Online Appendix for When Gig Workers No Longer Gig: The Impact of California Assembly Bill 5 on the Online Labor Market

Online Appendix A: The enforcement of AB5

It is important to establish that AB5 has a direct impact on workers. We provide evidence of this from several perspectives:

1. **We should first understand how the law defines who can be classified as contractors and what the ABC test is.**

   Based on the California Labor and Workforce Development Agency (https://www.labor.ca.gov/employmentstatus/ABCTest/), under the ABC test, a worker is considered an employee and not an independent contractor unless the hiring entity satisfies all three of the following conditions:

   a. The worker is free from the control and direction of the hiring entity in connection with the performance of the work, both under the contract for the performance of the work and, in fact;

   b. The worker performs work that is outside the usual course of the hiring entity's business; and

   c. The worker is customarily engaged in an independently established trade, occupation, or business of the same nature as that involved in the work performed.

   The application of these criteria is rigorous, as illustrated by examples provided by the California Labor and Workforce Development Agency. For instance,

   A) the Agency notes that work-at-home knitters and sewers producing clothing for a company were deemed employees because "the degree of control and direction over the production … is no different when the sweater is knitted at home at midnight than if it were produced between nine and five in a factory." Similarly, remote programmers or analysts on platforms like Upwork may be subject to comparable control and direction, regardless of whether they work from home or on-site. Factors such as deadlines, project guidelines, and deliverable expectations could signify control analogous to that exercised over employees.

B) a 2022 Upwork study involving over 1,000 U.S. hiring managers highlights that U.S. businesses increasingly rely on independent talent to meet their workforce needs. 60% of hiring managers participating in the study indicate that they face challenges finding quality talent, leading them to incorporate independent professionals into their core workforce strategy. This reliance on independent talent to perform essential business functions aligns with the second criterion of the ABC test, which specifies that workers performing duties central to the hiring entity's business are employees.

C) the third prong of the ABC test requires that workers engage in an independently established trade or business, as evidenced by incorporation, licensure, advertisements, or other indicators of independence. On platforms like Upwork, there is no evidence suggesting that most workers operate as incorporated entities or maintain such independence.

The takeaway from those examples is that the ABC test imposes strict requirements to classify a worker as an independent contractor, and all three criteria must be satisfied. Given the nature of work performed through platforms like Upwork, workers are likely to fall within the scope of AB5 and be classified as employees rather than independent contractors. This interpretation underscores the law's emphasis on protecting workers from misclassification.

2. **Penalty of AB5 violation.**

As detailed in Point 1, it is highly likely that, based on the definition of the law, a majority of gig workers on Upwork meet the criteria for classification as employees. Under Labor Code Section 226.8, which prohibits the willful misclassification of individuals as independent contractors, civil penalties range from $5,000 to $25,000 per violation. It is unlikely that rational employers would take on the financial and reputational risks associated with knowingly violating AB5.

3. **The impact of AB5 on various industries and exemptions.**

AB5 has had a widespread impact on millions of independent contractors across various industries. Due to this extensive impact, it prompted swift and coordinated lobbying efforts. As a result, Assembly Bill 2257 was signed into law, expanding the list of exemptions to include

professionals such as artists, musicians, photographers, translators, and others. Another notable amendment to the law is Proposition 22, which allows rideshare and delivery companies to continue classifying their drivers as independent contractors. Instead of the full benefits and protections afforded to employees, the proposition offers a wage floor, accident insurance, and healthcare subsidies for drivers who work at least 15 hours per week. These ongoing modifications to the law underscore the significant and far-reaching impact of AB5 on various industries, businesses, and individuals.

4. **AB5 presumes that workers are employees, and the burden of proof that a worker should be classified as an independent contractor belongs to the hiring entity.**

In the 2020 (and subsequent years) annual report of upwork.com,[1] the Risk Factors section highlighted the risk of worker misclassification (p. 24): "*There may be adverse tax, legal, and other consequences if the contractor classification or employment status of freelancers that use our work marketplace is challenged.*" More specifically, "*A misclassification determination, allegation, claim, or audit creates potential exposure for users and for us, including but not limited to reputational harm and monetary exposure arising from or relating to failure to withhold and remit taxes, unpaid wages, and wage and hour laws and requirements (such as those pertaining to minimum wage and overtime); claims for employee benefits, social security contributions, and workers' compensation and unemployment insurance; claims of discrimination, harassment, and retaliation under civil rights laws; claims under laws pertaining to unionizing, collective bargaining, and other concerted activity; and other claims, charges, or other proceedings under laws and regulations applicable to employers and employees, including risks relating to allegations of joint employer liability. Such claims could result in monetary damages (including but not limited to wage-based damages or restitution, compensatory damages, liquidated damages, and punitive damages), interest, fines, penalties, costs, fees*

[1] https://investors.upwork.com/static-files/3e32780b-95da-429b-9f36-22b5e508d6f7 (last accessed on September 23, 2025).

(including but not limited to attorneys' fees), criminal and other liability, assessment, injunctive relief, or settlement."

To help employers mitigate these risks, upwork.com has provided a service called "Upwork payroll", "*For clients that subscribe to this service, subject to applicable law and the terms of our agreement with the client, we identify clients from misclassification risk and make warranties to the client, such as to compliance with applicable laws.*" These declarations from the annual reports of upwork.com confirm the impact of worker classification laws on the platform.

Based on all the evidence, it is clear that the law enforcement department and the platform (Upwork) have made their maximum efforts to ensure that AB5 is enforced in California.

Online Appendix B: Potential Spillover Effect of AB5

We leverage a natural experiment setting to explore the impact of AB5 on California workers compared to those from other states before and after AB5 took effect. In this setting, we consider California as the treatment group and other states as the control group. One may argue that after AB5 was implemented in California, due to the rising cost of employing workers there, employers could turn to other states for recruitment; thus, the treatment might also impact the control group, which could potentially violate the Stable Unit Treatment Value Assumption (SUTVA). We argue that this will not be of concern to this study from three aspects.

First, assuming there is a spillover effect and employers recruit from other states, job demands will increase in other states and will decrease in California. If the job supply holds constant, there will be a rise in earnings in other states and a decline in earnings in California. However, with the hypothetical existence of the spillover effect, we found that AB5 leads to higher earnings in California compared to other states. Therefore, our results are rather conservative when taking the spillover effect into account. If there is no spillover effect, we would find an even larger positive effect of AB5 on earnings in California. In other words, the direction of the effect will not change with or without the spillover effect, and if there is any, our findings are underestimating the positive impact of AB5 on earnings.

Second, to support the above rationale, we conduct a robustness analysis in which we include only the top 15 states with the highest income (excluding New York and New Jersey from the list due to their announcement or proposal of similar laws).[2] The rationale is that if employers would like to recruit workers from other states to lower costs, they are more likely to recruit from states with lower wages. Therefore, by including only these "expensive" states, we are creating a relatively clean setup and minimizing any potential spillover effects. We report the results in Table D1, and they are consistent with our main results.

[2] https://en.wikipedia.org/wiki/List_of_U.S._states_and_territories_by_income (last accessed on September 23, 2025).

Table B1. Impact of AB5 on gig workers' monthly earnings in "expensive" states

Variable	DV = Log (Monthly Earnings)
Post × Treat	0.133* (0.05)
Unemployment Rate	-0.022 (0.011)
Median Income	0.0002 (0.000)
Population	0.000** (0.000)
Constant	2.974*** (0.57)
Month Fixed Effects	Yes
User Fixed Effects	Yes
No. of Observations	168,384
No. of Users	12.620

Notes: Cluster-robust standard errors in parentheses; $*$ p < 0.05; $**$ p < 0.01; $***$ p < 0.001

Third, to further empirically rule out the possibility that after the implementation of AB5, employers are inclined to hire fewer (or more) California workers by hiring more (or less) workers from other states, we collected another dataset that represents the employers on Upwork.com. With this data formed into an employer-month panel, we estimated a fixed-effect model. In other words, we aim to show that the observed change in earnings for California workers (treatment group) after the implementation of AB5 is not due to changes in worker demand in other states (control group). The specification of the analysis is as follows:

$$y_{jt} = \beta_1 \times Post_t + \beta_2 \times \mathrm{X}_{jt} + \delta_j + \varepsilon_{jt} \quad (3)$$

where y_{jt} is the ratio of hired California workers to the total number of hired workers by j, which denotes the employer. t denotes the month, and X_{jt} is a vector representing time-variant control variables, including the average ratings given by employers to workers, the average ratings given by workers to employers, and the average price of jobs offered by employers in the focal month. δ_j is the employer-fixed effect that captures the time-invariant characteristics of employer j, and ε_{jt} is the error term. The dummy variable Post equals one if month t occurs after the AB5 took effect, i.e., January 2020, and zero otherwise. We are interested in the estimated coefficient β1, which estimates the effect of AB5 on the ratio of California workers to all workers hired.

The results are reported in Table B2. Based on the results, there is no significant change in the ratio of California workers to all workers hired by employers, indicating there is no change in the hiring inclination of the employers post-AB5.

Table B2. Impact of AB5 on the ratio of CA workers to all hired

Variable	DV = Ratio of CA workers to all hired
Post × Treat	0.003(0.003)
Workers' Ratings	0.0004(0.001)
Employer's Ratings	0.0004(0.001)
Average Job Price	0.000(0.003)
Employer Fixed Effects	Yes
No. of Observations	165,811
No. of Users	79,445
Notes: Cluster-robust standard errors in parentheses; $*$ p < 0.1; $**$ p < 0.05; $***$ p < 0.01	

Next, we take the standpoint of the supply of the workers and carry out two additional analyses. Our aim is to show that the increase in the workers' supply in CA does not stem from the influx of workers from other states, nor from switching jobs within states from full-time employment to freelancing. Instead, we show that there was an increased engagement of the users who have already been on the platform.

1. No significant increase in new users in the CA

   For this analysis, we first trimmed our original dataset to only include the first month of a focal user who has ever had job records on the platform. For example, if user A started their job on the platform in Jan 2018, and has finished six other jobs (or however many) by Dec 2021, we only retain the month Jan 2018 for user A in our dataset to indicate that they were a new user of the platform in Jan 2018.

   Second, we collapse the dataset into city and month by counting the number of new users in a focal city and a focal month and we estimate the following Equation (4),

$$y_{jt} = \beta_1 \times Post_t \times Treat_j + \beta_2 \times \mathrm{X}_{jt} + \gamma_t + \delta_j + \varepsilon_{jt} \quad (4)$$

   where y_{jt} is the dependent variable, the number of new users in a focal city *j* and month *t*. X_{jt} is a vector representing the same set of control variables included in our main model. γ_t is the time-

fixed effect including a set of monthly time dummies that control for time trends, δ_j is the city-fixed effect that captures the time-invariant characteristics of city *j*, and ε_{jt} is the error term. The estimated results are presented in Table B3.

Table B3. Impact of AB5 on the number of new users

Variable	DV = log of # of new users
Post × Treat	-0.020 (0.022)
No. of Comments	0.001 (0.001)
Worker's Ratings	-0.006 (0.003)
Population	0.000 (0.000)
Median Income	0.000 (0.000)
Unemployment Rate	0.011* (0.005)
Month Fixed Effects	Yes
City Fixed Effects	Yes
No. of Observations	27,381
No. of Cities	8,972
R-squared	0.112
Notes: Cluster-robust standard errors in parentheses; $*$ p < 0.05; $**$ p < 0.01; $***$ p < 0.001	

As the results show, we see there is no significant difference between the number of new users in CA compared to those in other states.

A natural question to this finding will be, if the increase in supply did not come from new users, were there any changes in the activity level of the existing users? Our second analysis aims to answer this question by showing there was a significant increase in the engagement of the active users (i.e., those who are active both pre- and post-AB5 on the platform) in CA relative to other states.

2. A significant increase in active users in the CA.

   To conduct this analysis, we first trimmed our original dataset to only include the users who are active both pre- and post-AB5. Next, similar to the new user analysis, we collapse the dataset into city and month by counting the number of active users in a focal city and a focal month. We then estimated Equation (4) with y_{jt} being the number of active users in a focal city *j* and month *t*. The results reported in Table B4 show that for cities in CA, there was a significant increase in engagement (i.e., the number of active users) compared to that in other states.

Table B4. Impact of AB5 on the engagement of active users

Variable	DV = log # of new users
Post × Treat	0.026* (0.013)
No. of Comments	-0.000 (0.001)
Worker's Ratings	-0.001 (0.003)
Population	0.000 (0.000)
Median Income	0.000 (0.000)
Unemployment Rate	0.001 (0.002)
Month Fixed Effects	Yes
City Fixed Effects	Yes
No. of Observations	127,287
No. of Cities	4,527
R-squared	0.146

Notes: Cluster-robust standard errors in parentheses; $*$ $p < 0.05$; $**$ $p < 0.01$; $***$ $p < 0.001$

In sum, these two analyses collectively suggest that the increase in supply in CA is mainly due to the post-AB5 increased engagement of the users who have already joined the platform before AB5, and not because of the influx of new users who could move from other states or switched from full-time works within CA. Based on these findings, we are confident that the violation of SUTVA is not a serious concern in our research context.

Online Appendix C: Relative time model on the matched sample

Table C1. Relative time model on the matched sample

Variable	DV = Log (Monthly Earnings)
23 months until AB5	-0.065 (0.156)
22 months until AB5	0.013 (0.181)
21 months until AB5	-0.091 (0.180)
20 months until AB5	-0.022 (0.197)
19 months until AB5	-0.066 (0.175)
18 months until AB5	-0.024 (0.172)
17 months until AB5	0.052 (0.148)
16 months until AB5	0.013 (0.142)
15 months until AB5	-0.100 (0.127)
14 months until AB5	-0.113 (0.140)
13 months until AB5	-0.134 (0.118)
12 months until AB5	-0.293* (0.145)
11 months until AB5	-0.065 (0.115)
10 months until AB5	0.005 (0.116)
9 months until AB5	-0.092 (0.128)
8 months until AB5	-0.052 (0.099)
7 months until AB5	-0.050 (0.116)
6 months until AB5	-0.124 (0.099)
5 months until AB5	0.066 (0.102)
4 months until AB5	-0.011 (0.112)
3 months until AB5	-0.006 (0.107)
2 months until AB5	-0.167 (0.087)
1 month until AB5	-0.095 (0.087)
0 month since AB5	0.288*** (0.069)
1 month since AB5	0.279** (0.085)
2 months since AB5	0.320** (0.092)
3 months since AB5	0.368*** (0.099)
4 months since AB5	0.313** (0.108)
5 months since AB5	0.291** (0.102)
6 months since AB5	0.379*** (0.107)
7 months since AB5	0.380** (0.109)
8 months since AB5	0.512*** (0.094)
9 months since AB5	0.275** (0.095)
10 months since AB5	0.205 (0.103)
11 months since AB5	0.313* (0.126)
12 months since AB5	0.548*** (0.128)
13 months since AB5	0.649*** (0.130)
14 months since AB5	0.612*** (0.132)
15 months since AB5	0.668*** (0.138)
16 months since AB5	0.646*** (0.132)
17 months since AB5	0.788*** (0.147)
18 months since AB5	0.612*** (0.152)
19 months since AB5	0.665*** (0.165)
20 months since AB5	0.650** (0.190)

21 months since AB5	0.494* (0.189)
22 months since AB5	0.584** (0.191)
23 months since AB5	0.881*** (0.233)
No. of Comments	0.607*** (0.015)
Worker's Ratings	-0.077 (0.089)
Population	0.000*** (0.000)
Median Income	-0.000 (0.000)
Unemployment Rate	-0.042* (0.020)
Month Fixed Effects	Yes
Worker Fixed Effects	Yes
No. of Observations	19,170
No. of Users	1,017
R-squared	0.113

Notes: Cluster-robust standard errors in parentheses; $*$ $p < 0.05$; $**$ $p < 0.01$; $***$ $p < 0.001$

Online Appendix D: Random Implementation Test

The potential positive impact of AB5 on the monthly income of Upwork workers could simply be an outcome of *idiosyncratic* factors associated with California workers instead of AB5 itself. If so, the observed effect would be significant with any ordering of experiencing the treatment event (AB5) among the workers from California. To rule out this possibility, we conduct a random implementation test (Burtch et al. 2018, Cheng et al. 2020, Pamuru et al. 2021) to examine whether a *random implementation* of AB5 would produce an aggregate effect size comparable to the estimate in our main results.

We employ two strategies of *random implementation*. In the first strategy, we establish a false treatment variable by randomly shuffling the binary treatment indicator (i.e., *Post* AB5) across months for all workers. We then conduct a regression analysis with our dependent variable (monthly earnings) on this false treatment variable, with the same controls used in Equation (1), and record the coefficient of the false treatment variable. After executing this procedure 500 times, we generate Figure D1a, displaying the distribution of the false treatment variable's coefficients. The second strategy mirrors the first, but with the binary treatment indicator randomly reassigned exclusively to California workers, as shown in Figure D1b.

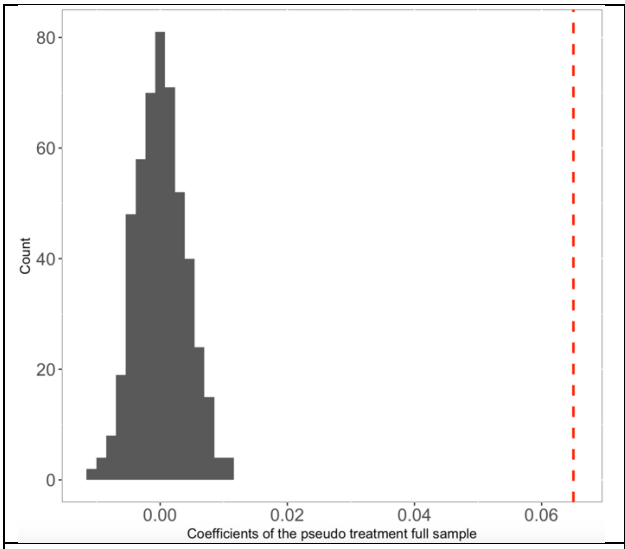

Figure D1a

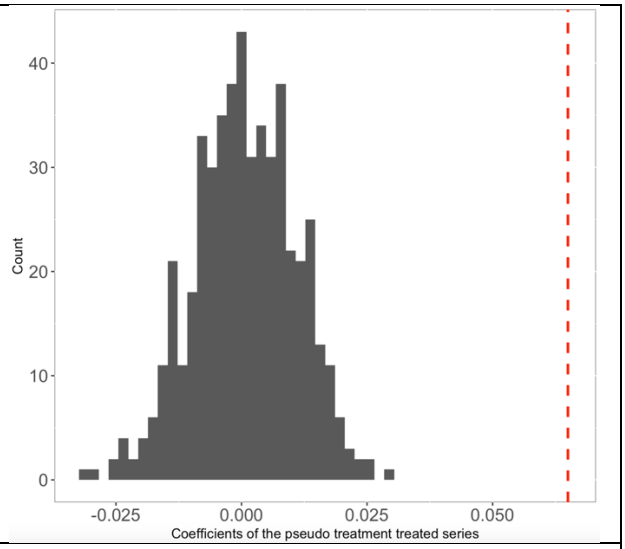

Figure D1b

Figure D1. The distribution of the false treatment variable's coefficients

Results in both Figure D1a and D1b augment the causal inference of AB5's positive effect on California Upwork workers' monthly income. First, the red vertical lines indicate that the actual DID estimate of *Post* AB5 is situated at the right tail of the distributions (more than 99%), demonstrating that the probability of randomly obtaining a similar estimate is minimal. Second, the mean estimated effect based on random treatment isn't significantly different from zero, implying that there are no unexplained idiosyncratic variances between the treatment and control groups. We report the results in Table D1.

Table D1. Random Implementation Test

	(1) Random Shuffle in All-workers	**(2) Random Shuffle in California Workers**
μ of Random β	0.0001	0.001
σ of Random β	0.004	0.010
Replications	500	500
Estimated β	0.078	0.078
Z-score	19.48	7.7
P-Value	P<0.001	P<0.001

Note: This table reports the results from difference-in-difference regression using randomly generated placebo treatment variables as independent variables. μ is the mean of the placebo estimator, and σ is its standard error. This diagnostic test is to determine the probability of the observed effect occurring purely by chance. The comparison between a placebo effect and an estimated effect is statistically different ($p<0.001$), thus eliminating the aforementioned possibility.

Online Appendix E: Staggered DID with other states

To date, only California has passed the law (i.e., AB5) aiming at reclassifying independent contractors and employees. Although other states have not taken official action, some are considering implementing laws similar to AB5.[3] For example, New Jersey introduced a proposal in November 2019 that would require a test to be used to determine whether a worker is an employee or an independent contractor. New York City's local government is also taking steps to implement similar worker reclassification laws. Like New Jersey, New York's Senate introduced a bill in November 2019 establishing criteria for determining whether labor or services performed for compensation qualify as employment. Similarly, the Oregon State Legislature introduced a proposed bill in January 2021 to the same effect. While a proposal might not have legal effects as strong as a law, we might still expect some signaling effects from those proposals. Therefore, we follow Babar and Burtch (2020) and Alyakoob and Rahman (2022) and conduct a staggered DID. Specifically, in addition to California (January 2020) being considered as the treatment group, we include New York, New Jersey, and Oregon, proposing their laws at different points in time, i.e., November 2019, November 2019, and January 2021, respectively. We rerun model (1) using the updated setup and report the results in Table E1. The results of the staggered DID estimation further validate our main results.

Table E1. Staggered DID with multiple states

Variable	DV = Log (Monthly Earnings)
Post × Treat	0.051* (0.020)
No. of Comments	0.391*** (0.012)
Worker's Ratings	-0.068 (0.010)
Population	-0.000 (0.000)
Median Income	0.000 (0.000)
Unemployment Rate	-0.006 (0.007)
Month Fixed Effects	Yes
Worker Fixed Effects	Yes
No. of Observations	398,599
No. of Users	40,992
R-squared	0.089

Notes: Cluster-robust standard errors in parentheses; $*$ $p < 0.05$; $**$ $p < 0.01$; $***$ $p < 0.001$

[3] https://mtac.us/proposed-state-bills-classifying-gig-workers-as-employees-can-affect-the-way-independent-contracting-works-in-trucking-industry/

Furthermore, one might argue that if the proposal of the laws in NJ, NY, and OR could have some effect, the proposal of AB5 (December 2018) would also have some effect. To this end, we present theoretical and empirical evidence to support that this would not be of concern in our case. First, when NJ, NY, and OR proposed similar laws in their states, these proposals came after the enactment of AB5 in California in September 2019 (Please see Figure E1 for a graphic timeline). Given the successful implementation of AB5 in California, it is reasonable to assume that workers in New Jersey, New York, and Oregon might anticipate that their states will eventually pass and implement similar legislation. Consequently, we argue that the proposals in these three states could have a noticeable impact. In contrast, prior to December 2018, no state had introduced legislation comparable to AB5. As a result, we do not expect that workers in California paid significant attention to such laws before AB5 was enacted.

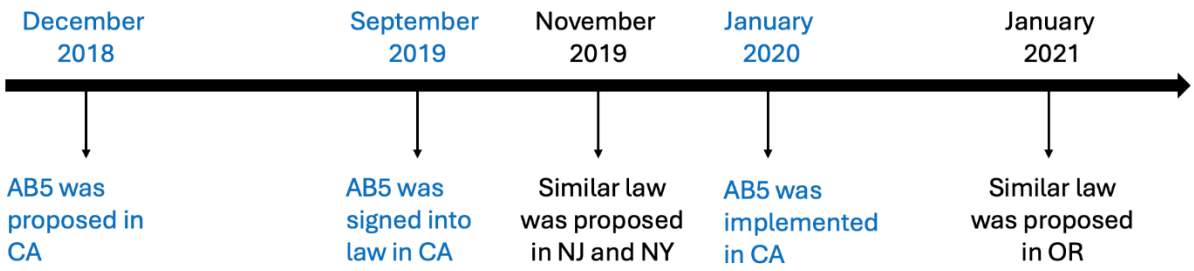

Figure E1. The timeline of AB5 in CA and similar laws in NJ, NY, and OR

To show evidence for this assumption, we conducted another robustness check using both the proposal date (December 2018) of AB5 and the implementation date (January 2020) of AB5 as two shocks in one model to examine the effect of the proposal when controlling for the implementation. Table E2 reports the results of this analysis. The results show that while the implementation impacts the monthly earnings (consistent with the main analysis), the proposal of AB5 has no significant effect.

Table E2. Impact of the proposal and implementation of AB5 on gig workers' monthly earnings

Variable	DV = Log (Monthly Earnings)
Proposal × Treat	-0.004 (0.016)
Implementation × Treat	0.079*** (0.017)
No. of Comments	0.391*** (0.012)
Worker's Ratings	-0.068*** (0.010)
Population	-0.000 (0.000)
Median Income	0.000 (0.000)
Unemployment Rate	-0.006 (0.008)
Month Fixed Effects	Yes
Worker Fixed Effects	Yes
No. of Observations	398,599
No. of Users	40,992
R-squared	0.089

Notes: Cluster-robust standard errors in parentheses; $*$ $p < 0.05$; $**$ $p < 0.01$; $***$ $p < 0.001$

Online Appendix F: Ashenfelter's Dip

Although the results of the relative time model indicate minimal concern of difference existing in the pre-treatment trend between the treatment and control groups, one may still be concerned that the existence of any difference in such trends may bias our estimates, which is commonly termed Ashenfelter's Dip in the econometrics literature (Ashenfelter and Card 1984). We follow the common practice to correct Ashenfelter's Dip by excluding the sample periods around the shock (Chen et al. 2022). Specifically, we exclude (1) the observations three months before and three months after the law implementation (i.e., October 2019 to March 2020) and (2) the observations three months before the law implementation (October to December 2019). The results are reported in Table F1, and the estimated effects are qualitatively consistent with our main results.

Table F1. DID results by excluding periods around the implementation of AB5

Variable	**(1) Excluding the time window: Oct 2019 – Mar 2020**	**(2) Excluding the time window: Oct 2019 – Dec 2019**
Post × Treat	0.092*** (0.023)	0.082*** (0.020)
No. of Comments	0.388*** (0.012)	0.393*** (0.012)
Worker's Ratings	-0.071*** (0.011)	-0.071*** (0.010)
Population	-0.000 (0.000)	-0.000 (0.000)
Median Income	0.000 (0.000)	0.000 (0.000)
Unemployment Rate	-0.007 (0.009)	-0.006 (0.008)
Month Fixed Effects	Yes	Yes
Worker Fixed Effects	Yes	Yes
No. of Observations	347,623	377,683
No. of Users	39,621	40,827
R-squared	0.091	0.091

Notes: Cluster-robust standard errors in parentheses; $*$ $p < 0.05$; $**$ $p < 0.01$; $***$ $p < 0.001$

Online Appendix G: Mediation analyses on the number of working days

While we find that CA workers might work more hours to maintain their income levels, they might also work more days in a month for the same reason. To examine this, we conduct a mediation analysis using the standard practice suggested by Baron and Kenny (1986).[4]

Step 1. Examine the effect of the AB5 on gig workers' monthly earnings without controlling for the number of working days, which are our main results. The results reported in Table 2 (column (1)) confirm that AB5 has a significantly positive effect on monthly earnings.

Step 2. Use the number of working days as the dependent variable and examine the effect of AB5 on it. Table G1 presents the results, which indicate that there is a significantly positive effect of AB5 on the number of working days. In other words, after the implementation of AB5, California gig workers work more days in a month compared to the workers in other states.

Table G1. Impact of AB5 on gig workers' number of working days

Variable	**DV = The number of working days**
Post × Treat	0.132* (0.063)
No. of Comments	-0.154*** (0.018)
Worker's Ratings	-0.895*** (0.060)
Population	0.000 (0.000)
Median Income	0.000 (0.000)
Unemployment Rate	0.014 (0.018)
Month Fixed Effects	Yes
Worker Fixed Effects	Yes
No. of Observations	398,599
No. of Users	40,992
R-squared	0.020

Notes: Cluster-robust standard errors in parentheses; $*$ $p < 0.05$; $**$ $p < 0.01$; $***$ $p < 0.001$

Step 3. Examine the effect of AB5 on monthly earnings, controlling for the number of working days in the main model. The results reported in Table G2 show that, after controlling for the number of working days, AB5 still has a significantly positive effect on gig workers' number of working days, with an estimated beta coefficient of 0.071, which is slightly smaller than 0.078, as shown in Table 2 (column

[4] We thank an anonymous reviewer for suggesting this approach.

(1)). This finding indicates a partial mediating effect as some of the AB5's effect on monthly earnings runs through the number of working days.

Table G2. Impact of AB5 on gig workers' monthly earnings

Variable	DV = Log (Monthly Earnings)
Post × Treat	0.071*** (0.019)
# of Working Days	0.054*** (0.000)
No. of Comments	0.399*** (0.013)
Worker's Ratings	-0.020 (0.011)
Population	-0.000 (0.000)
Median Income	0.000 (0.000)
Unemployment Rate	-0.006 (0.008)
Month Fixed Effects	Yes
Worker Fixed Effects	Yes
No. of Observations	398,599
No. of Users	40,992
R-squared	0.190

Notes: Cluster-robust standard errors in parentheses; $*$ $p < 0.05$; $**$ $p < 0.01$; $***$ $p < 0.001$

In sum, these results suggest that the number of working days mediates the impact of AB5 on gig workers' monthly earnings, further supporting our theoretical mechanism for the reduction of the hourly rates and the increase of working hours and working days.

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