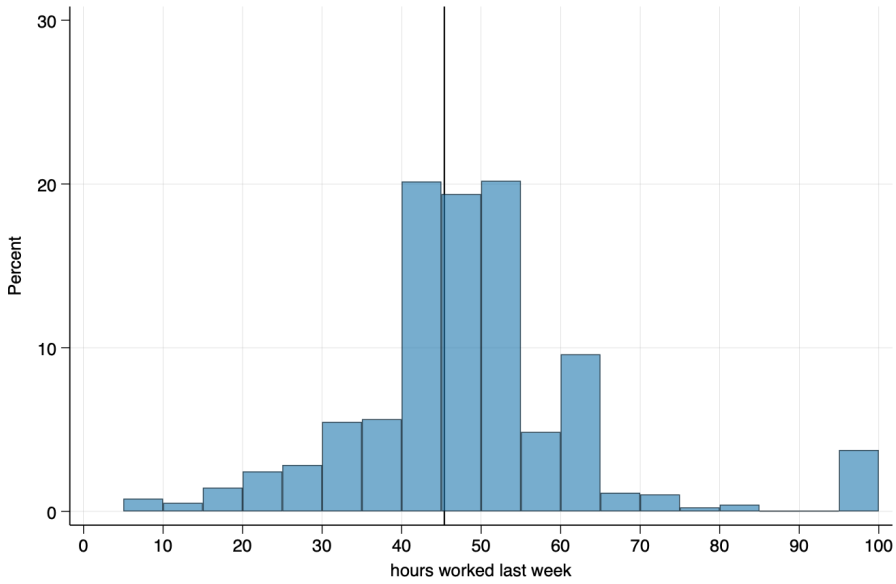
Notes: All estimates relative to the proportion of the workforce with hours at or below those levels in 2018.

C Evidence from the American Community Survey

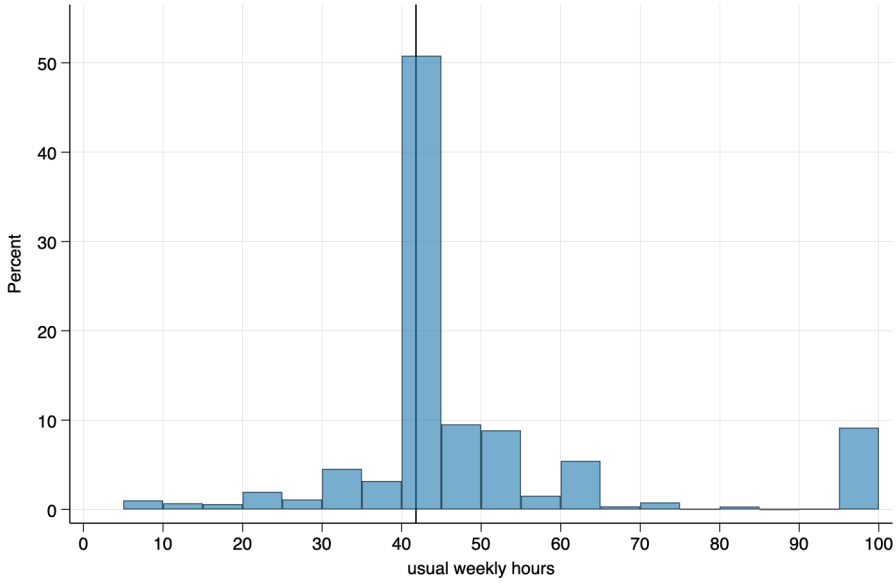
The American Community Survey includes a relatively large sample of people employed in crop agriculture. However, identifying the field workers who are subject to the new overtime regulations is not straightforward. For simplicity, I define the crop worker sample as surveyed in the ACS, who report their primary industry code as 170 (corp production) and with occupation code 6050 (miscellaneous agricultural workers). Of all ACS respondents employed in crop production from 2009-2022, roughly 40 percent used this occupation code; the next most frequent occupation codes are 205 (Farmers, Ranchers, and Other Agricultural Managers; 35% of the sample) and 9130 (Driver/Sales Workers and Truck Drivers; 3% of the sample). Because farmers and ranchers should not be included in this analysis, and there is such a steep drop off in other occupation codes, this is a reasonable method for identifying farmworkers for the purposes of this analysis.

Figure C.1: Distributions of California Crop Worker Hours 2009-2018 in the NAWS and ACS

(a) NAWS



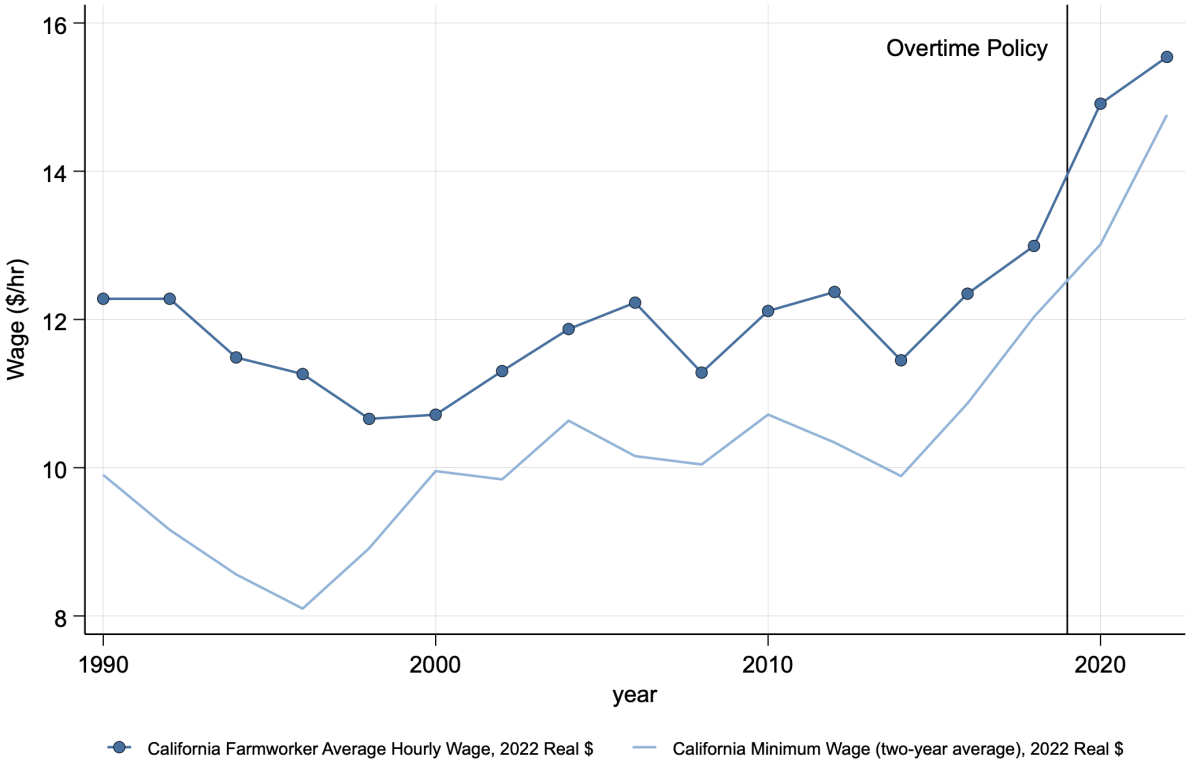
(b) ACS



Notes: Figure shows distributions of hours in 5 hour increments. I remove reports of 0 hours in the ACS so that both samples include only employed farmworkers. Both measures are top coded at 100 hours a week. Both density plots are constructed applying respective survey sampling weights.

D Evidence on Minimum Wages

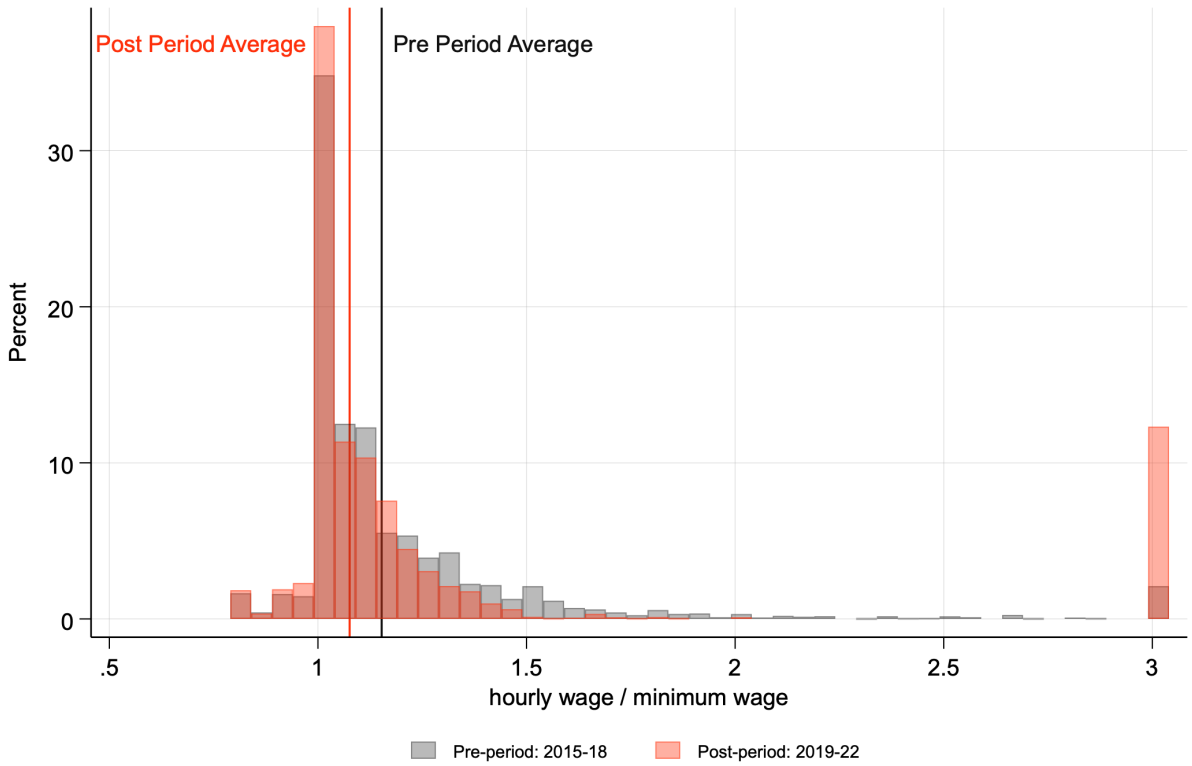
Figure D.1: California Average Farmworker Wage and State Minimum Wage, 2022 Real $



Notes: Figure shows XX

Figure **??** shows coefficient estimates and associated confidence intervals (95% and 90%) for the year indicator variables from estimating equation **??** with logged adjusted hourly wages as the outcome variable. All coefficients represent differences in wages relative to 2018, the year before the overtime phase-in began. Coefficients are estimated in a regression that includes region, quarter, and region-by-quarter fixed effects, and vectors of worker (indicators for categories of age, education, gender, years of farm experience, having children, and legal documentation status) and job (indicators for categories of crop, task, and payment) covariates. The sample is restricted to workers who are paid by the hour to avoid conflating changes in wages with changes in productivity for workers paid a piece rate (that is, per unit of output). This restriction removes XX% of observations in California sample over

Figure D.2: California Distribution of Hourly Wages Relative to State Minimum Wage, 2022 Real $



Notes: Figure shows XX I truncate wages at 3 times the state minimum to minimize the length of the x-axis.

this period.[32] Coefficient estimates in the pre-policy period (2009-2017) are generally not statistically significantly different from zero with the exception of 2013, where wages are statistically significantly larger than in 2018. There are no obvious trends in logged adjusted wages in this pre-treatment period. Consistent with the hours effects, in the first year of the overtime policy (2019) there is little change in the wage rate relative to 2018, whereas in the following two years (2020-2021), mean adjusted wages decrease relative to those in 2018, and the differences are statistically significant at the 1% level. In 2022, the last year of the overtime phase-in, wages increase relative to the two prior years and are not statistically significantly different from those in 2018. Table **??** in the appendix presents the coefficients for each of the years in the post-period (2019-2022) for this specification (column XX) and for specifications with alternative sets of control variables. Coefficient estimates generally indicate consistent directions and similar magnitudes of effects across specifications, but statistical significance varies.

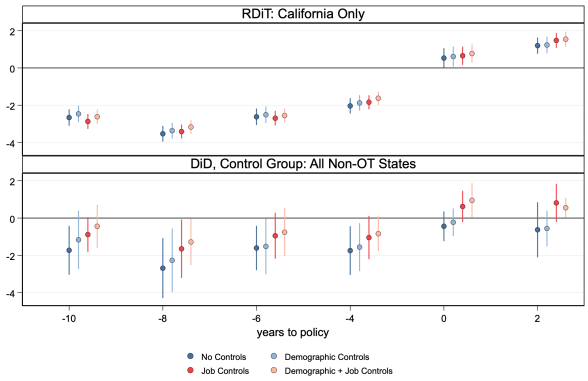
Reductions in mean wages for male workers, older workers, more educated workers, (no diff for those with and without children), more experienced workers, and those with documentation status.

Compare with wages not adjusted around minimum wage?

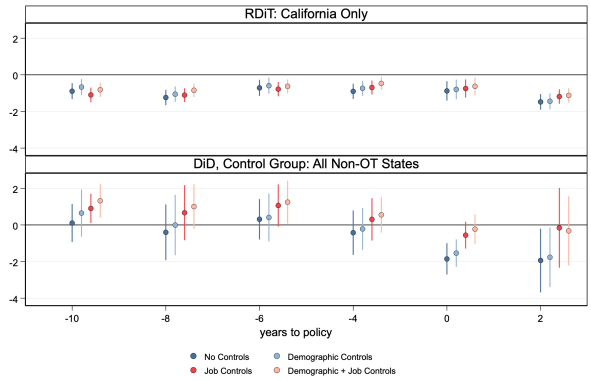
[32] Figure XX in the appendix replicates this analysis including workers who are paid hourly, a piece rate or a combination of the two.

Figure D.3: Average Wage Effects with Alternative Pre-Treatment Trend Adjustments

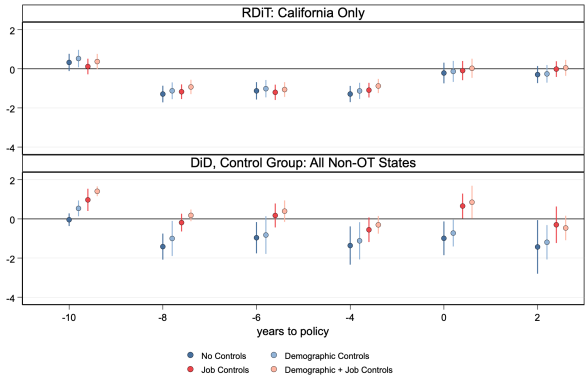
(a) No Trend Adjustment



(b) Minimum Wage Adjustment



(c) Linear Trend Adjustment



Notes: Figure shows XX