Cornell University

Cornell SC Johnson College of Business
and the Charles H. Dyson School for
Applied Economics and Management

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Dear Reviewers,

Becca B.R. Jablonski, Nancy Chau and I would like to submit the manuscript, “Firm Responses to the Effect of Agricultural Overtime Wage Laws,” for consideration in the NBER Risk and Risk Management in the Agricultural Economy NBER program on November 21, 2025. This research is the first to examine the causal effects of a change in overtime payment requirements on wage distribution and hour distribution to agricultural workers and labor utilization by farmers. We use quasi experimental evidence, the implementation of overtime agricultural worker laws in some states and not others.

The authors primarily used restricted access data from the Census of Agriculture in this analysis. Due to ongoing disputes between Cornell University and the Federal government, our ability to export data is currently frozen. While we planned to have results to present in this paper, due to these circumstances we are not able to present the full results but are able to generally demonstrate our findings. We are optimistic that the University and Federal government will come to an agreement and that we might have our results released in time for the conference, but the timeline is unknown at this time.

This research was not funded, and researchers do not have any relevant and material financial relationship that bears on our research.

Thank you for your consideration.

Sincerely,



Allison Bauman
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Firm Responses to the Effect of Agricultural Overtime Wage Laws

Allison Bauman, Becca B.R. Jablonski and Nancy Chau

1. INTRODUCTION

The United States' Fair Labor Standards Act of 1938 (FLSA) exempts agricultural employers from paying employees the federal overtime payment (1.5 times regular rates) for overtime work defined as working more than 40 hours per week (The Fair Labor Standards Act of 1938, 2011). States can enact regulations that mandate overtime requirements for farmworkers. Indeed, many states have enacted or are in the process of considering including farmworkers in overtime requirements (see figure 1) (Hill & Tanabe, 2023). For example, New York State passed the Farm Laborers Fair Labor Practices Act in 2019, which required that farm workers receive overtime pay, a day of rest each week, disability and paid family leave coverage, unemployment benefits, and other labor protections starting in 2020 (*New York State Department of Labor*, n.d.).[1]

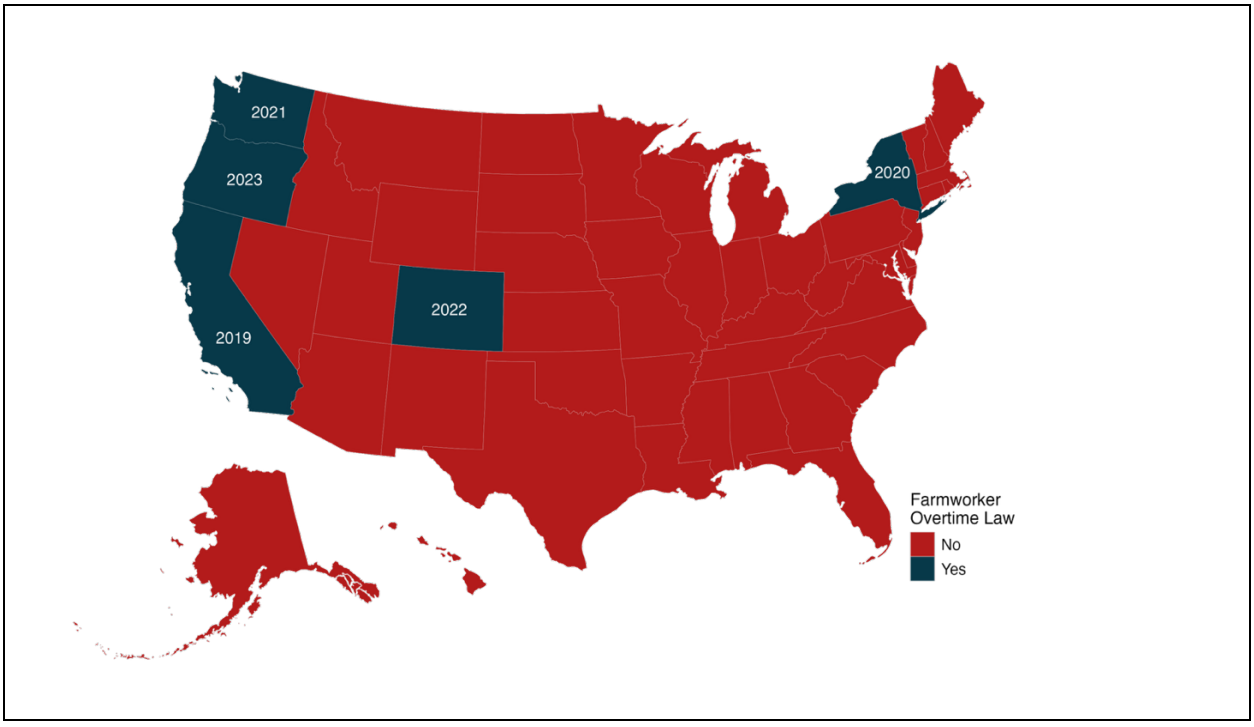


Figure 1. States that implemented recent farmworker overtime laws and date of initial implementation

Notes: The law in Colorado was implemented at the end of 2022 in November, all other laws were implemented January 1st. was Hawaii, Minnesota, and Maryland have longstanding laws enacted prior to 2017 (The National Agricultural Law Center, n.d.) and California has had a less stringent law in place since 1976 (Martin, 2020).

[1] In 2021, a bill was introduced in U.S. congress that would require employers to pay farmworkers overtime; the bill was read and referred to the Committee on Health, Education, Labor and Pensions in 2022, but no further action was recorded (Fairness for Farm Workers Act, 2021).

Laws governing overtime for farmworkers sit at the intersection of labor rights, immigration policy, and racial justice, reflecting both historical inequities and contemporary political tensions. Proponents argue that extending overtime protections addresses racialized exclusions in labor law and improves working conditions for a predominantly immigrant workforce (e.g., Khan, 2023). Further, they argue that these laws may attract domestic workers from other sectors to enter into agriculture (Richards, 2018). Opponents counter that amid declining labor supply and rising input costs, overtime mandates may lead farmers to cap individual work hours, potentially reducing overall earnings for some workers (e.g., Khan, 2023).

Due to the recent nature of the overtime laws, we could identify only four articles that assess the effects (or potential effects) of these changes, and none provide a causal framework. Preliminary research from Oregon predicted that overtime laws will decrease farm profitability and decrease earnings for some farmworkers (Delbridge & Reimer, 2025). Evidence from California found that farmworker overtime laws lead to decreased weekly hours and weekly take-home pay for crop workers (Hill, 2023). Hill & Tanabe (2023) predict that overtime laws will lead farmers to pay crop workers a premium for working overtime, with payments concentrated among U.S. citizens and those located in the Midwest and Northwest regions. They estimate a change in weekly crop worker income resulting from a mandate of overtime pay at 40 hours per week ranging from a $60 decrease to a $30 increase. Richards (2018) examined the argument that increasing farm worker wages will attract domestic workers from other sectors into agriculture. However, he estimated that farmers would not be able to pay crop workers enough to adequately address the issue of labor supply given the large wage differential between the agricultural sector and competing sectors such as hospitality and construction.

This research is the first to examine the causal effects of a change in overtime payment requirements on wage distribution and hour distribution to agricultural workers and labor utilization by farmers. The research uses quasi experimental evidence, the implementation of overtime agricultural worker laws in some states and not others. As some (but not all) employers are likely to ration hours when overtime pay is allowed, we make a counterfactual estimate of the hour distribution and labor utilization. If employers indeed strategically change the number of hours allowed after the policy change, we should see "bunching" along the counterfactual hourly distribution. We find consistent evidence that overtime mandates altered the allocation of labor on dairy farms, though the magnitude and direction of these changes varied by state and policy design. Across California, Washington, and New York, overtime laws generally reduced the number of hired workers per farm and curtailed weekly hours worked by individual employees, while increasing average wages for those who remained employed.

In this study, we estimate the impact of farmworker overtime laws in California, New York, and Washington on labor utilization on dairy farms and on livestock farmworker hours and wages. These states represent three of the top ten dairy producing states in 2022 (USDA NASS, 2024a). The dairy industry is particularly impacted by changes in the labor market given its year-round labor demands. Because it is year-round, dairy farms cannot utilize the H2-A Temporary Agricultural Program, which was created to provide a legal framework for farmers to hire workers from other countries to perform seasonal farm labor for up to 10 months at a time if they are unable to find domestic worker to fill those roles (Castillo et al., 2025). Accordingly, the dairy industry is very vulnerable to labor supply shocks. Hired labor expense accounts for a significant share of operating costs for dairy operations, with larger farms relying almost entirely on hired labor compared to smaller farms that typically utilize unpaid family labor (MacDonald

et al., 2020). From 2017 to 2022, production costs for dairy farms increased by 32 percent where feed and hired labor were the two largest expenses, accounting for 46 and 13 percent of production costs, respectively, in 2022. Given the high labor demands, dairy producers are more likely than the general farm population to not work off-farm and for farming to be their primary occupation (USDA NASS, 2024b). While the adoption of labor-saving technology can reduce labor need (e.g., milking units with automatic take-offs, computerized milking systems, computerized feed delivery systems, use of a dairy parlor), Charlton & Kostandini (2021) found that increased labor efficiency and adoption of technology in the dairy industry were not sufficient to offset a decrease in production resulting from a reduction in labor supply, at least in the short run.

The remainder of this paper is organized as follows. We begin with a discussion of the implementation of farmworker overtime laws in each state followed by a discussion of our theoretical framework and development of our equilibrium conditions. Next, we provide a discussion of our data, empirical methods, and results. We conclude with a discussion of the results and policy implications.

2. FARMWORKER OVERTIME LAWS, BY STATE

Five US states enacted farmworker overtime state policies between 2018 and 2023: California (2019), New York (2020), Washington (2021 for dairy, 2022 all other), Colorado (November 2022), and Oregon (2023). Hawaii, Minnesota, and Maryland have longstanding laws enacted prior to 2012 (The National Agricultural Law Center, n.d.) and California has had a less stringent law in place since 1976 (Martin, 2020). Each of the laws has different associated rules and regulations; table 1 provides more details on the implementation timeline (most states include a step-down approach wherein the overtime hours cap decreases overtime until it reaches 40) for the five states with recently enacted legislation including the thresholds for hours worked per week.

Table 1. Implementation timeline of current farmworker overtime law thresholds for hours worked per week

Year implemented	**California**		**New York**	**Washington**		**Colorado**		**Oregon**
	Less than 26 employees	26 or more employees	All operations	Dairy	All operations	Highly seasonal employers	Non-Highly seasonal employers	All operations
<2019	60	60						
2019		55						
2020		50	60					
2021		45	60	**40**				
2022	55	**40**	60	**40**	55	60[1]	60[1]	
2023	50	**40**	60	**40**	48	60	60	55
2024	45	**40**	56	**40**	**40**	48/56[2]	54/56[3]	55
2025	**40**	**40**	56	**40**	**40**	48/56[2]	48	48
2026	**40**	**40**	52	**40**	**40**	48/56[2]	48	48
2027	**40**	**40**	52	**40**	**40**	48/56[2]	48	**40**
2028	**40**	**40**	48	**40**	**40**	48/56[2]	48	**40**
2029	**40**	**40**	48	**40**	**40**	48/56[2]	48	**40**
2030	**40**	**40**	44	**40**	**40**	48/56[2]	48	**40**
2031	**40**	**40**	44	**40**	**40**	48/56[2]	48	**40**
2032	**40**	**40**	**40**	**40**	**40**	48/56[2]	48	**40**

Source: Compiled by author from: Martin (2020), AB-1066 Agricultural Workers: Wages, Hours, and Working Conditions (2016), *New York State Department of Labor* (n.d.), ESSB 5172 (2021), Colorado Department of Labor and Employment, Division of Labor Standards and Statistics (2024), House Bill 4002 (2022).

Notes: [1]Starting November 1, 2022; [2]Overtime required at 48 hours except 56 hours for up to 22 peak weeks; [3]Overtime required at 56 hours for small employers and 54 for all other employers. Hawaii, Minnesota, and Maryland have longstanding laws enacted prior to 2012 (The National Agricultural Law Center, n.d.) and California has had a less stringent law in place since 1976 (Martin, 2020).

In California, starting in 1976, farm employers were required to pay overtime after 10 hours per day or 60 hours per week (Martin, 2020). In 2016, Assembly Bill 1066 was signed into law requiring farm employers with 26 or more employees to pay overtime after 9.5 hours per day or 55 hours per week starting in January 2019, and reaching 8 hours per day/40 hours per week by 2022. Employers with 25 or fewer employees were not required to pay overtime until January 2022, and were given until 2025 to reach the 8 hours per day/40 hours per week threshold (AB-1066 Agricultural Workers: Wages, Hours, and Working Conditions, 2016). In New York, all employers were required to pay overtime after 60 hours per week as of 2020 (*New York State Department of Labor*, n.d.). This was reduced to 56 hours in 2024 and then by four hours every two years until it reaches 40 hours per week. In Washington, as of 2021, dairy workers are entitled to overtime pay for all hours worked over 40 per week (ESSB 5172, 2021). All other farmworkers are entitled to overtime pay for hours worked over 55 beginning January 2022, over 48 beginning in January 2023, and over 40 beginning in January 2024. We focus on California, New York and Washington as they have all implemented new laws within our study time period.[2]

Colorado and Oregon implemented farmworker overtime laws after our study period. In Colorado, from November 2022 through the end of 2023, all farm employers were required to pay overtime after 60 hours per week (Colorado Department of Labor and Employment, Division of Labor Standards and Statistics, 2024). Starting in 2024 and continuing each year, highly seasonal employers were required to pay overtime at 48 hours except 56 hours for up to 22 peak weeks. For non-highly seasonal employers, in 2024, small operations were required to pay overtime at 56 hours and all other operations at 54 hours. In 2025 onward all non-highly seasonal operations were required to pay overtime after 48 hours per week. In Oregon, employers were required to pay overtime after 55 hours per week in 2023 and 2024, 48 hours per week in 2025 and 2026, and 40 hours per week starting in 2027 (House Bill 4002, 2022).

3. THEORETICAL FRAMEWORK AND EQUILIBRIUM HYPOTHESES

In response to farmworker overtime laws, farmers have many choices: they do not make any changes and pay overtime wages as applicable, they adopt labor saving technology, they shift to less labor-intensive commodities, they move farming operations to other states/countries, they reduce output, they stop farming, or they hire more workers. Our study develops and tests several hypothesis equilibrium scenarios regarding how the dairy industry responds to such regulations. We draw from the public finance literature on wage bunching, which examines how kinks or discontinuities in labor cost schedules affect behavior. Prior research finds that adjustment costs and hour constraints influence labor supply decisions (e.g., Rogerson et al., 2005).

Chetty et al. (2011) provide a useful theoretical foundation for understanding employer responses to overtime laws. Their bunching model (used in their case to understand impacts of higher taxes on labor supply) predicts that: (1) larger kinks generate greater elasticities in taxable income; (2) kinks affecting a broader group of workers generate larger aggregate effects; and (3) in equilibrium, the distribution of job offers reflects workers' preferences in the presence of such kinks. In our context, the "kink" is created by the overtime wage threshold, and the behavioral response differs from Chetty's tax setting: rather than workers adjusting hours via job search to optimize after-tax income, dairy employers adjust worker hours to remain below the overtime

[2] Due to the data used for our analysis, described below, we focus on changes before and after the two more recent Census' of Agriculture, 2017 and 2022.

threshold and avoid higher marginal labor costs. This framing suggests two labor-market equilibria that emerge directly from this adaptation of Chetty's framework to the agricultural labor market.

> **Equilibrium 1 (Unconstrained).** Unconstrained equilibrium in which hours are set at the joint employer-employee optimum, farmworker overtime laws do not constrain the optimal number of hours on dairy farms.
>
> **Equilibrium 2 (Constrained, labor available).** Constrained equilibrium in which overtime laws compel employers to weigh the transaction costs of hiring additional labor against the costs of paying overtime wages. In this case, to reduce labor costs in the face of overtime laws, dairy farmers reduce weekly hours worked per employee to be just under the overtime threshold and hire more workers.

Gourio & Roys (2012) provide a theoretical basis for understanding size dependent regulations in the labor market. They evaluate the size distribution of firms in France, where those with at least 50 employees face much higher regulations than those with fewer than 50 employees. They find the size distribution of farms is distorted, with a large number of firms with 49 employees and much fewer with 50. In the case of overtime laws, if we were to see similar distortions in the number of hours employees worked, we could make the case that overtime laws created a constrained market equilibrium. Overtime laws likely create a similar threshold effect where employers pay their employees to work exactly up to the threshold for overtime but not over. Preliminary evidence of crop workers in California estimated this was true: farmers reduced hours worked per crop worker and hired more workers, with a reduction in worker hours to be just below the overtime threshold (Hill, 2023).

However, U.S. agricultural labor supply has been decreasing since the mid-twentieth century when the U.S. workforce began transitioning out of agriculture: the number of hired farmworkers declined by 51 percent from 1950 to 2000 (Castillo et al., 2025). Due to a lack of domestic labor supply for agricultural work (Richards, 2018), the H2-A Temporary Agricultural Program was created for farmers to hire workers from other countries to perform seasonal farm labor (Castillo et al., 2025). As the U.S. farm labor supply has decreased, the number of H2-A certifications has increased significantly: fivefold since 2005 and doubled since 2014 (Castillo et al., 2022). However, dairy producers cannot hire H-2A workers as they require year-round employees, giving them less flexibility to avoid paying overtime by reducing hours and hiring more workers. Charlton & Kostandini (2021) analyzed the impact of labor shortages in the dairy industry due to changes in immigration policy and found decreased labor expenditures, fewer dairies, and lower total milk production because of labor shortages. Dairy farmers did become more labor efficient and increased use of technology, but gains in efficiency did not outweigh losses resulting from a decreased labor supply. Jodlowski (2025) found evidence of wage compression in the agricultural sector, which implies that high quality workers will exit the agricultural sector to earn high enough wages to compenstae for their skills. This leads us to our third potential equilibria related to farm labor supply.

> **Equilibrium 3 (Constrained, labor scarce).** Constrained equilibrium in which the supply of qualified dairy workers is limited, and an adequate workforce is not available to hire. In this setting, overtime laws raise marginal labor costs, but employers cannot offset

them by increasing headcount. As a result, dairy farms may respond by adopting labor-saving technologies, scaling back production, shifting to less labor-intensive commodities, or exiting dairy farming.

Charlton & Taylor (2016) predicted that the farm labor supply of both U.S. and Mexican born workers will continue to fall and farmers will need to shift to less labor-intensive commodities and adopt labor saving technologies and management practices to remain in farming. While decreased labor supply will lead to higher farmworker wages, Richards (2018) estimated that farmers would not be able to pay crop workers enough to adequately address the issue of labor supply given the large wage differential between the agricultural sector and labor competing sectors such as hospitality and construction. As the shift to less labor-intensive commodities occurs, imports are likely to increase to meet domestic demand, and indeed we see this shift. Since 2008, imports of non-manufactured fruits and vegetables increased significantly: from 2008 to 2022 the import share of consumption of vegetables and melons increased from 26 to 40 percent and of fruits and tree nuts from 36 to 59 percent (Williams & Kaufman, 2025). Calvin et al. (2022) find that the very labor-intensive crops (e.g., asparagus, green onions, raspberries) are almost entirely imported from Mexico. However, we do not see the same shift for dairy products, the import share of consumption has remained relatively stable, increasing less than 1 percent over the same time period (Williams & Kaufman, 2025). Due to high perishability and transportation costs, local production of dairy is more common than for other agricultural commodities. While dairy products are less likely to be imported than other labor-intensive crops, to remain competitive in the face of increasing operating costs, consolidation has been a driving force in the industry. Son et al. (2022) estimated the probability of dairies exiting and found an increase in the probability of exiting for all size classes since 2002 with the exit probability the highest for small and medium size dairies, and a decrease in the likelihood of new entrants. Based on their results, they expect roughly half of U.S. dairies to exit the industry over the long term.

Our final potential equilibrium outcome is that current market dynamics enable dairy operations to sustain higher labor costs without significant changes to production practices or workforce structure. In this setting, farms—often those with larger herd sizes or greater operational efficiency—maintain existing schedules and production levels despite overtime regulations. As a result, dairy workers' hours remain stable, and total earnings rise due to overtime pay. While smaller operations are less likely to experience this outcome (though there are successful dairy farms at all scales), it remains feasible: in 2021, fewer than 30 percent of dairies with under 200 cows had positive returns, compared with nearly 70 percent of those with 2,000 cows or more (Gillespie et al., 2024; MacDonald et al., 2020).

Equilibrium 4 (Constrained, market absorbs costs). Market dynamics support higher wages for farmworkers. Dairy operations remain operating in a similar manner, maintaining working schedules and dairy workers receive higher earnings as a result of overtime pay.

In the next section, we describe the data we use to test our four potential equilibrium outcomes and provide descriptive statistics.

4. DATA AND DESCRIPTIVE STATISTICS

While there is no one data source that allows us to fully answer our research question, we can use multiple data sets to triangulate an answer to our research question and to test our equilibrium hypotheses. Our main dataset is farm-level microdata from the U.S. Department of Agriculture, National Agricultural Statistics Service (USDA NASS) Census of Agriculture, and we bolster our analysis with data from the US Census Bureau, American Community Survey (ACS), and the USDA NASS Farm Labor Survey.[3]

4.1. Census of Agriculture

We use data from the Census of Agriculture, administered by the U.S. Department of Agriculture's National Agricultural Statistics Service (NASS) every five years. The Census of Agriculture is a complete count of U.S. farms and ranches and the people who operate them and includes data on land use and ownership, operator characteristics, production practices, income, and expenditures. It is the only source of comprehensive data on the current and past state of U.S. agriculture, providing uniform agriculture data for every county and is the only data source that allows us to track farm operations over time. In the Census of Agriculture, a farm is defined as a place from which $1,000 or more of agricultural products were produced and sold, or normally would have been sold, during the census year.

We use the restricted access farm-level data to create a panel data frame of farms with at least 10 dairy cows and one hired worker in 2012 and track them through 2022, including those operations that did and did not fill out the survey in all years.[4] Millimet & Bellemare (forthcoming) discuss the key, and underdiscussed, assumption of a fixed effects model that effects are time-invariant. While this can often be considered true in short time periods, it becomes increasingly difficult with longer time periods. When using the data from the Census of Agriculture, we have a panel data set where we track individual operations over time. The use of a fixed effects term in our model assumes that the on a farmers' labor choices are stable over time. Given the long-time frames associated with Census of Agriculture data, we select a 10-year time-period (using data from 2012, 2017 and 2022), in which we assume farmers' choices are stable over this time period.

The Census of Agriculture asks two questions about paid farm workers: 1) What was the total number of hired farm or ranch workers, including paid family members and office workers, who (a) worked less than 150 days on this operation in 2022 (b) worked 150 days or more on this operation in 2022; 2) What was the number of foreign and domestic migrant workers on this operation in 2022? Additionally, the Census asks farms to report the total production expense paid to hired labor (includes employer's costs for social security, worker's compensation, health and life insurance premiums, pension plans, etc.) and contract labor (includes expenses for labor, such as harvesting of fruit, vegetables, berries, etc. performed on a contract basis by a contractor, crew leader, etc.). Our variables of interest include: (1) total number of paid workers (regardless

[3] In future analysis, we will also use the USDA Economic Research Service (USDA ERS), Agricultural Resource Management Survey (ARMS) Dairy survey. Of particular interest, the ARMS Dairy survey reports average hourly wage rate and average weekly hours worked per hired employee for the dairy operation.

[4] Our sample includes those farms that filled out the census in 2012 and 2017 and allow for farms to exit or remain farming in 2022. We do not include farms that entered the sample during or study time frame nor those that moved states within the sample time frame (<5 farms).

of migrant status[5]), (2) salary (hired labor expense/number of paid workers), (3) contract labor expense, and (4) labor expense per cow.

Using data from the Census of Agriculture, we can evaluate changes in number of workers and labor expenses for dairy operations, as well as farm exit, but we do not know average hours worked per worker or average hourly wage. Using these data, we have farm-level data and can track operations over time, providing the only dataset for a difference-in-difference analysis using panel data.

4.2. American Community Survey (ACS)

The ACS provides yearly data on usual hours worked, by industry and occupation and we use IPUMS USA to gather microdata from the ACS (Ruggles et al., 2025). Our main data of interest are usual hours worked per week for livestock workers (unfortunately, we do not have data on hourly wage rate in these data nor on dairy specifically). We define livestock workers as respondents who indicated they had an occupation code for miscellaneous/other farmworkers (OCC 6050), an industry NAICS code for animal production and aquaculture (INDNAICS 111), were of a class of worker that works for wages (CLASSWKR 2). We calculate the average usual hours worked per week, where data are weighted using the person weight (PERWT). The focus of our analysis is on full-time livestock workers, those who worked 40 or more usual weekly hours.

4.3. Farm Labor Survey

Using data from the USDA NASS Agricultural Farm Labor Survey we provide summary data, aggregated by region, on the number of hired workers, hours worked per week, and wage per hour. Additional data are broken out for average wage by crop workers and livestock workers. Regions included in the data relevant to this research are California, Northeast I (New York, Vermont, New Hampshire, Maine, Massachusetts, Connecticut), and Pacific (Washington, Oregon).[6] Unfortunately, we do not have data on average hours worked for livestock workers; the data are aggregated across all workers. Because data are aggregated regionally, we only use these data for background information and not in our modeling approach.

4.4. Comparing Descriptive Statistics Across Data Sets

In this section, we compare labor related summary statistics across datasets.[7] Each of our datasets provide a different measure of labor usage from which we can test our hypotheses.
Table 2 provides a description of each labor variable of interest, including the dataset, years available, and how it is used in the analysis.

[5] While migrant labor is typically not a large part of dairy hired labor due to the year-round nature of the dairy business, ~5 percent of operations in our final sample of interest employ migrant workers.

[6] While the National Farmworkers Survey (NAWS) has much of the data that would be useful for this project, it only includes crop workers and thus cannot be used to answer questions about labor on dairy or livestock operations.

[7] Summary statistics using data from the Census of Agriculture did not pass disclosure review at the time of writing and will be included in subsequent drafts.

Table 2. Labor variables of interest by data set

Variable	**Data set**	**Aggregation**	**Unit**	**Years**
Number of paid workers	Census of Agriculture	Dairy	Dairy farms	2007, 2012, 2017, 2022
Salary	Census of Agriculture	Dairy	Dairy farms	2007, 2012, 2017, 2022
Contract labor expense	Census of Agriculture	Dairy	Dairy farms	2007, 2012, 2017, 2022
Hired labor expense per cow	Census of Agriculture	Dairy	Dairy farms	2007, 2012, 2017, 2022
Hours per week	ACS	Livestock workers	Individuals	2010-2024
Hours per week	Farm Labor Survey	Farmworkers	Regions	2012-2024
Hourly wage	Farm Labor Survey	Farmworkers	Regions	2012-2024

Source: Created by authors

Using data from the ACS, Figure 2 shows the proportion of livestock workers that received overtime pay for the three states that passed farmworker overtime laws between 2016 and January 1, 2022. In California, in 2019, when the law was first implemented, 16 percent of livestock workers received overtime pay for working more than 55 hours per week. The share of workers responding that they received overtime pay increased to 40 percent in 2022. New York first implemented its law in 2020 requiring overtime pay after 60 hours per week: 18 percent of livestock workers received overtime pay in 2020 and the number steadily decreased to 3 percent in 2023. Washington has the highest percent of livestock workers receiving overtime pay, starting at 79 percent in 2021 when the law was first implemented requiring overtime pay after 40 hours per week and has decreased to 69 percent in 2023.

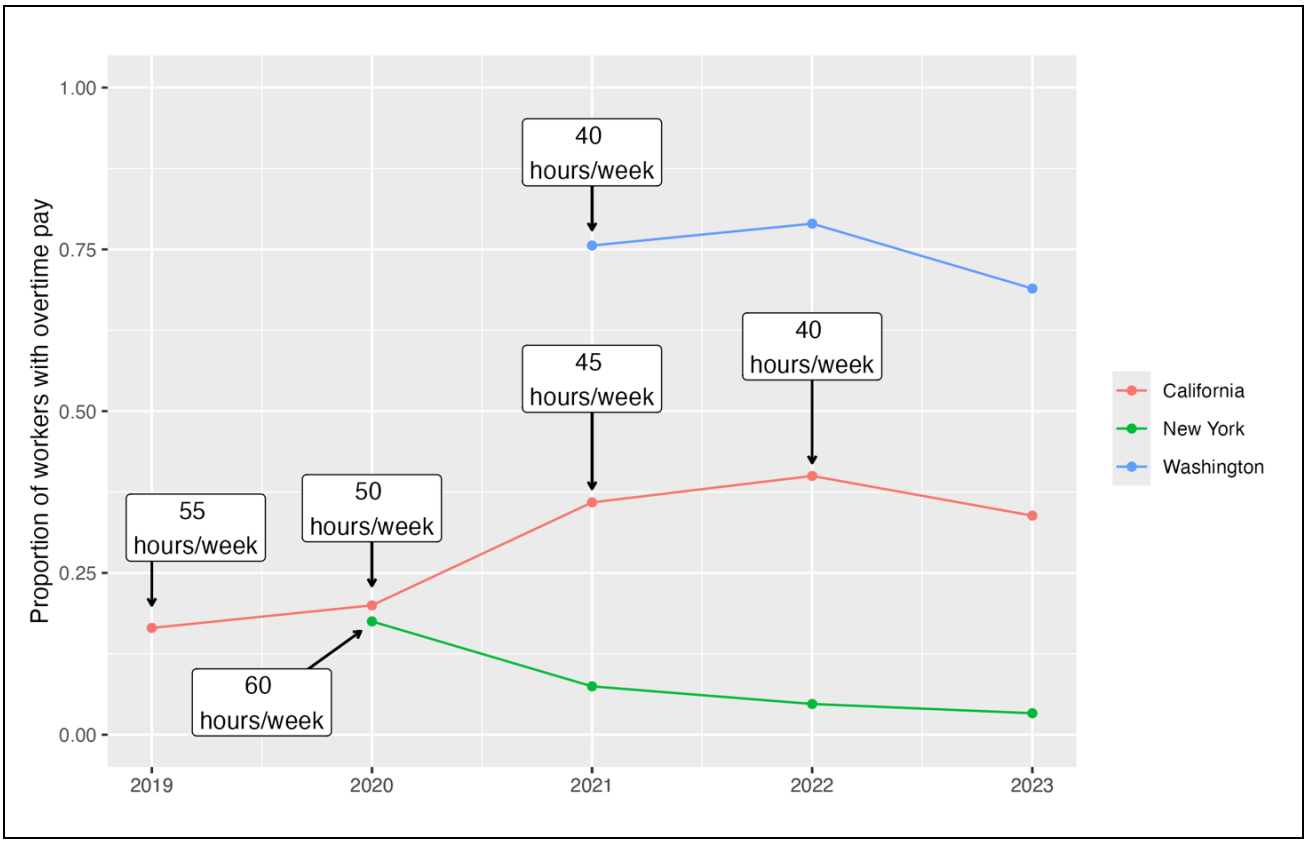


Figure 2. Proportion of livestock workers receiving overtime pay in California, New York, and Washington after implementation of farmworker overtime laws

Notes: Hours listed in boxes indicate the hours at which farmworkers received overtime pay in each year and state. Includes all livestock workers who reported at least one usual hours per week. In Washington, only dairy operations were subject to the 40 hours per week overtime threshold in 2021.

Source: U.S. Census Bureau, American Community Survey microdata, IMPUMS USA

Results from New York show a correlation between implementation of the overtime law and decreased average weekly hours worked by individual employees. During our study time frame, New York had the least restrictive law, requiring overtime after 60 hours per week, providing more flexibility for farmers than in the California and Washington to not pay overtime wages. Starting in 2021 in Washington and 2022 in California, the law required overtime pay after 40 hours per week. The proportion of workers receiving overtime increased in both states after implementation of the law through 2022 has since decreased. As of 2023, similar to New York, livestock producers in California and Washington are decreasing weekly hours worked by individual employees.

If we assume the sample of workers that will be most impacted by overtime laws are those that work at least full time, it is useful to evaluate the average hourly work for this subset of livestock workers. Additionally, full-time workers are those that are more likely to be dairy workers rather than other livestock works given the high labor requirements for dairy operations on a continuing basis. Figure 3 shows average usual weekly hours for livestock workers who reported usually working at least 40 hours per week in California, New York, and Washington from 2010 through 2023. Of the sample of full-time livestock workers, those in New York worked the most hours in every year of sample time frame. When the overtime law was

implemented in New York in 2020, average weekly hours for full-time workers was 56.4 and has decreased to 50.2 in 2023. We see as similar pattern for California and Washington: in California average weekly hours for full-time livestock workers were 48 in 2019 when the law was first implemented and down to 45.9 in 2023, and in Washington weekly hours were 45.5 in 2021 when the law was first implemented and 44.2 in 2023. The implementation of agricultural overtime laws was associated with a reduction in average weekly hours worked for full-time livestock workers in each of the states with recently enacted agricultural overtime laws. Providing initial evidence to support our equilibrium condition that overtime laws *do* constrain the optimal number of hours on dairy farms labor and additional labor is available to hire.

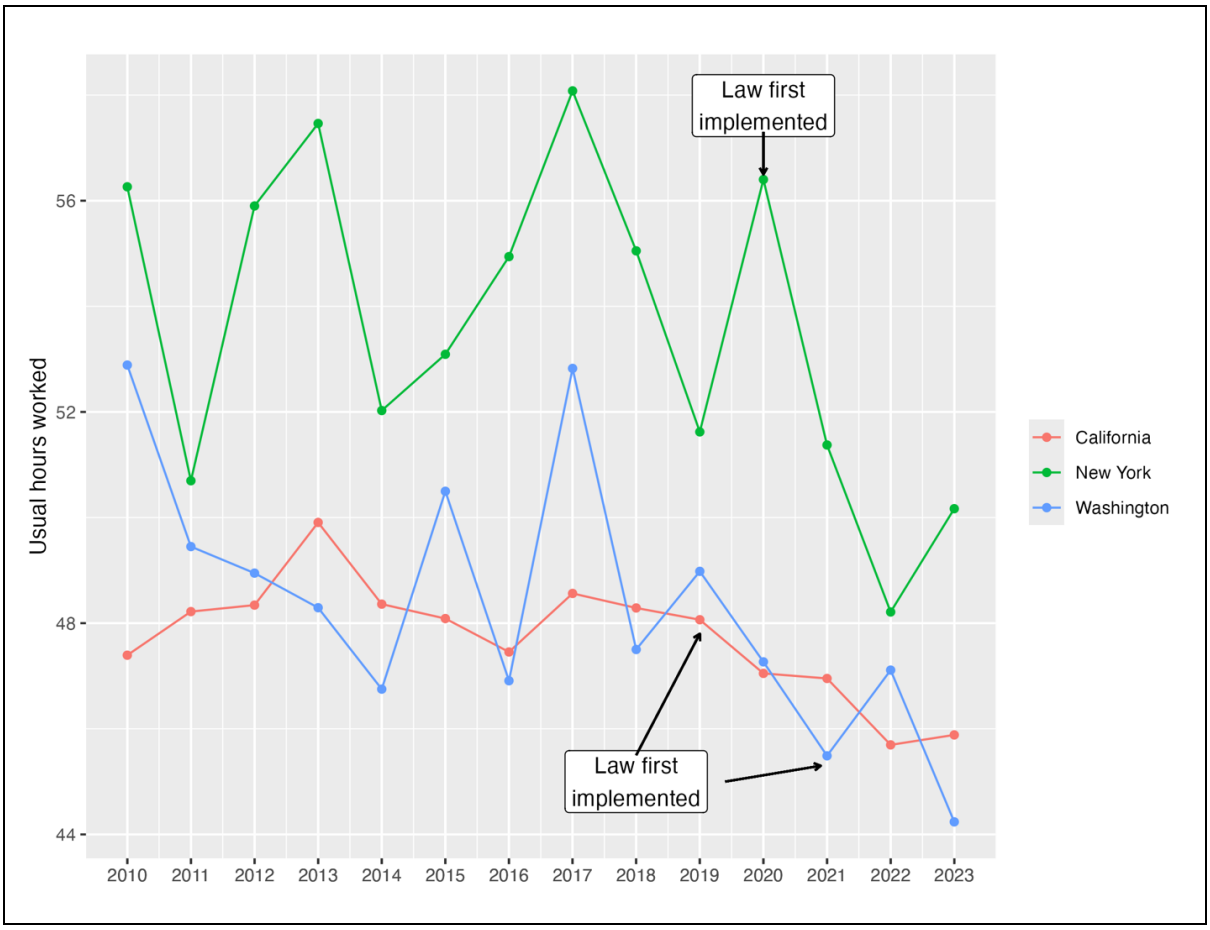


Figure 3. Average usual hours worked per week for full-time livestock workers in California, New York, and Washington after implementation of farmworker overtime laws
Source: U.S. Census Bureau, American Community Survey microdata, IMPUMS USA
Notes: Includes all livestock workers who reported at least 40 usual hours per week

California was the first state in our time period of interest to implement farmworker overtime laws and the only where we can see the impacts of the stepwise implementation of the law over time. Employers with more than 25 employees were first required to pay overtime at 55 hours per week in 2019, decreasing by 5 hours each year until 2022 when the cutoff reached 40 hours per week. Figure 4 shows the average number of overtime hours for livestock workers before and after the implementation of the law. In California (Figure 4, left panel), average overtime hours ranged from 1.6 hours in 2019 when employers were required to pay overtime

after 55 hours per week up to 2.1 in 2023 when employers were required to pay overtime after 40 hours per week. Although the law became much stricter each year, on average workers did not receive considerably more overtime pay. On average, livestock workers in New York worked fewer overtime hours after implementation of the overtime law requiring overtime pay after 60 hours per week, going from 1.7 overtime hours in 2020 when the law was first implemented to 0.2 overtime hours in 2023 (Figure 4, middle panel). In Washington, livestock workers received and average of 4.1 hours of overtime in 2021 when the law was first implemented requiring overtime after 40 hours per week, increasing to 5.6 in 2022 and then decreasing to 2.9 hours in 2023 (Figure 4, right panel).

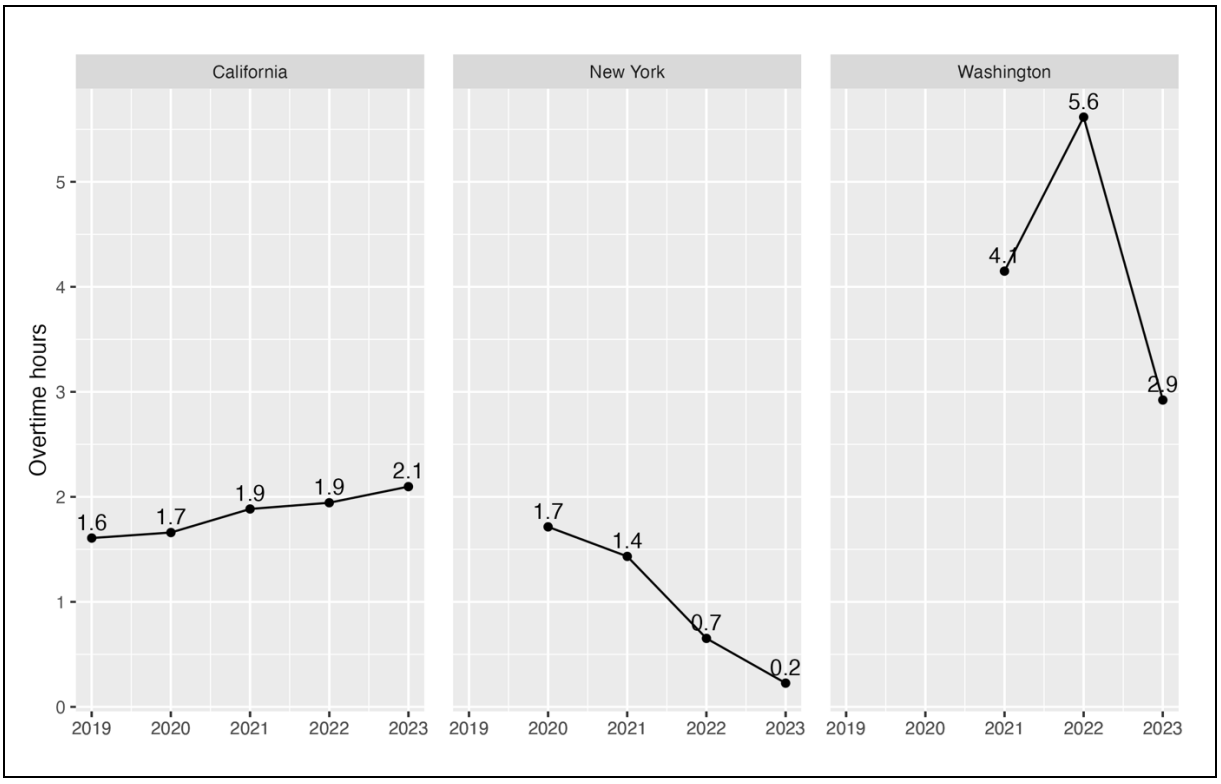


Figure 4. Average overtime hours for livestock workers in California, New York, and Washington

Source: U.S. Census Bureau, American Community Survey microdata, IMPUMS USA

Notes: Includes all livestock workers who worked usual hours above the overtime threshold

Using data from the Farm Labor Survey, Figure 5 shows hired labor hours per week (top panel) and wage rate (bottom panel) from 2012-2024, by region for all crop and livestock workers.[8] California was the first state to implement farmworker overtime laws, in 2019. From 2012 to 2019, the average hours per week hovered around 43. In 2020, average hours per week was 41.5 and dropped each year to less than 40 by 2024. Similarly in Washington and Oregon, from 2012 to 2019, average hours per week hovered around 41 or 42 and since implementation of the farmworker overtime law in 2020, average hours per week are at or below the 40 hour per

[8] Data disaggregated by crop and livestock is available starting in 2019 and only includes wages, so we chose to use data where crop and livestock workers are combined. We see similar trends in when using the livestock wage data only, but with higher overall wage rates.

week overtime threshold. In the Northeast (CT, ME, MA, NH, NY, RI, VT) there is not a clear trend in average hours per week after the implementation of overtime laws in New York in 2020. These data also support our equilibrium hypothesis that farmworker overtime laws *do* constrain the optimal number of hours on dairy farms and labor is available. Dairy farmers reduce weekly hours worked per employee to be under the overtime threshold.

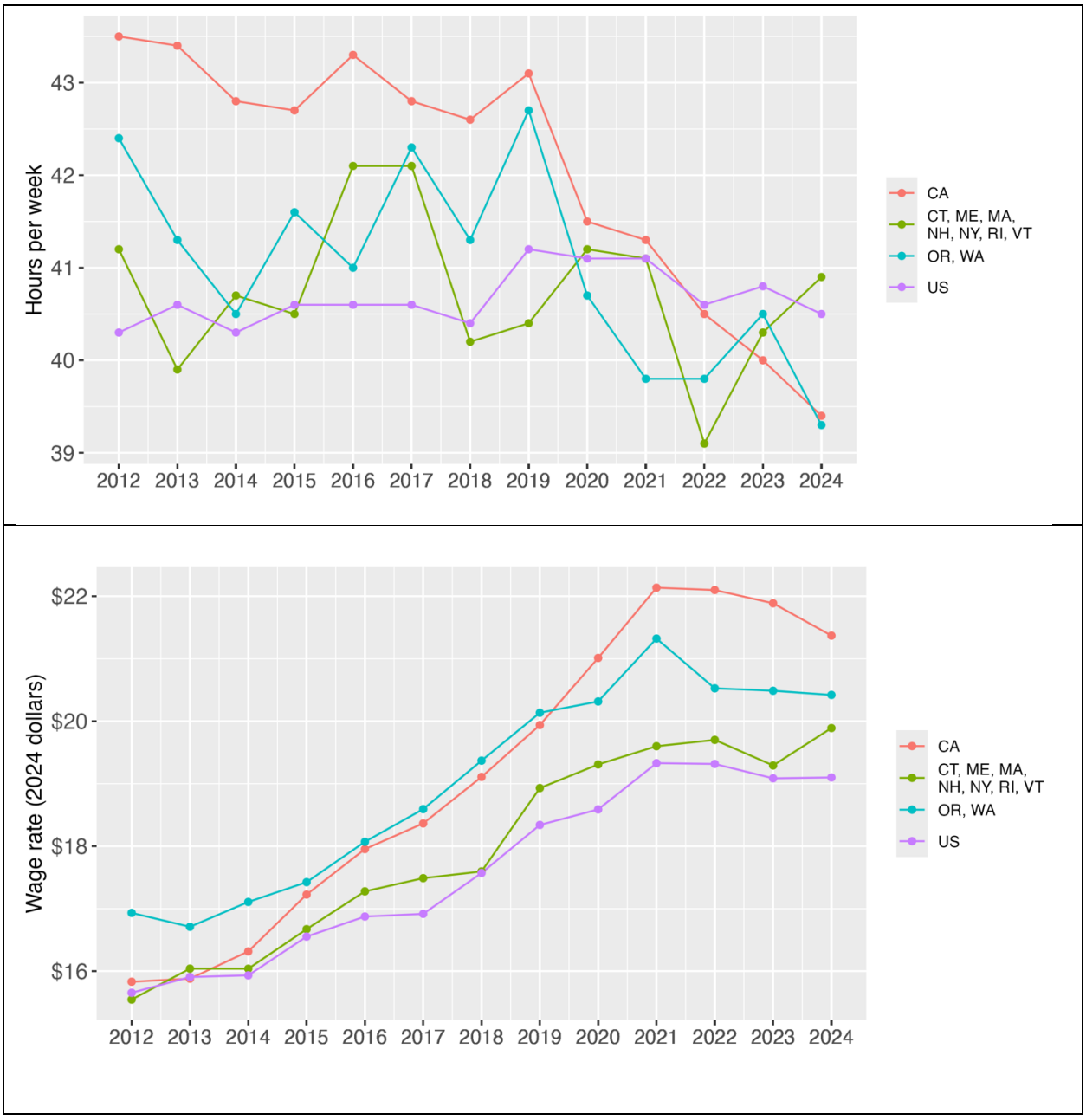


Figure 5. Hired labor hours per week and wage rate from 2012-2024, by region for all crop and livestock workers

Source: U.S. Department of Agricultural, National Agricultural Statistics Service (USDA NASS), Farm Labor Survey, 2012-2024

In California since 2021, when the law required overtime pay after 45 hours per week, the real average wage rate (in 2024 dollars) has declined slightly each year from an average of $22.14/hour in 2021 to $21.37/hour in 2024. Hill (2023) found similar results using data from the National Agricultural Workers Survey (NAWS). In the Northwest region (OR, WA) wages peaked in 2021 at $21.32/hour and have since declined to $20.42/hour in 2024. Trends in the region containing New York are not clear. This could be that data are too aggregated or could reflect the fact that the overtime threshold is high enough (60 hours per week). For California and Washington/Oregon, these data also support our equilibrium hypothesis that farmworker overtime laws *do* constrain the optimal number of hours on dairy farms and labor is available: dairy farmers will reduce weekly hours worked per employee to be under the overtime threshold, resulting in lower hourly wages for employees.

The Census of Agriculture is the only dataset that we can use to evaluate if farms shifted out of dairy production or stopped farming.[9] In looking at aggregate changes in the number of farms, we see the number of farms with milk cows has decreased each year in each of our states of interest indicating a consistent pattern of farm exit (Figure 6). New York saw the sharpest decline in farm exits with a slightly increase rate of exit during the time where farmworker overtime laws were implemented, between 2017 and 2022. California and Washington do not appear to show an increase in the rate of exit during the same time period.

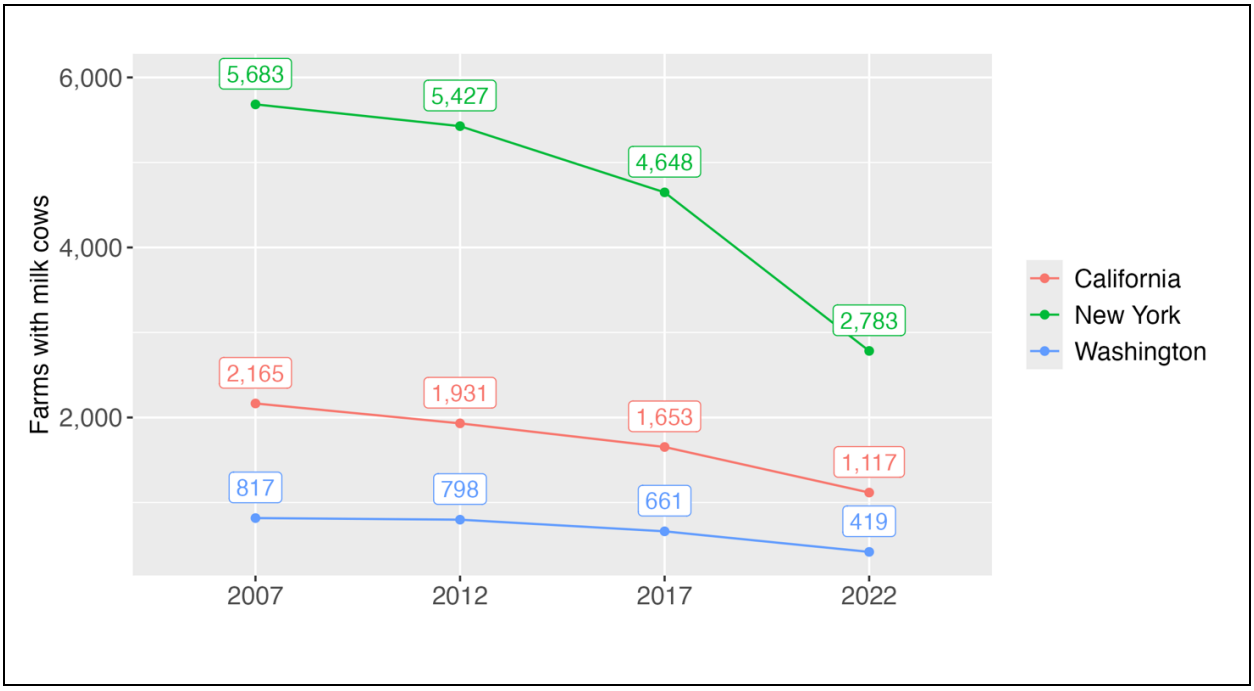


Figure 6. Number of dairy farms in the California, New York, and Washington from 2007-2022
Source: U.S. Department of Agriculture, National Agricultural Statistics Service (USDA NASS), Census of Agriculture, 2007, 2012, 2017 and 2022.

5. EMPIRICAL STRATEGY

[9] Data in this section will be updated once the restricted access data is approved for export and will include more detailed data on dairy farm exit rates.

To estimate the causal impact of farmworker overtime laws on dairy farm labor usage and average weekly hours for hired workers, our main approach is to estimate an event study, a difference-in-difference (DiD) design where units in the sample are treated at different points in time, using the framework as proposed by Callaway & Sant'Anna (2021). This approach addresses key challenges addressed in the recent literature associated with DiD estimations that have multiple treatment periods, variation in treatment timing, treatment effect heterogeneity, and when parallel trends does not hold unless conditioned on observable differences between the treated and control units prior to treatment (Athey & Imbens, 2022; Borusyak, Jaravel, et al., 2024; Callaway & Sant'Anna, 2021a; De Chaisemartin & D'Haultfoeuille, 2020; de Chaisemartin & D'Haultfoeuille, 2023b; Goodman-Bacon, 2021; Roth et al., 2023; Sun & Abraham, 2021). We estimate two sets of models using data from the Census of Agriculture and the ACS.

Additionally, when using data from the Census of Agriculture in which we have data for two time periods, we estimate a traditional canonical two-way fixed effects model (TWFE) (e.g., Abadie, 2005; Athey & Imbens, 2006; Callaway et al., 2018; De Chaisemartin & D'Haultfoeuille, 2020). This specification provides a variance-weighted average treatment effect (ATE) across all units in the sample. We estimate this model using ordinary least squares with standard errors clustered at the state level. To enhance the robustness of our estimates, we implement the doubly robust difference-in-difference model, as proposed by Sant'Anna & Zhao (2020), providing an estimate of the average treatment effect on the treated (ATT), an easier to interpret parameter than the weighted average treatment effect estimated in the traditional TWFE model. We estimate a conditional doubly robust difference-in-difference model that accounts for potential selection bias resulting from observable differences between the treated and control units prior to treatment and allows for the parallel trends assumption to hold after conditioning on pre-treatment covariates. This estimator combines inverse probability weighting and outcome regression in a doubly robust framework, where the estimator is robust to misspecification of either the propensity score model or the outcome regression model (Sant'Anna & Zhao, 2020). Given differences in implementation farmworker overtime laws in each state, we compare each treated state (New York, California, and Washington) separately to all states that did not implement farmworkers overtime laws during the study period (control states).

5.1. Identification Challenges

In order to claim causality based and for unbiased results from our DiD analysis, two key assumptions must hold (e.g., Abadie & Cattaneo, 2018; Angrist et al., 1996; Athey & Imbens, 2006; Bertrand et al., 2004; de Chaisemartin & D'Haultfoeuille, 2023). First is parallel trends: farmworker hours, wages, and employment would have followed similar trends in the treated and control observations in the absence of the implementation of the farmworker overtime laws. Second, the treatment effect should be constant between groups and over time. Additional identification challenges include the Stable Unit Treatment Value Assumption (SUTVA) (e.g., Abadie & Cattaneo, 2018; Angrist et al., 1996; RUBIN, 1980), requiring no spillover effects between treated units or treating an observations does not change the treatment status of other observations; no anticipation of treatment (e.g., Athey & Imbens, 2022; Sun & Abraham, 2021): in those states that had not yet implemented overtime laws, farmers did not anticipate the implementation of the laws; random treatment assignment (e.g., Abadie & Cattaneo, 2018; Athey & Imbens, 2006; Borusyak, Jaravel, et al., 2024), farmworkers overtime laws were not passed

due to excessive labor hours specifically in the states where the laws were passed; and, endogenous sample selection (e.g., Ghanem et al., 2024): missingness is not systematically correlated with our treatment or outcome. We discuss these assumptions in the context of our study and the potential challenges that may result in the remainder of this section.

5.1.1. Parallel Trends

While we cannot test for parallel trends directly, due to lack of counterfactual data, common practice is to test for differences in trends prior to treatment as a way of assessing the plausibility of parallel trends. Recent literature has criticized these traditional methods of testing for parallel trends citing lower power (Freyaldenhoven et al., 2019; Rambachan & Roth, 2023; Roth, 2022) and potential for bias resulting from conditioning the analysis on passing pre-trend tests (Roth, 2022). In addition to a visual inspection, we utilize the pre-test of parallel trends assumption provided in the R packages developed by Callaway & Sant'Anna (2021) and Sant'Anna & Zhao (2020) to determine if the model passes the assumption of parallel trends. Future modeling efforts will utilize the HonestDiD R package developed by Rambachan & Roth (2023) and provide a sensitivity analysis of our main results to violations of the parallel trends assumption.

5.1.2. Constant Treatment Effect

The second key assumption is the treatment effect should be constant between groups and over time. If we were to group each of our three treated states together (California, Washington, and New York), the assumption of constant treatment effects between groups would likely be violated because the laws implemented in each state were different, requiring that farmers pay overtime after different thresholds. We run all regression for each treated state separately compared to all control states in an effort to account for these differences. One remaining challenge it that California's law was implemented differently by size of farm. Utilizing the methods set forth in Callaway & Sant'Anna (2021), we treat these two types of farms as separate groups allowing for treatment effects to vary across groups. Outside of differences in the laws, it is possible that some farms responded to the treatment more or less than other farms, resulting in treatment heterogeneity. By utilizing the estimators, as proposed by Callaway & Sant'Anna (2021), we provide a estimation that is more robust to heterogenous treatment effects than the standard TWFE model.

5.1.3. Random Treatment Assignment

If the farmworker overtime laws were passed due to excessive labor hours specifically in the states where the laws were passed, treatment groups would not be assigned randomly and could lead to biased results. We address this concern in two ways. First, we provide evidence that the laws were largely passed for political reasons and not directly related to differences in hours worked specifically in the states where laws were passed. Second, we compare average usual hours worked for states that did and did not pass overtime laws.

The passage of farmworker overtime has been political in nature with clear divides between Republicans and Democrats. All states that have passed farmworker overtime laws are states that consistently vote democratic in presidential elections and typically have a democratic majority in their state legislature. The most common reasons cited in the popular press for

passage of the laws included enabling farmworkers the ability to make a living wage and support their families, rights of immigrants, and racial justice (Brown, 2021; Romero, 2023). In New York, the Labor Commissioner cited equity for farmworkers as the outcome of new overtime regulations in the state (*New York State Department of Labor*, n.d.). The California Assembly voted in favor of the bill 44-32, largely split along party lines, and was signed by Democratic governor Jerry Brown (Castillo, 2016). In Washington, the law for all farms in the state was spurred by a 2020 supreme court case that found that it was unconstitutional to deny dairy workers in the state overtime pay (*JOSE MARTINEZ-CUEVAS and PATRICIA AGUILAR, individually and on behalf of all others similarly situated, Petitioners, v. DERUYTER BROTHERS DAIRY, INC., GENEVA S. DERUYTER, and JACOBUS N. DERUYTER, Respondents, and WASHINGTON STATE DAIRY FEDERATION and WASHINGTON FARM BUREAU, Intervenor-Respondents.*, 2020).

Using the ACS data for livestock workers who reported working at least 40 usual hours per week, we plot the average usual hours worked from 2010-2023 in the top 5 dairy producing states (in 2022), which include California, Wisconsin, New York, Idaho, and Texas (USDA NASS, 2024b), plus Washington (Figure 7). Wisconsin, Idaho, and New York consistently had higher average hours worked for full-time livestock workers compared the other top dairy states, both before and after implementation of the overtime law. Whereas California and Washington had consistently lower average hours worked than the other top dairy states. We do not see any specific pattern of more hours worked for the top dairy producing states that that did pass overtime laws versus those that did not prior to the passage of the overtime laws, providing evidence that treatment assignment was not based on excessive labor hours specifically in the states that passed laws.

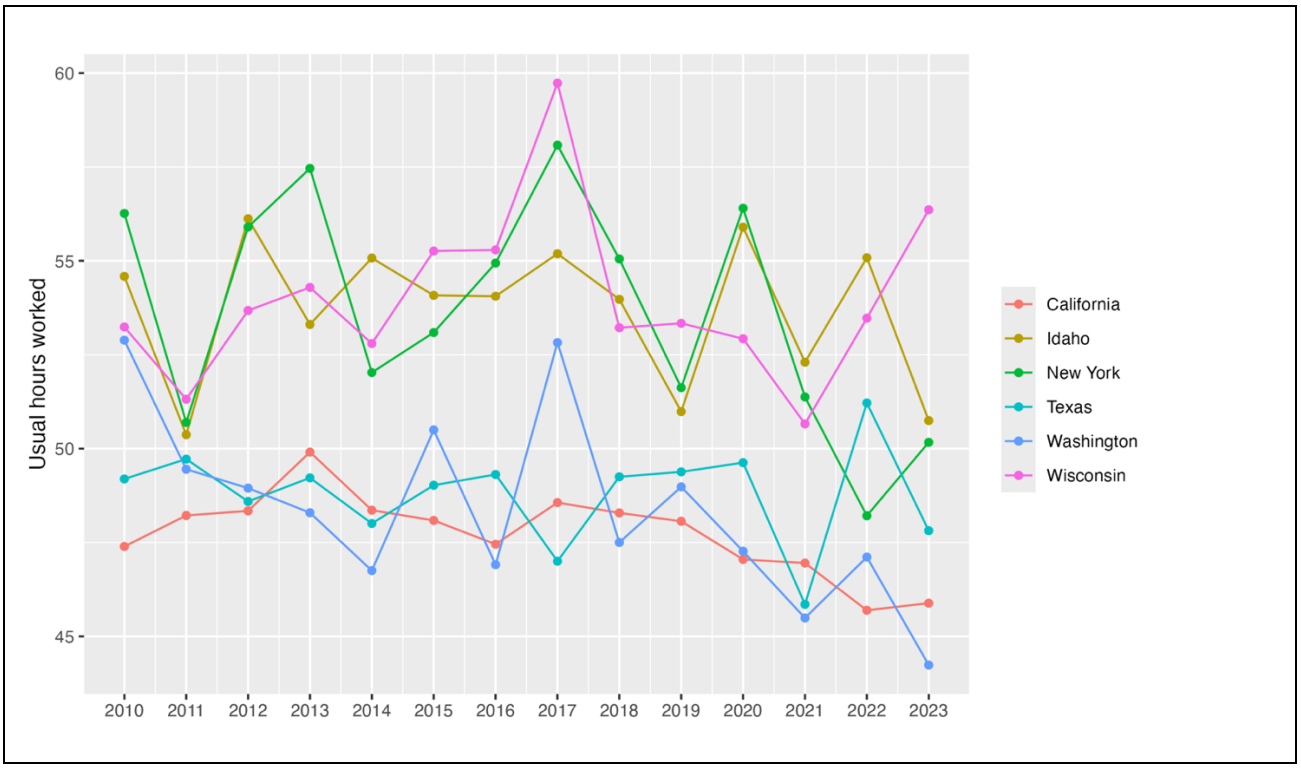


Figure 7. Usual hours worked per week from 2010-2023 for full-time workers in the top five dairy producing states for livestock workers plus Washington

Source: U.S. Census Bureau, American Community Survey microdata, IMPUMS USA
Notes: Full-time is defined as at least 40 hours per week

5.1.4. Anticipation of Treatment

Anticipation of treatment could reasonably be expected in the states that have passed farmworker overtime laws, but not yet implemented them, leading to biased results. Colorado and Oregon implemented farmworker overtime laws after our study period (based on data availability from the Census of Agriculture), but passed legislation during our study period (Colorado Department of Labor and Employment, Division of Labor Standards and Statistics, 2024; House Bill 4002, 2022). In Colorado, a farmworker overtime law was passed in 2021 and implemented at the end of 2022. In Oregon, employers were first required to pay overtime after 55 hours per week in 2023, the bill passed in 2022 (House Bill 4002, 2022). Operations in these states could plausibly have made changes to labor usage on their farms during the last year of our study time frame (2022) in anticipation of the implementation of the law, which would lead us to underestimate the effects. Similarly, in California, the farmworker overtime bill was signed in 2016, prior to this enactment, farmworkers were paid overtime if they worked more than 10 hours in a day or 60 hours in a week. As a result, we might have anticipation of treatment thus under estimating effects of the law. Using data from the ACS, we do not see a clear pattern of anticipation of treatment (Figure 8).

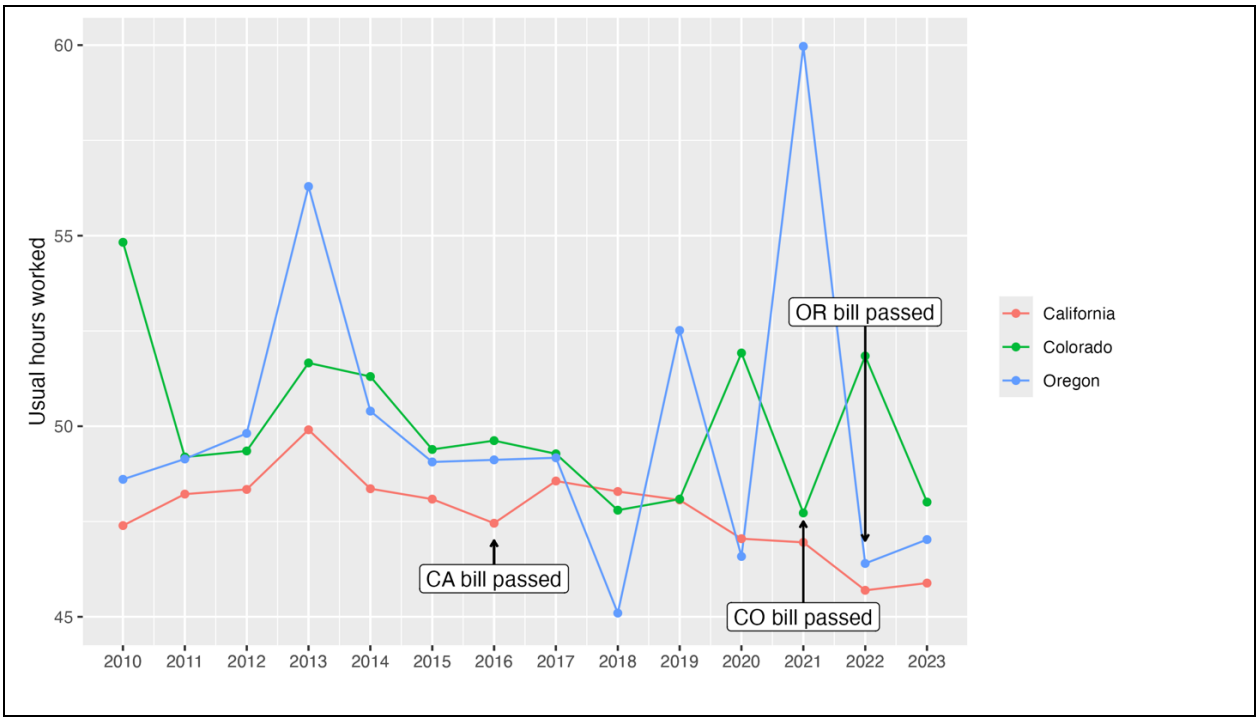


Figure 8. Usual hours worked per week from 2010-2023 for full-time workers in California, Colorado and Oregon
Source: U.S. Census Bureau, American Community Survey microdata, IMPUMS USA
Notes: Full-time is defined as at least 40 hours per week

5.1.5. SUTVA

We can reasonably assume that SUTVA holds as all farms in a state that has passed farmworker overtime legislation are subject to the same law, or in the case of California where all farms with of the same size were subject to the same law. There is no potential for changes in labor usage on one farm in a treated state to respond differently based on treatment of another farm as all farms are subject to the same law. The only case this might be an issue is in a hyperlocal region with a very tight labor supply where farms are fighting over the same small pool of employees.

5.1.6. Endogenous sample selection

Sample selection could be an issue if missingness is systematically correlated with our treatment or outcome. When using data from the ACS, we do not utilize a panel data approach and this is likely not a concern. However, when using data from the Census of Agriculture, an observation is missing if it went out of business or the respondent did not fill out the survey. While the latter could be considered random, the former could plausibly be related to our treatment, where increased labor costs caused a farm to go out of business, producing potentially biasing results.

Sample attrition is conditional on appearing in the initial Census of Agriculture.[10] The attrition rate in 2022 was around 25 percent and the sample size appearing in the initial year was around 20,000. As a first step, we estimate the impact of being in a treated state on exit rates in 2017 and exit rates in 2022. We include controls for scale in previous year, defined as 100-499 dairy cows, 500-999 dairy cows, 1,000 or more dairy cows (all categories are compared to 10-99 dairy cows), and state dummy variables for the top 10 dairy states. If exit rates in California, New York and Washington are different in 2022 compared to 2017 and those differences are not seen in the other top dairy producing states, that would provide some evidence that exit rates are correlated with farmworker overtime laws.

We see positive and statistically significant impacts for farms located in our treated states (California, Washington, New York) and Idaho on exit rates in 2017 prior to implementation of the farmworker overtime laws (Table 3, column 1), whereas farms located in Wisconsin and Michigan were less likely to exit. If we compare that to exit rates after implementation of the farmworker overtime law (Table 3, column 2), results are similar for our treated states: being in a treated state is positive and significantly associated with exit rates. Exit rates for most of the remaining top ten dairy states (Wisconsin, Michigan, Minnesota, and Iowa) are negative. Overall, we see higher exit rates both before and after implementation of farmworker overtime laws associated farms located in treated states (California, New York, and Washington), with a larger magnitude estimated in 2017. Results provide preliminary evidence that implementation of farmworker overtime laws did not have a significant impact on farm exits in treated states.

[10] We include only the set of farms that appeared in the sample in 2012 and in 2017 and allow for farms to either survive or exit in 2022. If a farm entered during the study time frame, they are not included in our sample. Additionally, we restrict the sample to have at least 10 dairy cows and 1 hired worker in the initial year.

Table 3. Probit regression results estimating the association between farm location and exit rates before and after implementation of farmworker overtime laws

Term	Exit year 2017, prior to implementation (1)	Exit year 2022, after implementation (2)
CA	(+)***	(+)***
WA	(+)*	(+)**
NY	(+)***	(+)***
WI	(-)***	(-)***
ID	(+)**	(+)***
TX	(-)	(-)***
MI	(-)***	(-)*
MN	(+)	(-)***
PA	(-)	(+)
IA	(-)***	(-)**
100-499[1] dairy cows	(-)***	(-)***
500-999[1] dairy cows	(-)***	(-)***
1,000 or more[1] dairy cows	(-)***	(-)***

Notes: [1] All scale categories are compared to farms with 10-99 dairy cows, states are compared to all non- top ten dairy.
Statistic: Estimate (standard error)
Source: U.S. Department of Agriculture, National Agricultural Statistics Service (USDA NASS), 2012, 2017, 2022 Census of Agriculture, calculated by the author using restricted access data.

To formally test and correct for sample attrition bias (i.e., labor usage and expenditures for farms that exited during our study time frame are significantly different from those that did not), we estimate a two-stage sample selection model (Heckman, 1976), following Goldstein & Pender (2025). Our first set of results show the results prior to controlling for selection bias. And then we control for selection bias and see how results change. Future results will consider incorporating the methods as discussed in Ghanem et al. (2024) for a robust methodology on addressing sample selection, using a changes-in-changes approach.

5.2. Event Study

Our main model specification is an event study, a DiD design where units in the sample are treated at different points in time, using the framework as proposed by Callaway & Sant'Anna (2021a), using the *did* package in R (Callaway & Sant'Anna, 2021b). The standard event study specification takes the form

$$Y_{it} = \sum_{\ell=-\infty}^{\infty} \beta_\ell \Delta T_{i,t-\ell} + \alpha_i + \gamma_t + X_{it} + \varepsilon_{it} \quad (1)$$

where Y_{it} represents labor usage at farm *i* in year *t* or hours worked by individual *i* in year *t*. We use four measures of farm labor usage: number of paid workers, salary, contract labor expense, and hired labor expense per milk cow. Farm fixed effects are represented by α_i to control for time-invariant unobserved heterogeneity across farms, γ_t represents year fixed effects that control for common time trends affecting all farms/individuals, and ε_{it} is the error term. For the

years after the overtime law was implemented ($\ell \geq 0$), the parameter β is the dynamic treatment effect ℓ. For the years prior to implementation of the overtime law ($\ell < 0$), β are used to test for parallel pre-treatment trends (Schmidheiny & Siegloch, 2023). Standard errors are clustered at the state to account for potential serial correlation in the error terms within states over time. A set of time-invariant, exogenous controls for scale of the dairy operations, X_{it}, are also included, which allow for parallel trends to hold after conditioning on covariates.[11] We follow the scale categories as presented in the publicly available Census of Agriculture data, but with some categories collapsed. We define scale based on herd size, where operations are defined based on <100, 100-499, 500-999, 1,000 or more milk cows (<100 is the reference category).

Additional covariates were considered that indicated the type of production system and adoption of technology. Due to their high correlation with scale additional covariates are not included and the simplest model was utilized. Dairy operations with a pasture-based production system allow cows to graze for a portion of their feed. Gillespie et al. (2024) use the ARMS Dairy version and defined a pasture-based system as one where cows receive at least 50 percent of their forage needs from pasture during the grazing season. MacDonald et al. (2020) show that farm consolidation as lead to a decrease in the amount of land used for pasture and fewer cows grazed on pasture, and that most large dairy operations do not graze their cows. Gillespie et al. (2024) found larger operations tended to have a higher purchased feed expense and smaller operations tended to rely more heavily on grazing. Similarly, MacDonald et al. (2020) found regional variability in grazing, driven largely by scale, where dairy production in the Northeast and Midwest were more likely to graze. Gillespie et al. (2024) used milk produced per cow as a measure of technology adoption. Similarly, (MacDonald et al., 2016) used ARMS data to estimate labor productivity as milk production in hundredweight per hour of labor and found that large dairy operations realize higher labor productivity as a results of different production practices and technology adoption compared to small dairy operations. Milk yields (hundredweight per cow) typically differ by size of operation, where larger operations typically milk three times per day compared to twice a day for smaller operations, and by climate with lower yields in warmer climates (MacDonald et al., 2016). Another measure of technology adoption is the value of machinery and equipment. Gillespie et al. (2024) found larger operations are more likely to adopt advanced technologies.

5.2.1. Two-stage sample selection

To account for the potential of endogenous sample selection resulting from farms exiting the sample as a result of the farmworker overtime laws, we estimate a two-stage Heckman sample selection model. In the first stage, we estimate the probability that a farm survived from 2017 to 2022, predicting the inverse Mills ratio, where:

$$S_{it} = 1 \; if \; S_{it}^{*} > 0; \; S_{it} \; otherwise$$

$$S_{it}^{*} = \alpha_0 + \alpha_1 Treat_i + \alpha_2 Post_t + \alpha_3 Treat_i Post_t + X_{i,2017}\gamma + \epsilon_{it} \quad (2)$$

where $X_{i,2017}$ include scale, reliance on government payments, profitability, average land values in a county, and labor supply in a county. All farm-level variables are defined based on their

[11] Covariates are not included when using data from the ACS.

value in 2017.[12] Scale is defined as described above with categories including <100, 100-499, 500-999, 1,000 or more milk cows (<100 is the reference category). Reliance on government payments is a variable that ranges from 0 to 1, where 0 is an operation that receives no government payments and 1 is one that receives all farm income from government payments and is defined as government payments as a percent of gross cash farm income. Profitability is defined as the operating profit margin. The price a farmer receives for their land is likely to have an impact on their choice to sell their farm. Average land value is proxied by the percent of farmland acres in a county designated as prime farmland[13] (U.S. Department of Agriculture, National Resource Conservation Service (USDA NRCS), 2012) and well as the Rural-Urban Continuum Code in the county (USDA ERS, 2024). Lastly, we include a measure of dairy farm labor supply in a county as a shift share (Borusyak, Hull, et al., 2024), calculated as the total dairy hired workers in a state in 2017 multiplied by a county's share of labor in the state in 2012. The regression is weighted using the weight from 2017. In the second stage, we estimate an event study, following the same methodology as described in the previous section with the inverse Mills ratio included as an additional covariate.[14]

5.3. Two-Way Fixed Effects

Our base model, using data from the Census of Agriculture, is two time periods and two groups and estimates a traditional canonical TWFE specification of the form:

$$Y_{it} = \alpha_i + \gamma_t + \beta Treated_i Post_t + \varepsilon_{it} \quad (3)$$

where Y_{it} represents labor usage at farm *i* in year *t*. We use four measures of labor usage: number of paid workers, salary, contract labor expense, and hired labor expense per milk cow. α_i represents farm fixed effects that control for time-invariant unobserved heterogeneity across farms, γ_t represents year fixed effects that control for common time trends affecting all farms, $Treated_i$ is a binary variable that is equal to 1 if the farm *i* was subject to farmworker overtime laws and 0 otherwise, $Post_t$ is a binary variable that is equal to 1 for the year after implementation of the farmworker overtime law and 0 otherwise, β is the difference-in-difference coefficient, representing the variance-weighted average treatment effect (ATE) of farmworker overtime laws on labor usage, and ε_{it} is the error term. Standard errors are clustered at the state to account for potential serial correlation in the error terms within states over time. Given differences in the implementation of the law and the resulting likelihood of heterogenous treatment effects across groups, the model is run model separately for each treated state compared to all control states.

Data includes a balanced panel of dairy farms that had at least 10 dairy cows and one hired worker in 2012 and filled out the Census in both 2017 and 2022. While the TWFE analysis

[12] Data used for prime farmland comes is from 2012.

[13] Defined as land that has the best combination of physical and chemical characteristics for producing food, feed, forage, fiber, and oilseed crops and that is available for these uses.

[14] In California, for operations with less than 26 hired workers that were subject to overtime laws starting in 2022, we cannot estimate the model when we include the inverse mills ratio and all scale categories. When we remove the scale category of 100-499 dairy cows, we can estimate the model. As a result, we estimate the second stage for all models with matching covariates 500-999 dairy cows, 1,000 or more dairy cows, and the inverse Mills ratio.

only uses data from the time periods before and after the implementation of the law (2017 and 2022), we use data on the same set of farms from prior years to address the assumption of parallel trends. The model is estimated using the *fixest* package in R (Berge et al., 2024).

5.4. Conditional Doubly Robust Two-Way Fixed Effects

Recent literature has discussed the potential challenges with interpreting the ATE estimated from a traditional TWFE model as it estimates a weighted ATE, where the weights can be difficult to interpret (e.g., Callaway & Sant'Anna, 2021; Sant'Anna & Zhao, 2020), particularly in the context of observational data where the true data generating process is unknown. Sant'Anna & Zhao (2020) proposed a model that estimates the average treatment effect on the treated (ATT), which allows for estimation of the effect of farmworker overtime laws on specifically those farms that were subject to the law.

We estimate conditional doubly robust difference-in-differences model as proposed by Sant'Anna & Zhao (2020) (using the *DRDID* package in R), which result in consistent estimation of the ATT even under misspecification of the propensity score model or outcome regression model. Dairy farms located in the treated states might be systematically different than dairy farms located in control states, potentially biasing results and resulting in a violation the parallel trends assumption. Propensity score matching helps to create comparable groups of farms from which to conduct a difference-in-difference analysis. We match on selected covariates to account for observable differences in farms located in treatment and control states prior to implementation of the farmworker overtime law and estimate a propensity score model (i.e., the probability of being in the treatment group) and outcome regression model (i.e., predicted evolution of labor usage), providing a doubly robust model that is robust to misspecification of either.[15]

We estimate a difference-in-difference model of the form:

$$Y_{it} = \alpha_i + \gamma_t + \beta Treated_i Post_t + X_{it} + \varepsilon_{it} \quad (4)$$

where X_{it} is a set of time-invariant controls that include scale of dairy operation. We follow the scale categories as presented in the publicly available Census of Agriculture data, but with some categories collapsed. We define scale based on herd size, where operations are defined based on <100, 100-499, 500-999, 1,000 or more milk cows (<100 is the reference category).

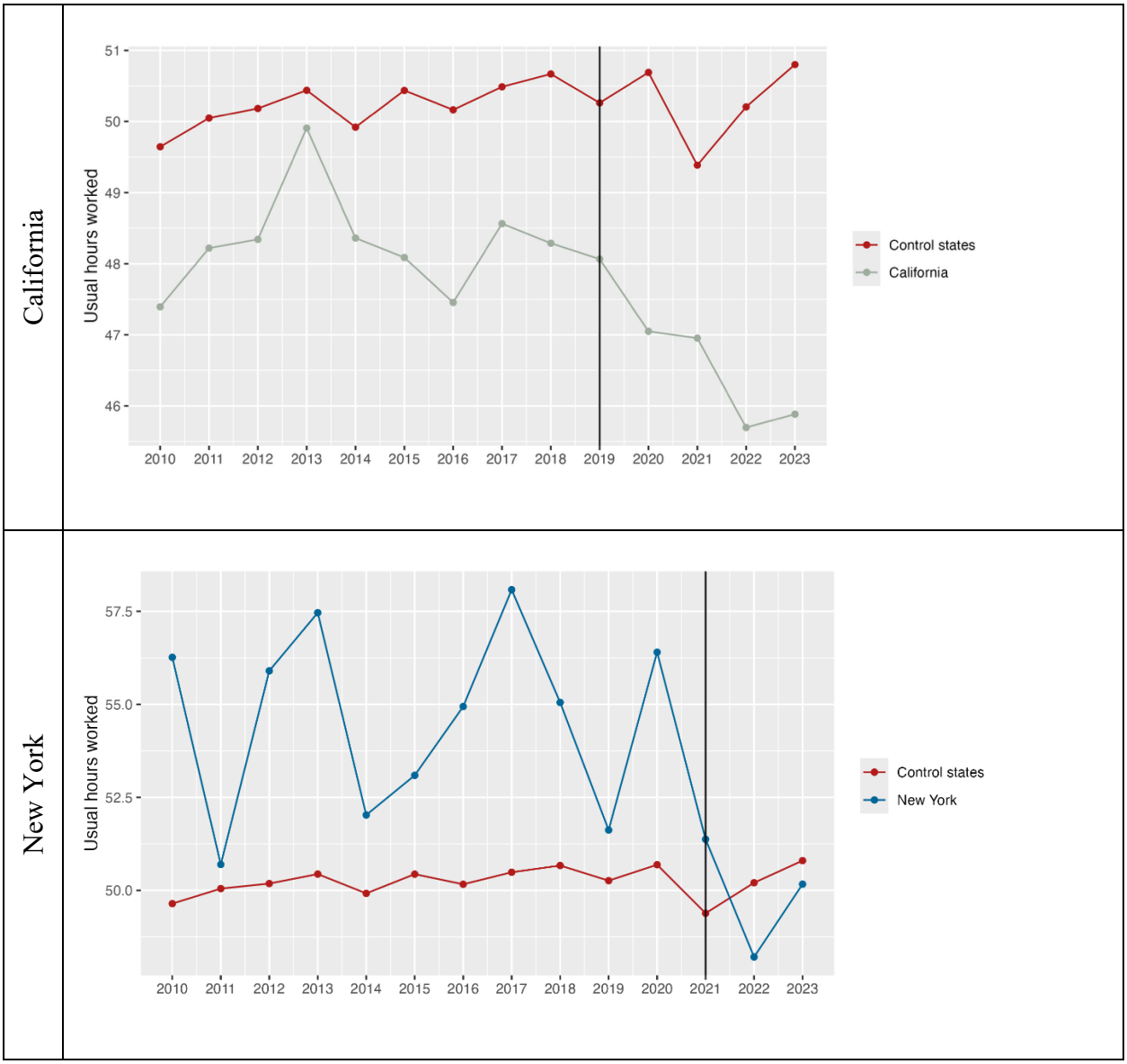
6. RESULTS

We begin by using data from the ACA to compare usual hours worked in treated states compared to control states, using an event study design. Next, we pivot to using data from the Census of Agriculture[16] and estimate an event study model comparing the number of hired workers, salary and contract labor expense in California, New York, and Washington separately compared to all other states. We then present the same set of results but after controlling for sample selection bias as a result of farms exiting the sample as a result of overtime laws. Lastly, we present results from a TWFE and conditionally doubly-robust DiD model.

[15] We use the DRDID package developed by Sant'Anna & Zhao (2020).
[16] Results have not yet passed disclosure review but are presented to show the sign and significance of the estimate.

6.1. American Community Survey (ACS) – Livestock workers hours

We first estimate the impact of farmworker overtime laws on farmworker hours using ACS data. Figure 9 shows trends in usual hours worked for each of our treated states compared to control states before and after implementation of farmworker overtime laws. Upon visual inspection of these data, there are some differences in pre-trends in each treated state compared to the control states, but they appear to be driven in part by larger variation in the data at the state-level compared to the national level. We rely on the results from the *did* package that report a pre-test for parallel trends; all models pass.



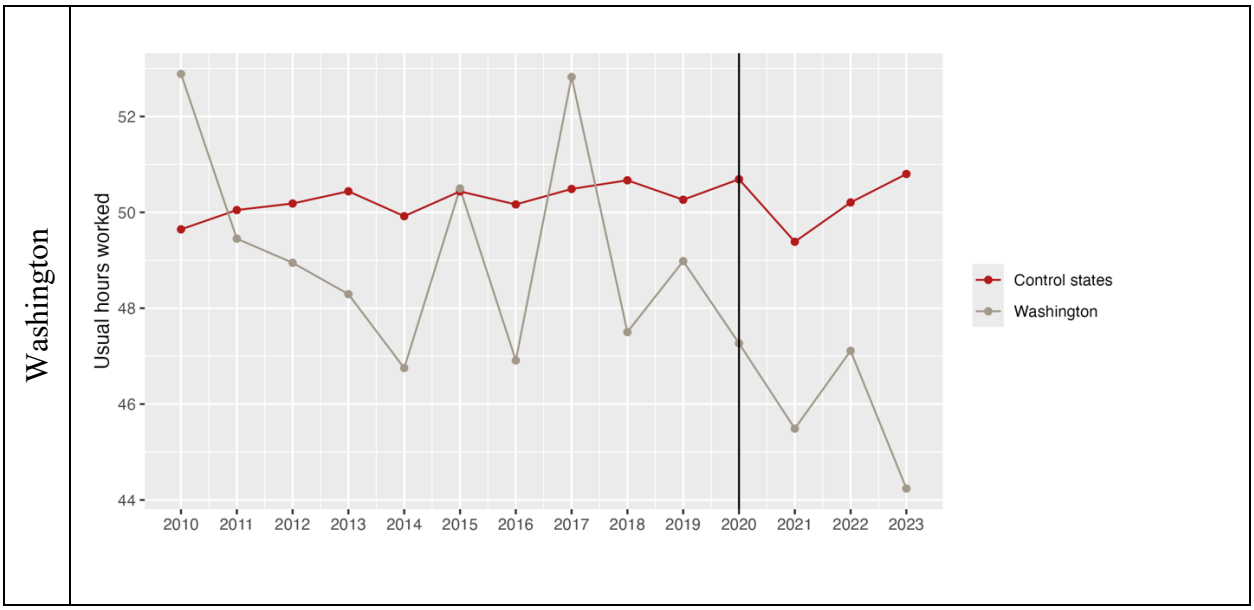


Figure 9. Average usual hours worked per week for full-time livestock workers in treated states compared to control states, 2020-2023

Source: U.S. Census Bureau, American Community Survey microdata, IMPUMS USA

Notes: Includes all livestock workers who reported at least 40 usual hours per week. Control states include all other states along with those with longstanding laws enacted before 2017. Oregon and Colorado are dropped from the analysis.

Figure 10 presents the event study ATT from equation 1, using data on usual weekly hours. The ATT was estimated under the assumption of unconditional parallel trends. Time period 0 corresponds to the year in which the overtime policy was first implemented, 2019 for livestock workers in California, 2020 in Washington and 2021 in New York. The red bars indicate the average treatment effect prior to the implementation of the law, this effect is not statistically different from zero, providing evidence that the test of parallel pre-trends is not violated. The blue dots with 95 percent simultaneous confidence intervals are the average treatment effect after implementation of overtime laws. While we do see a slight trend in fewer usual hours worked per week after implementation of the overtime laws, differences are not statistically significant.

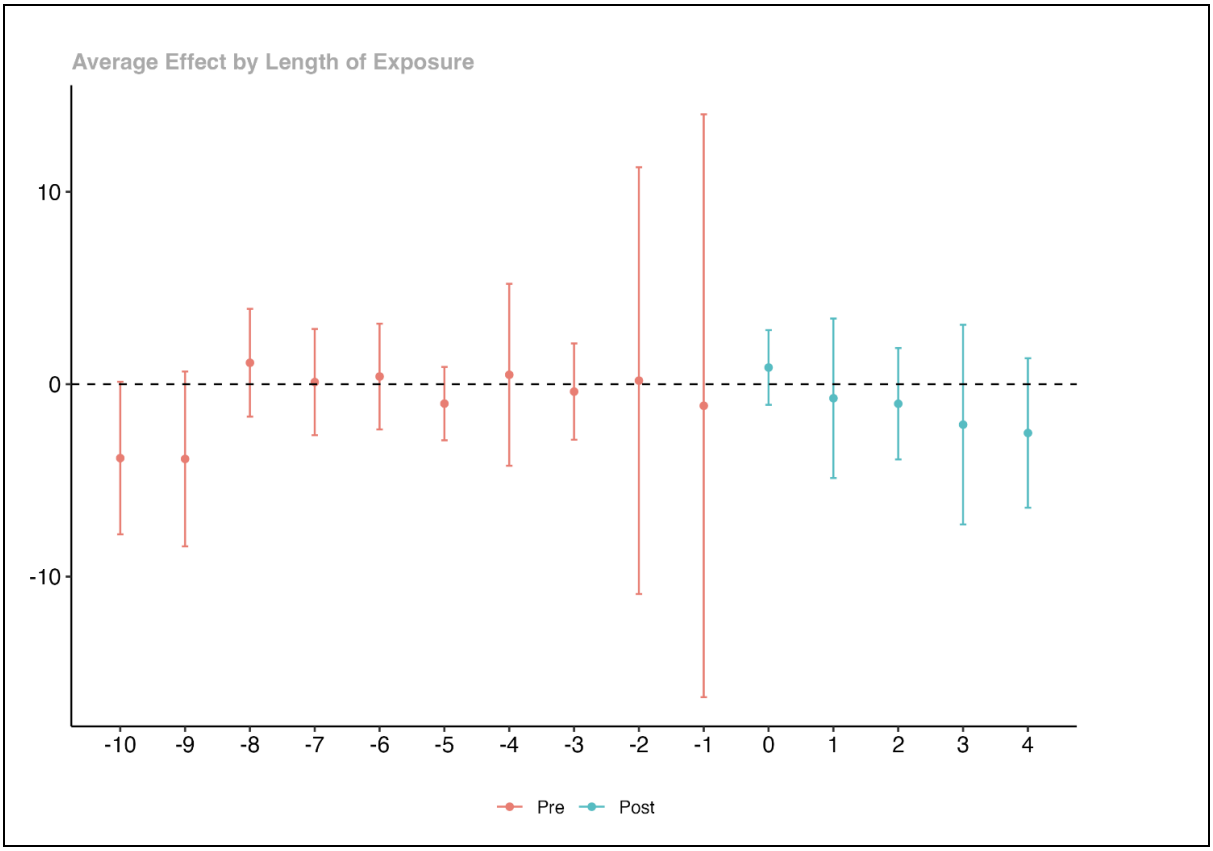
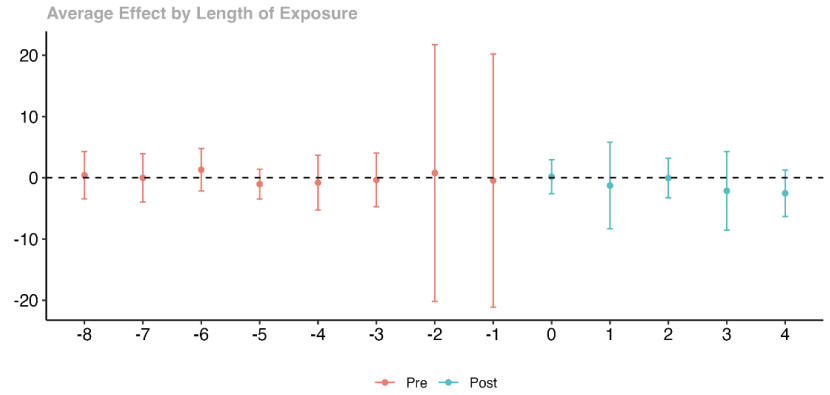


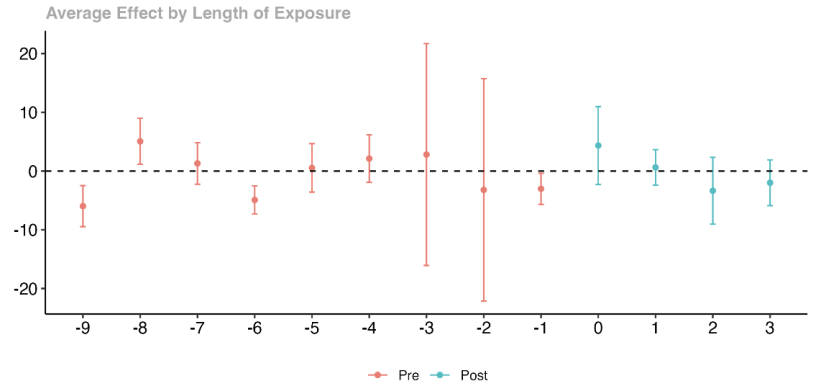
Figure 10. Average treatment effect of farmworker overtime laws on average usual hours worked per week for full-time livestock workers in treated states compared to control states, 2020-2023
Source: U.S. Census Bureau, American Community Survey microdata, IMPUMS USA
Notes: Event study plot estimated using the *did* package by R (Callaway & Sant'Anna, 2021b). Point estimates and 95 percent confidence bands for pre- and post- implementation of farmworker overtime laws and shown in red and blue, respectively. Confidence bands are based on standard errors clustered at the state-level. Data include all livestock workers who reported at least 40 usual hours per week.

Modeling the impact of the law in California is challenging. The law was first implemented in 2019, but the overtime threshold decreased by 5 hour per week each year until it reached 40 hours in 2021. Additionally, the laws implemented in each state had different thresholds where farmworkers received overtime pay. When we model data from each treated state separately, we do not see materially different results (Figure 11). In general, the treatment effect after implementation of the overtime law results in fewer hours, but results are not statistically significant.

California



New York



Washington

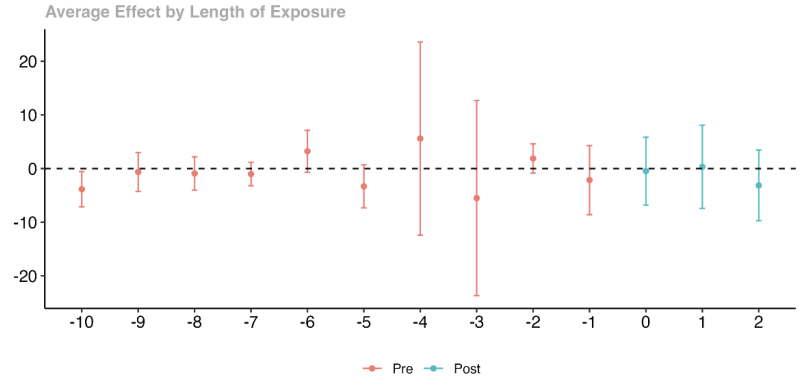


Figure 11. Average treatment effect of farmworker overtime laws on average usual hours worked per week for full-time livestock workers in treated states separately compared to control states, 2020-2023

Source: U.S. Census Bureau, American Community Survey microdata, IMPUMS USA

Notes: Event study plot estimated using the *did* package by R (Callaway & Sant'Anna, 2021b). Point estimates and 95 percent confidence bands for pre- and post- implementation of farmworker overtime laws and shown in red and blue, respectively. Confidence bands are based on standard errors clustered at the state-level. Data include all livestock workers who reported at least 40 usual hours per week.

6.2. Census of Agriculture – Dairy farm labor usage

Using data from the Census of Agriculture we can track individual farms over time to evaluate changes in dairy farm labor usage that result from farmworker overtime laws. We first estimate an event study model, as described in equation 1, where we estimate the causal impact of farmworker overtime laws on the number of paid workers, salary, contract labor expense, and hired labor expense per milk cow utilized by dairy operations. Our first set of results is for the set of dairy farms that survived over the time period of 2012 to 2022. We then follow equation 2 and estimate a Heckman selection model to account for operations that exited in 2022. Lastly, we show results from a TWFE model (as described in equations 3 and 4).

6.2.1. Event study – Dairy operations that survived from 2012 to 2022

Estimation of results from Equation 1 are presented in Table 4. In California, for those dairy operations that survived we see a positive and statistically significant impact of farmworker overtime laws on average salary and a negative and statistically significant impact on the number of paid workers. Contract labor expense and hired labor expense per cow were both positive but not statistically significant. In New York, we see higher labor expense per cow after implementation of the law, with no other significant impacts. Lastly, in Washington, we see positive and statistically significant impacts of farmworker overtime laws on hired labor expense per cow and contract labor expense. The number of total paid workers decreased, but was only significant at the 10 percent level.

Farmworker overtime laws resulted in fewer paid workers (California and Washington), higher average salary per worker (California), higher labor expense per cow (Washington and New York), and higher contract labor expense (Washington) for those dairy farms that survived from 2012 through 2022. Fewer workers support our equilibrium hypothesis that overtime laws resulted in a constrained equilibrium and adequate workforce was not available to hire (California and Washington). Operations in these states could have shifted (partially or fully) out of dairy into less labor-intensive commodities and/or adopted labor saving technologies.[17] Higher average salary per worker, labor expense per cow, and contract labor expense supports our equilibrium hypothesis that farmworker overtime laws did constrain optimal hours and the market absorbed the costs. Results suggest that, for those dairy operations that survived, market dynamics supported higher wages paid to farmworkers and contract labor expense, at least in the short term.

[17] In this analysis we only include operations that survived, so we cannot evaluate those operations that stopped farming.

Table 4. Dynamic average treatment effect of farmer labor usage before and after implementation of farmworker overtime laws in California, New York, and Washington for operations that survived from 2012-2022

Event time	Paid workers	Salary	Hired labor expense per cow	Contract labor expense
California				
-5	(-)	(-)	(+)	(+)
-2	(-)	(+)	(-)	(+)
0	(+)	(+)	(+)	(+)
3	(-)**	(+)**	(+)	(+)
Overall	(-)**	(+)	(+)	(+)
Covariates	Yes	Yes	Yes	Yes
Parallel trends p-value	>10% (passed)	>10% (passed)	>10% (passed)	>10% (passed)
New York				
-3	(+)	(-)	(-)	(+)
2	(-)	(+)	(+)**	(+)
Overall	(-)	(+)	(+)	(+)
Covariates	Yes	Yes	Yes	Yes
Parallel trends	>5%	<1% (did not pass)	>10% (passed)	>10% (passed)
Washington				
-4	(+)	(+)	(-)	(-)
1	(-)*	(+)	(+)**	(+)**
Overall	(-)**	(+)	(+)**	(+)
Covariates	Yes	Yes	Yes	Yes
Parallel trends	>10% (passed)	>10% (passed)	>5%	>10% (passed)

Notes: Covariates include scale categories 10-99, 100-499, 500-999, and 1,000 or more dairy cows.
Source: U.S. Department of Agriculture, National Agricultural Statistics Service (USDA NASS), 2012, 2017, 2022 Census of Agriculture, calculated by the author using restricted access data. Event study estimated using the *did* package by R (Callaway & Sant'Anna, 2021b). Stars represent statistical significance at the 95 percent confidence for pre- and post- implementation of farmworker overtime laws. Standard errors are clustered at the state.

6.2.2. Event study – Heckman Selection Model

In our previous set of results, we do not account for farms that exited the sample, which could have been a result of farmworker overtime laws and thus bias results. In this section, we present results from our Heckman selection model where we first estimate a selection model based on probability of farm exit and then incorporate the inverse Mills ratio into our event study model. Estimation of results in Equation 2 are presented in Table 6. Overall, results are similar to the previous model. Farmworker overtime laws resulted in fewer paid workers and higher average salaries in California, increased labor expense per cow in New York and Washington, and

increased contract labor expense in Washington. Future modeling efforts will seek to better understand the dynamics of dairy farm exit and farmworker overtime laws.[18]

Table 5. Dynamic average treatment effect of farmer labor usage before and after implementation of farmworker overtime laws in California, New York, and Washington

Event time	Paid workers	Salary	Hired labor expense per cow	Contract labor expense
California				
-5	(-)	(+)	(+)	(+)
-2	(-)	(+)	(-)	(+)
0	(+)	(+)	(-)	(+)
3	(-)**	(+)*	(-)	(+)
Overall	(-)	(+)	(-)	(+)
Covariates	Yes	Yes	Yes	Yes
Parallel trends p-value	>10% (passed)	>5% and <10%	>10% (passed)	>10% (passed)
New York				
-3	(+)	(-)	(-)	(+)
2	(-)	(+)	(+)**	(+)
Overall	(-)	(+)	(+)	(+)
Covariates	Yes	Yes	Yes	Yes
Parallel trends	<1% (did not pass)	<1% (did not pass)	>10% (passed)	>10% (passed)
Washington				
-4	(+)	(+)	(-)	(-)
1	(-)	(+)	(+)**	(+)**
Overall	(-)**	(+)	(+)**	(+)
Covariates	Yes	Yes	Yes	Yes
Parallel trends	>10% (passed)	>10% (passed)	>10% (passed)	<5% (did not pass)

Notes: Covariates include scale categories 10-499, 500-999, and 1,000 or more dairy cows and the inverse Mills ratio calculated from a first stage regression estimating the probability of farm exit in 2022.
Source: U.S. Department of Agriculture, National Agricultural Statistics Service (USDA NASS), 2012, 2017, 2022 Census of Agriculture, calculated by the author using restricted access data. Event study estimated using the *did* package by R (Callaway & Sant'Anna, 2021b). Stars represent statistical significance at the 95 percent confidence for pre- and post- implementation of farmworker overtime laws. Standard errors are clustered at the state.

[18] The model would not estimate with the same set of controls, it only worked when the two smallest scale categories were combined. This provides evidence that we still need to uncover important dynamics of firm exit, particularly for smaller scale dairy farms.

6.2.3. Two-way fixed effects

Estimation of results from Equations 2 and 3, from our base model specification of a DiD and a TWFE model, are shown in Table 6. Data are only presented for those operations that survived from 2012 to 2022[19] and run separately for each treated state compared to all control states, standard errors are clustered at the state-level. Panel A shows results from our baseline model with no covariates and Panel B shows the same results using a conditional doubly robust TWFE DiD model as proposed by Sant'Anna & Zhao (2020) and includes a scale covariate indicating if a farm has at least 1,000 dairy cows or not.

In the base TWFE model, almost all effects of overtime laws on labor usage are positive and statistically significant. But, as explained above, the TWFE estimator could be biased in the case of heterogenous treatment effects and has been questioned expensively in the recent literature on DiD methods. The results from Panel B, a more robust methodology, very closely follow those estimated in the event study model. Farmworker overtime laws resulted in a decrease in the number of hired workers (California and Washington), an increase in average salary per worker (California), and an increase in hired labor expense per cow and contract labor expense (Washington).

Table 6. Effect of overtime laws on dairy farm labor usage

	California	New York	Washington
Panel A: Two-way fixed effects Average Treatment Effect (ATE)			
Total paid workers	(+)***	(+)	(+)***
Average salary per worker	(+)***	(+)***	(+)***
Contract labor expense	(+)***	(+)***	(+)***
Hired labor expense per cow	(+)***	(+)***	(+)***
Panel B: Conditional Doubly Robust Two-Way Fixed Effects Average Treatment Effect on the Treated (ATT)			
Total paid workers	(-)**	(-)	(-)*
Average salary per worker	(+)***	(+)	(+)
Contract labor expense	(+)**	(+)	(+)**
Hired labor expense per cow	(+)	(+)	(+)**
Observations	~21,000	~22,000	~20,000

Notes: Covariates include in panel B include scale categories 10-499, 500-999, and 1,000 or more dairy cows. Source: U.S. Department of Agriculture, National Agricultural Statistics Service (USDA NASS), 2012, 2017, 2022 Census of Agriculture, calculated by the author using restricted access data. Panel A is estimated using the *fixest* package in R (Berge et al., 2024) and panel B is estimated using the DRDID package in R (Sant'Anna & Zhao (2020). Standard errors are clustered at the state-level.

[19] In the TWFE model, we only use data from 2017 and 2022, data from 2012 is used to address the assumption of parallel trends.

7. DISCUSSION AND CONCLUSIONS

This paper provides the first causal estimates of the effects of state-level farmworker overtime laws on dairy farm labor usage, wages, and employment outcomes. Drawing on multiple datasets—including the USDA Census of Agriculture and the American Community Survey—and applying recent advances in DID estimation, we find consistent evidence that overtime mandates altered the allocation of labor on dairy farms, though the magnitude and direction of these changes varied by state and policy design.

Across California, Washington, and New York, overtime laws generally reduced the number of hired workers per farm and curtailed weekly hours worked by individual employees, while increasing average wages for those who remained employed. The findings are most consistent with Equilibrium Hypotheses 2 and 3: overtime thresholds constrained optimal hours for dairy farms, and limited availability of qualified dairy labor restricted farms' ability to substitute by hiring additional workers. The resulting adjustments—higher per-worker pay, increased hired labor expense per cow, and greater reliance on contract labor—suggest that the laws raised labor costs for surviving operations. At the same time, our analysis finds little evidence that the laws directly accelerated dairy farm exit during the study period, though higher baseline exit rates in treated states complicate interpretation.

The results also underscore important heterogeneity in policy impacts. States with lower overtime thresholds (e.g., Washington's 40-hour cap) experienced larger cost increases and greater reductions in worker counts than states with higher thresholds (e.g., New York's 60-hour cap during the study period). These differences highlight the role of policy design and implementation timelines in shaping economic outcomes for both employers and employees.

From a policy perspective, our findings suggest that while farmworker overtime laws can raise hourly pay for dairy workers, they also incentivize reductions in hours worked. For labor-intensive, non-seasonal sectors such as dairy, limited access to H-2A workers and year-round production requirements constrain substitution margins, potentially amplifying cost pressures. Future research should examine longer-term effects, including technology adoption, shifts in production practices, and impacts on worker well-being, as more states implement and phase in overtime requirements.

In sum, overtime regulations in agriculture achieve at least part of their intended objective—raising pay for many farmworkers—but also trigger adjustments that can limit gains and reshape labor demand. Understanding these tradeoffs is important for designing labor policies that balance farmworker protections with the economic sustainability of U.S. dairy production.

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JOSE MARTINEZ-CUEVAS and PATRICIA AGUILAR, Individually and on Behalf of All Others Similarly Situated, Petitioners, v. DERUYTER BROTHERS DAIRY, INC., GENEVA S. DERUYTER, and JACOBUS N. DERUYTER, Respondents, and WASHINGTON STATE DAIRY FEDERATION and WASHINGTON FARM BUREAU, Intervenor-Respondents., 16-2-03417-8 (Supreme Court of Washington, En Banc. 2020). https://scholar.google.com/scholar_case?case=7147007640143858482&q=Martinez-Cuevas+v.+DeRuyter+Bros.+Dairy,+Inc&hl=en&as_sdt=6,48&as_vis=1

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