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Since 2015, several sizable jurisdictions have implemented predictive scheduling laws where the intent is to regulate unpredictable work schedules – schedules which may affect the ability of workers to arrange child care, care for other family members, or attend school. These laws raise the cost to employer of adjusting a worker's schedule near to the time of work. Such laws were phased in over time, and specifically targeted workers in the retail and food services industries, but largely not other industries. When labor costs are increased for cancelling shifts if demand turns out to be low, one potential employer response is to not schedule as many workers for uncertain periods of demand. Using a difference-in-differences (DD) framework (based on geography and time within affected industries) and the 2014-2020 March Current Population Survey (CPS), I find that among workers, the composition of employees working part-time increased by approximately 9.2 percentage points. Approximately two-thirds of this shift – 6.3 percentage points – comes from those reporting to be part-time involuntarily (e.g., due to economic reasons, such as "slack work", "unfavorable business conditions", "inability to find full-time work" and "seasonal declines in demand"). Very little of the shift is explained by non-economic reasons (such as "childcare problems", "family or personal obligations", or "in school or training"). As such, it appears that predictive scheduling laws failed to provide some of the key anticipated benefits, while limiting opportunities for at least some workers.

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1. Introduction

Alternative work arrangements have grown significantly over the last several decades (Katz and Krueger, 2019), and recent work has shown that in some circumstances workers value that scheduling flexibility relative to less-flexible arrangements (Chen, et al., 2019). At the same time, a recent development in labor market regulation are laws related to “fair scheduling.” San Francisco enacted the first law related to scheduling in 2015, and several other large cities or states have followed suit. Unlike other workplace mandates – such as minimum wages, paid sick leave, or health insurance – which generally increase the cost of low-wage workers for all hours that they work, these scheduling laws essentially penalize schedule changes, but impose no penalty on employers with static work schedules.

To date, most of the analysis of scheduling laws has been prospective or experimental. Yelowitz and Corder (2016) find that there were few part-time workers in San Francisco who were working that schedule involuntarily (just one in seven) and most were working part time voluntarily. A key premise in San Francisco’s law is that part-time workers were plagued by insufficient hours, and a critical, untested assumption is that work scheduling laws would fix that problem. The same study – surveying 52 employers – found that one key response to such laws would be scheduling *fewer* employees per shift. The same motivations were found in Washington, D.C.’s attempted legislation where advocates argued the law was necessary to promote full time work, stating that workers “struggle with low wages, too few hours, and fluctuating hours.” (Corder and Yelowitz, 2016). In Washington, D.C., half of the 100 employers surveyed stated that they would schedule fewer employees per shift. In a recent field experiment, Mas and Pallais (2017) find that workers are willing to give up 20 percent of wages to avoid a schedule set by an employer on a week's notice, but that this largely represents workers' aversion to evening and weekend work, not scheduling unpredictability.

Predictive scheduling laws – enacted in five jurisdictions by early 2020 – raise the costs of changing a worker's schedule. They narrowly target several industries (primarily retail and food services), require written schedules well in advance of a worker's shift, and impose additional costs for either cancelling or adding worker's hours on short notice. Although there are a variety of possible employer responses – for example, employers surveyed in Corder and Yelowitz (2016) noted they may "offer employees less flexibility to make schedule changes," "offer fewer part-time positions," "change the hiring composition of full-time vs. part-time employees," "offer fewer jobs across the board," "schedule fewer employees per shift," and "reduce customer service," ultimately examining actual employment patterns sheds the most light on actual impacts.

This study examines several of the potential responses to these laws, using workers in affected industries, in geographic areas subject to fair scheduling or not, both pre- and post-implementation. Some of the key arguments made by proponents for fair scheduling – such as fair scheduling laws reducing the rate of involuntary part-time employment – are not borne out in the data; indeed, such laws led to a shift toward part-time employment, primarily driven by workers who wanted to work full-time. This response is consistent with the employer motive of "scheduling fewer employees per shift" from Corder and Yelowitz (2016); when demand is difficult to forecast far in advance, employers may become more conservative in scheduling worker shifts, which would lead to the patterns found here.

2. Data and Empirical Specification

Worker Outcomes: Part-Time Employment and Associated Reasons

The analysis relies on the 2014 to 2020 March Current Population Survey (CPS) Annual Social and Economic Supplement (ASEC). The CPS is chosen because it asks about full-time and part-time work, and also reasons for part-time work for the reference week. Predictive scheduling laws may increase part-time work for reasons on both the employer-side and employee-side; as a consequence, the CPS allows the opportunity to explore both *whether* and *why* a shift towards or away from part-time work occurs.

The first set of reasons include "economic reasons," and in this context with predictive scheduling laws can be viewed as an employer response to uncertain demand since the part-time work is involuntary from the worker's point of view. The reasons include: unfavorable business conditions, inability to find full-time work, and seasonal declines in demand. The U.S. Bureau of Labor Statistics notes that "People who usually work part time and were at work part time during the reference week must indicate that they want and are available for full-time work to be classified as part time for economic reasons."[1] A second set of reasons include "noneconomic reasons," and predictive scheduling laws can be viewed as enabling employees to achieve a better "work-life" balance. For such employees, predictive scheduling laws may ensure not being scheduled for shifts that would interfere with other obligations. The key,

[1] Although each of these employer responses leads to involuntary part-time work for employees, the key issue with respect to scheduling laws is the *volatility* of demand. Anticipated changes in business conditions even if unfavorable or seasonal – such as an ice cream store selling less product in the winter – should be accounted for in normal workplace scheduling (and thus, should not raise labor costs). However, an unanticipated warm day during the winter could lead to a surge in demand for ice cream, and such scheduling laws would impose a penalty on adjusting schedules by calling a worker in.

ongoing reasons for part-time work include childcare problems/family or personal obligations, and schooling/training. In addition, workers may also report illness or other health or medical limitations, retirement or Social Security limits on earnings, or having a job where full-time work is less than 35 hours.

Policy Variable: Predictive Scheduling Laws

In the 2014-2020 period examined, four large jurisdictions (and one small one) implemented predictive scheduling laws (with several additional laws planned for Chicago, IL and Philadelphia, PA). The large jurisdictions include San Francisco, CA (implemented 2015), New York, NY (implemented 2017), Oregon (implemented 2017) and Seattle, WA (implemented 2017). Emeryville, CA (part of Alameda County) is part of the San Francisco/Oakland/Hayward metro area and its 2018 predictive scheduling law is not separately considered.

Although the nuances of the laws vary from one jurisdiction to another, they have several common threads. First, they explicitly target the retail and food services industries (and occasionally some others).[2] In the CPS, such industries will be characterized by the NAICS two-digit codes 44-45 (retail trade) and 72 (accommodation and food services). In San Francisco, affected businesses include bars, restaurants, liquor stores, sales and service providers (including banks and other financial institutions) and take-out food shops. In New York, affected businesses include fast-food employers and retail employers engaged "primarily in the sale of consumer goods." In Oregon, employers in the retail, hospitality, and food service industries are included. And in Seattle, WA, retail and food service establishments are included. Generally

[2] https://www.hrdive.com/news/a-running-list-of-states-and-localities-with-predictive-scheduling-mandates/540835/

speaking, characterizing an industry as "treated" based on the two-digit NAICS code is quite reasonable. In a report produced by the City of San Francisco in 2014 (see Figure V-3 on page 59), affected industries were documented at the four-digit level of granularity (and included the two-digit codes 44, 45, 72, and also specific to San Francisco, NAICS code 52 for financial services).[3] To assess the reasonableness of the approach in this study, we compared private employment for all four-digit subindustry NAICS codes subsumed in those two-digit codes using annual data from 2014 from the Quarterly Census of Employment and Wages (QCEW) for the entire United States.[4] Overall, there were 27 four-digit NAICS codes in retail trade (NAICS 44-45) and 6 four-digit NAICS codes in accommodation and food services (NAICS 72) from the QCEW.[5] Based on the four-digit NAICS codes provided in the San Francisco report, approximately 96 percent of employment in retail trade would be covered by the law, and 85 percent of employment in accommodation and food services. Second, such laws have size thresholds, with the intent of targeting large establishments and chains, rather than "mom and pop" stores. For example, in San Francisco the law targets businesses with at least 40 retail

[3] https://default.sfplanning.org/legislative_changes/form_retail/Final_Formula_Retail_Report_06-06-14.pdf
[4] https://www.bls.gov/cew/downloadable-data-files.htm
[5] For NAICS code 44-45, this includes: Automobile dealers NAICS code 4411, Other motor vehicle dealers NAICS code 4412, Auto parts, accessories, and tire stores NAICS code 4413, Furniture stores NAICS code 4421, Home furnishings stores NAICS code 4422, Electronics and appliance stores NAICS code 4431, Building material and supplies dealers NAICS code 4441, Lawn and garden equipment and supplies stores NAICS code 4442, Grocery stores NAICS code 4451, Specialty food stores NAICS code 4452, Beer, wine, and liquor stores NAICS code 4453, Health and personal care stores NAICS code 4461, Gasoline stations NAICS code 4471, Clothing stores NAICS code 4481, Shoe stores NAICS code 4482, Jewelry, luggage, and leather goods stores NAICS code 4483, Sporting goods and musical instrument stores NAICS code 4511, Book, periodical, and music stores NAICS code 4512, Department stores NAICS code 4521, Other general merchandise stores NAICS code 4529, Florists NAICS code 4531, Office supplies, stationery, and gift stores NAICS code 4532, Used merchandise stores NAICS code 4533, Other miscellaneous store retailers NAICS code 4539, Electronic shopping and mail-order houses NAICS code 4541, Vending machine operators NAICS code 4542, and Direct selling establishments NAICS code 4543. For NAICS code 72, this includes: Traveler accommodation NAICS code 7211, Rv parks and recreational camps NAICS code 7212, Rooming and boarding houses NAICS code 7213, Special food services NAICS code 7223, Drinking places, alcoholic beverages NAICS code 7224, and Restaurants NAICS code 7225.

sales establishments worldwide, while in Oregon, worldwide employment must be at least 500 employees. Tabulations of the CPS from 2014 (prior to these laws) show that in these affected industries, approximately half of all workers worked for large employers. In some specifications, we will examine effects only on employees in large firms. Third, the laws require large companies provide work schedules well in advance (often 7 to 14 days), provide good faith written estimates on work schedules, and imposes surcharges for unanticipated shifts (such as time-and-a-half rate for unpredictable shifts), being on-call, or changing a schedule.

CPS Extract

From the March 2014-2020 CPS, all workers from the San Francisco CBSA, New York CBSA, Seattle CBSA, and Oregon were extracted (and a subset of potentially affected workers will be part of the "treatment group"); in addition other workers from California, New York, and Washington were extracted (and will be part of the "control group"). Note that the New York CBSA also includes part of New Jersey. Given the need to understand reasons for part-time work, non-workers were excluded from the analysis. Workers with imputed values on key employment outcomes or demographics were also excluded. With these restrictions, there were 6,912 unweighted observations across the retail trade, accommodation and food services industries (3 two-digit NAICS codes). For some placebo test specifications, we also extracted 37,036 workers in other industries (21 two-digit NAICS codes).

Workers were classified into 24 different two-digit NAICS industry codes; approximately 16 percent were in an affected industry (retail trade or accommodation and food services). An individual's socioeconomic and demographic variables (including age, marital status, gender, race/ethnicity, educational attainment, military service, citizenship, mover, disability, and own children) are also included in each specification. Specifications control for state or local minimum wage ordinances (which vary by geographic unit and time).

Difference-in-differences Empirical Specification

The framework outline above provides a difference-in-differences (DD) specification, where the treatment group consists of workers in an affected geographic unit (San Francisco, New York, Seattle, or Oregon) and affected time period (varies depending on geographic unit), within the impacted industries of retail trade, accommodation and food services. Other industries are used as a placebo test, rather than a difference-in-difference-in-differences specification for two primary reasons. First, there might be spillover effects of predictive scheduling laws on low-wage industries that are not covered by the law. Such spillovers most plausibly come from the demand-side of the labor market. For instance, if employers in affected industries cut work hours to employees in response to uncertainty in demand for work hours over time, employees might respond by taking up part-time work in "untreated" low-wage industries; this would bias the estimated treatment effects. Alternatively, if employers in affected industries face a negative income shock from hours reductions, the demand for goods and services produced in "untreated" industries could affect employment there.

The CPS questions on part-time work and associated reasons refer to the reference week in March of the current year; the fraction of the year that the predictive scheduling law was in effect in the prior year is used in the parameterization (for example, San Francisco's law – effective July 2015 – would be coded as 0 for March 2014 and 2015, 0.5 for March 2016, and 1 for March 2017 and beyond). The specifications take the following form for a linear probability model:

$$(1) \qquad PARTTIME_{ijt} = \beta_0 + \beta_1 TREATMENT_{ijt} + \beta_2 GEOG_j + \beta_3 YEAR_t + \beta_4 X_i + \beta_5 MINWAGE_{jt} + \varepsilon_{ijt}$$

Where $PARTTIME_{ijt}$ indicates whether the individual worker *i*, in geographic unit *j*, in time period *t*, works part-time (versus full-time); in other specifications it represents the specific reason for part-time work (e.g., involuntary economic reasons, relative to not having that reason or being full-time). The key coefficient is the estimate of β_1, where $TREATMENT_{ijt}$ indicates the fraction of the prior year for which the worker would have been affected by the predictive scheduling law; it will generally be 0 or 1 except when a law was implemented part-way through a given year. The main effects for $GEOG_j$ and $YEAR_t$ are used; here geography is more delineated into 57 areas (mostly representing CBSAs within each of the states). Since the laws were staggered, there is not one single post-period; as a result, $YEAR_t$ represents individual years. The specification also includes the real, local minimum wage ($MINWAGE_{jt}$) which may affect work scheduling (Clemens and Strain, 2020). Individual observations are weighted using March supplemental weights, and robust standard errors are clustered at the state-level.

3. Results

The sample draws upon six years of the March CPS. The full sample (all industries) includes nearly 44,000 workers, and when weighted, represents approximately 15 million workers in each year. Table 1 provides summary statistics. Among all workers, the composition of part-time work declined slightly over this period from 19.1 percent in March 2014 to 17.8 percent in

March 2020; presumably other trends, such as robust economic growth until the pandemic, account for some of this shift. Consistent with more overall opportunity, there was a secular decline in involuntary part-time work, with the fraction of respondents reporting that reason falling from 5.2 percent to 2.4 percent. There are also modest declines in part-time work related to schooling or child care/family obligations.

Within the sample (essentially California, New York, Washington, and Oregon), several large jurisdictions ultimately passed predictive scheduling laws, so approximately 45 percent of all workers are in a geographic area with such laws. Given that the laws primarily targeted retail and food services, roughly 15 percent of workers were in an affected industry. Overall, the fraction of all workers affected reaches 6 percent of the sample by March 2020. Roughly half of all workers – and the same is true within the affected industries – work in very large firms (500 or more employees) and are likely subject to the regulations. Over the same time, different localities (CBSAs) and states raised minimum wages over this period; the impacts of minimum wage policy are separately controlled for (but insignificant in the part-time work specifications). The table also displays various demographics that are included in the analysis; overall, these demographics remain very stable over the period.

Difference-in-difference results are presented in Table 2 for various work outcomes. All specifications include socioeconomic and demographic variables and controls for the relevant local minimum wage. Columns (1), (5), (9), and (13) present the main specification for part-time work and potential reasons associated with it. We observe that predictive scheduling laws significantly increase the likelihood of part-time work by 9.2 percentage points among workers. Two key “work-life” reasons – enrollment in school and childcare/family obligations – do not significantly contribute to this shift, nor do they explain a substantive part of the shift (both coefficients are approximately one percentage point). In contrast, workers reporting part-time work for involuntary (economic reasons) increases by 6.3 percentage points, explaining a relatively large share of the change. Taken together, it appears that employer responses – consistent with limiting worker shifts when demand might be slack – are an important effect to the legislatively-imposed increased costs to having flexible schedules.

Several robustness checks are explored in Table 2, modifying the initial DD specification. First, we explore the geographic classifications in the CPS in columns (2), (6), (10), and (14). The CPS provides geographic identifiers of where people live, not where they work. The state of residence is provided for all respondents, and approximately 80 percent of the full sample can be identified within a metro area (CBSA, or "Core Based Statistical Area"). Within CBSAs, the CPS further identifies principal cities (e.g., separately identifying San Francisco from Oakland, Fremont, Hayward, and Berkeley) where a respondent may live. One may expect that some individuals that live within the CBSA but outside of the central city may commute (and therefore be subject to work scheduling laws), but overall, it is likely that individuals who reside within the central city are more likely to work there. This specification re-estimates the DD model, excluding individuals who live in the periphery of affected metro areas, leaving a sample of 5,306 workers in affected industries. As expected, the results for this more targeted group where the laws are likely to be more binding are larger than the initial specification. The shift to part-time work is now 10.3 percentage points rather than 9.2 percentage points. There continues to be no significant or substantive impact on part-time work for non-economic reasons. And now, the impact on involuntary part-time work from the laws is 7.2 percentage points.

Overall, when focused on the geographic areas most affected by the laws, the estimates strongly reinforce the basic results. It is important to emphasize that this stronger finding does not lead to different conclusions about broad geographic scheduling laws (e.g., the entire state of Oregon) versus narrow ones (e.g., the city of San Francisco within a larger metro area). Rather, most survey data – such as the CPS – provides geographic information on where people live, not where they work, yet to proceed with the empirical analysis and assign a worker as being “treated” by the law, one must assume that the individual works in the same area that they live. Given that a greater fraction of workers commute from outside a narrow political boundary within a metro area (e.g., commuting into San Francisco) than workers who commute across state lines, then for equally binding laws and similar labor market conditions, we would expect broad geographic laws to have stronger effects because more of the workers who are assigned as “treated” really are subject to the law.

Second, we explore the sensitivity to firm size, since the laws targeted larger firms and chains within retail and food services. The CPS asks respondents “Counting all locations where this employer operates, what is the total number of persons who work for ...’s employer?” with groupings from 1-9, 10-49, 50-99, 100-499, 500-999, and 1000-plus employees. Although the laws often specify number of establishments worldwide rather than total employment (e.g., San Francisco’s law specifies 40 establishments worldwide), firm size is highly correlated with being subject to the scheduling law. Columns (3), (7), (11), and (15) restrict the sample to workers who report firm sizes of 500 or more employees; the unweighted sample size is 3,568 workers. The impact on part-time work is now a shift of 7.6 percentage points (rather than 9.2 percentage points), while the effect on involuntary part-time work is now 7.3 percentage points (rather than 6.3 percentage points). The interpretation here is more nuanced. It is clear that such scheduling laws impact part-time work at large firms, yet the smaller estimated effect on part-time work suggests an impact as well on workers in firms with less than 500 employees. One interpretation is simply that the firm size variable reported in the CPS is only a rough proxy for impacted firms (either because of the laws counting number of establishments, or because respondents give poorly measured answers to firm size); as a consequence, such workers are actually "treated." Another plausible explanation is that there are spillovers within these industries. When larger retail or food chains are legislated to alter their compensation package by changing work scheduling, smaller (untreated) firms in the same industry must respond to compete for workers. If this is correct, using these "untreated" workers in low-wage industries as a control group would bias estimated effects toward zero.

Third, we explore whether the responses differ with the inclusion of March 2020 CPS, when the coronavirus pandemic initially started and had unprecedented short-run disruption on the labor market. In columns (4), (8), (12), and (16), we exclude the final year of the sample (March 2020), reducing the sample size to 6,028 unweighted observations. The shift to part-time work is now 9.1 percentage points, virtually unchanged from the initial specification. The amount of part-time work due to involuntary reasons increases to 8.0 percentage points, somewhat higher than the 6.3 percentage points in the initial specification. As before, neither schooling nor family reasons are important factors. Thus, the overall shift to part-time work does not appear sensitive to the onset of the pandemic.

Table 3 explores an important placebo test – whether predictive scheduling laws impact *untargeted* industries. With one notable exception (San Francisco targeting financial firms), all of the scheduling laws affect chains in retail or food and accommodation services. Thus, there is little reason to think such laws would affect workers in other industries (the 21 two-digit NAICS codes outside of those targeted). This table examines 37,036 workers in other industries, and finds both substantive small and statistically insignificant effects of the laws. For example, there is a small, insignificant shift *away* from part-time work in these other industries of 1.3 percentage points, which strongly contrasts the significant shift towards part-time work in the impacted industries. The associated reasons are also all insignificant and small.

4. Conclusions

Predictive scheduling laws operate differently from other compensation mandates like minimum wage laws, paid sick leave mandates, and health insurance mandates. They penalize flexibility, which matters when demand may be unpredictable. Although there are many possible behavioral responses, a likely one is a reluctance by employers to schedule and commit workers to shifts where demand may be low. Put differently, firms may "play it safe", and if demand is actually high, simply provide lower quality service or have the workers on shift exert more effort. One way this may show up is less full-time work, more part-time work, and greater latent desire on the part of workers to work more hours. Such responses are consistent with the CPS analysis in this study.

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Table 1: Summary Statistics from March CPS (weighted)							
	3/2014	3/2015	3/2016	3/2017	3/2018	3/2019	3/2020
Part Time	0.191	0.183	0.189	0.181	0.177	0.172	0.178
	(0.393)	(0.387)	(0.392)	(0.385)	(0.381)	(0.378)	(0.382)
PT:	0.052	0.037	0.041	0.029	0.026	0.029	0.024
Involuntary	(0.221)	(0.189)	(0.199)	(0.169)	(0.16)	(0.167)	(0.154)
PT: School	0.035	0.034	0.034	0.033	0.033	0.032	0.028
	(0.183)	(0.182)	(0.18)	(0.179)	(0.178)	(0.177)	(0.166)
PT: Child	0.041	0.04	0.04	0.04	0.039	0.039	0.032
Care/Fam	(0.198)	(0.195)	(0.196)	(0.195)	(0.193)	(0.194)	(0.177)
Affected	0.416	0.441	0.436	0.435	0.436	0.444	0.456
Geography	(0.493)	(0.496)	(0.496)	(0.496)	(0.496)	(0.497)	(0.498)
Affected	0.17	0.163	0.166	0.162	0.143	0.145	0.151
Industry	(0.376)	(0.37)	(0.372)	(0.369)	(0.35)	(0.352)	(0.358)
Treatment	0	0	0.005	0.012	0.033	0.056	0.062
Group	(0)	(0)	(0.051)	(0.107)	(0.142)	(0.229)	(0.242)
Firm has 500+	0.463	0.481	0.504	0.496	0.502	0.502	0.499
employees	(0.499)	(0.5)	(0.5)	(0.5)	(0.5)	(0.5)	(0.5)
Real Min.	8.736	9.413	10.134	10.775	11.287	11.838	12.552
Wage	(0.693)	(0.554)	(1.059)	(1.343)	(1.741)	(1.626)	(1.251)
Age 16-24	0.101	0.093	0.089	0.091	0.078	0.088	0.084
	(0.301)	(0.29)	(0.284)	(0.288)	(0.269)	(0.283)	(0.277)
Age 35-44	0.225	0.221	0.221	0.228	0.229	0.232	0.229
	(0.418)	(0.415)	(0.415)	(0.419)	(0.42)	(0.422)	(0.42)
Age 45-54	0.232	0.236	0.234	0.209	0.205	0.219	0.202
	(0.422)	(0.425)	(0.423)	(0.407)	(0.404)	(0.414)	(0.402)
Age 55-64	0.169	0.176	0.178	0.179	0.183	0.17	0.177
	(0.375)	(0.381)	(0.382)	(0.384)	(0.387)	(0.376)	(0.381)
Age 65+	0.054	0.051	0.057	0.055	0.058	0.058	0.065
	(0.226)	(0.22)	(0.232)	(0.228)	(0.234)	(0.233)	(0.246)
Married	0.585	0.57	0.565	0.566	0.56	0.568	0.565
	(0.493)	(0.495)	(0.496)	(0.496)	(0.496)	(0.495)	(0.496)
Male	0.522	0.514	0.525	0.518	0.532	0.529	0.512
	(0.5)	(0.5)	(0.499)	(0.5)	(0.499)	(0.499)	(0.5)
Hispanic	0.183	0.173	0.175	0.189	0.173	0.171	0.175
	(0.386)	(0.379)	(0.38)	(0.392)	(0.378)	(0.376)	(0.38)
Black	0.057	0.071	0.068	0.06	0.064	0.067	0.075
	(0.233)	(0.256)	(0.252)	(0.237)	(0.245)	(0.251)	(0.264)
No Diploma	0.067	0.068	0.064	0.065	0.058	0.054	0.056
	(0.251)	(0.252)	(0.246)	(0.247)	(0.234)	(0.226)	(0.23)
HS Grad/GED	0.206	0.199	0.192	0.197	0.175	0.192	0.19
	(0.404)	(0.399)	(0.394)	(0.398)	(0.38)	(0.394)	(0.392)
Some College	0.291	0.29	0.29	0.284	0.269	0.278	0.267
	(0.454)	(0.454)	(0.454)	(0.451)	(0.444)	(0.448)	(0.442)
Military	0.053	0.05	0.051	0.043	0.045	0.046	0.042
Service	(0.225)	(0.217)	(0.22)	(0.203)	(0.207)	(0.208)	(0.2)
Non-citizen	0.105	0.1	0.112	0.109	0.099	0.102	0.096
	(0.307)	(0.3)	(0.315)	(0.312)	(0.299)	(0.303)	(0.294)
Mover	0.111	0.114	0.113	0.116	0.105	0.108	0.098
	(0.314)	(0.318)	(0.317)	(0.32)	(0.306)	(0.31)	(0.297)
Disabled	0.017	0.029	0.029	0.034	0.025	0.027	0.032
	(0.128)	(0.169)	(0.168)	(0.181)	(0.157)	(0.161)	(0.175)

Own children under 6	0.198 (0.507)	0.195 (0.514)	0.183 (0.493)	0.191 (0.506)	0.183 (0.488)	0.198 (0.519)	0.186 (0.496)
Own Children under 18	0.65 (0.994)	0.648 (0.995)	0.639 (0.993)	0.606 (0.973)	0.607 (0.98)	0.633 (0.995)	0.604 (0.985)
Unweighted N	5,324	6,696	6,492	6,876	6,271	6,481	5,808
Weighted N	15.15m	14.09m	14.86m	15.72m	14.93m	14.82m	15.06m

Notes: Sample drawn from March 2014-March 2020 Current Population Survey. Table presents mean values for each variable, with standard deviation in parentheses. March supplemental weights used. Geography is restricted to workers in California, New York, Washington, Oregon, and associated CBSAs that enacted predictive scheduling laws. Individuals with imputed values on key labor market variables or demographics were excluded.

Table 2: Difference-in-differences models of predictive scheduling laws on part-time work outcomes

	Part-time work				PT: School				PT: Child care or family				PT: Involuntary			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
Treatment	0.092[a]	0.103[b]	0.076[b]	0.091[b]	0.008	-0.002	0.006	-0.012	0.013	0.003	0.002	0.021	0.063[a]	0.072[a]	0.073[b]	0.080[a]
	(0.026)	(0.037)	(0.028)	(0.028)	(0.015)	(0.020)	(0.018)	(0.018)	(0.010)	(0.018)	(0.015)	(0.012)	(0.013)	(0.017)	(0.027)	(0.020)
Exclude periphery	No	Yes	No	No	No	Yes	No	No	No	Yes	No	No	No	Yes	No	No
Large firms only?	No	No	Yes	No	No	No	Yes	No	No	No	Yes	No	No	No	Yes	No
Exclude 3/2020?	No	No	No	Yes	No	No	No	Yes	No	No	No	Yes	No	No	No	Yes
Unweighted N	6,912	5,306	3,568	6,028	6,912	5,306	3,568	6,028	6,912	5,306	3,568	6,028	6,912	5,306	3,568	6,028

Notes: Sample drawn from March 2014-March 2020 Current Population Survey. All specifications include individual characteristics and control for relevant geographic minimum wage. In addition, all specifications include main effects for geography (57 units) and year (7 periods). Sample is workers in accommodation and food services and retail industries. All models run as linear probability models with March supplemental weights, with robust standard errors clustered at the state level.

a=p<0.01, b=p<0.05, c=p<0.10.

Table 3: Placebo test on unaffected industries

	Part-time work	PT: School	PT: Child care or family	PT: Involuntary
	(1)	(2)	(3)	(4)
Treatment	-0.013	0.005	-0.007	0.007
	(0.008)	(0.003)	(0.005)	(0.004)
Exclude periphery	No	No	No	No
Large firms only?	No	No	No	No
Exclude 3/2020?	No	No	No	No
Unweighted N	37,036	37,036	37,036	37,036

Notes: Sample drawn from March 2014-March 2020 Current Population Survey. All specifications include individual characteristics and control for relevant geographic minimum wage. In addition, all specifications include main effects for geography (57 units) and year (7 periods). Sample is workers *not* in accommodation and food services and retail industries. All models run as linear probability models with March supplemental weights, with robust standard errors clustered at the state level.

a=p<0.01, b=p<0.05, c=p<0.10.