Does regulation help? The impact of California's AB5 on Gig Workers

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Abstract

There is a widespread debate over how gig workers should be classified. The passage of California Assembly Bill 5 (AB5) - a landmark legislation that aims to correct the misclassification of gig workers, has significant implications for workers, platforms, regulators, and the economy. In this research, leveraging the passage of AB5 as a shock for a natural experiment, we empirically investigate the impact of AB5 on gig workers in California to provide insights. With the data collected from a leading online labor market that connects clients and gig workers, we applied a Difference in Difference approach, and we found that the monthly earnings of gig workers in California, compared to those in other states, have a significantly higher increase after AB5 was signed into law. This effect stems from both increased daily earnings and increased working days. We discuss the implications for policymakers and platforms.

Keywords: gig economy, regulation, online labor market

1. Introduction

In the past decade, we have witnessed a rising number of people joining the gig economy, which is known to possess nontraditional and contingent employment relationships. Examples of gig workers include Uber drivers, freelance writers, marketers, designers, programmers, data analysts, and many more. Reports suggest that in 2020, 35% of U.S. workers engaged in some type of on-demand gig economy,[1] which contributes more than $1 trillion to the US economy annually, and these figures are expected to grow continuously, with some predicting that freelance workers will make up more than half of the US workforce by 2023.[2]

While the proliferation of the gig economy creates new opportunities, it also invokes new regulatory, legal, and public policy challenges. On the one hand, proponents praise that the gig economy provides new employment opportunities, flexibility, extra earnings, and a sense of entrepreneurship. On the other hand, opponents criticize the lack of benefits and job security associated with gig jobs. This has led to a heated debate on the legal status of gig workers. In fact, long before the rise of the gig economy, much was at stake in determining whether a worker should be classified as an employee or as an independent contractor (Barron 1999), as this question strikes at the core of the structure of the economy, and it has important implications for both workers' and employers' rights (Cohen et al. 2022).

The current administration has supported workers' rights and advocated for greater gig economy regulations. For example, one of President Biden's plans for the nation, namely "The Biden Plan for Strengthening Worker Organizing, Collective Bargaining, and Unions,"[3] has called for labor law reform, including legal benefits and protections for gig workers, changes to confusing legal tests enabling gig workers to receive independent contractor status, and the adoption of stricter classification schemes such as California's ABC test.

Signed into law in September 2019, California Assembly Bill 5 (herein, AB5) is a landmark legislation that codifies and expands the scope of the ABC test established in the Dynamex ruling. In the Dynamex case, the court held that most wage-earning

[1] https://www.forbes.com/sites/forbesbusinesscouncil/2021/08/12/will-the-gig-economy-become-the-new-working-class-norm/?sh=27bcddd3aee6 Last accessed April 28, 2022

[2] https://www.forbes.com/sites/rebeccahenderson/2020/12/10/how-covid-19-has-transformed-the-gig-economy/?sh=408419aa6c99 Last accessed April 28, 2022

[3] https://joebiden.com/empowerworkers/# Last accessed April 28, 2022

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workers are employees and ought to be classified as such and that the burden of proof for classifying individuals as independent contractors belongs to the hiring entity. AB5 extends that decision to all workers. It entitles them to be classified as employees with the usual labor protections, such as minimum wage laws, sick leave, and unemployment compensation benefits, which do not apply to independent contractors. Many other states that are looking for an improved worker classification law seek to learn from California's AB5 "experiment." For example, New York, Illinois, Wisconsin, Oregon, and Washington have been trending toward following California's AB5 and becoming stricter about the misclassification of workers.[4] With an eye toward providing insights for those states that tend to follow California's legislation, in this study, we investigate the impact of AB5 on California's gig workers.

The main purpose of AB5 is to correct the misclassification of gig workers so that these workers are entitled to many safety-net protections that are not available to contractors. Therefore, it is natural to argue that AB5 can benefit gig workers and increase their earnings. However, some popular press has also provided a competing argument that AB5 could have unintended negative impacts on California workers. In particular, with the convenience of the online labor market, companies looking for remote freelancers have the flexibility to hire workers across the nation, even all over the world. With California adopting a striker law regarding worker classification, it could pose additional costs (e.g., extra benefits) and legal risks for employers to hire California-based workers. As a result, employers might simply hire workers from other states. If this holds true, workers in California would have fewer chances to be hired compared to workers from other states. Further, employers might offer a lower salary to workers from California to compensate for other overhead costs. Yet, at the same time, since workers are better protected in California, it is also possible that the quality of workers in California could increase compared to other states, as qualified workers would be willing to allocate more time to gig jobs. As a result, we may observe an increase in monthly earnings for California-based gig workers, driven by the demand for high-quality workers.

With these compelling perspectives in mind, in this paper, we empirically investigate the impact of gig economy regulations on gig workers. Specifically, we ask the following research questions: a) How does AB5 impact the earnings of gig workers from California? b) What are the underlying mechanisms of such impact?

To answer these questions, we collect data from one of the largest online labor platforms for gig workers - upwork.com. Using a classical Difference in Difference model, we found that the earnings of gig workers in California, compared to gig workers from other states, have a significantly higher increase after AB5 was signed into law. We conducted a battery of robustness checks and falsification tests to validate our main results. We further explored the mechanism of the effect and found that for California workers, both the number of working days in a month and the average daily earnings increased relative to other states after AB5.

Our research contributes to the gig economy literature in several ways. First, our work investigates how the regulations on the employer side of the gig economy would impact the gig workers. Our results show that, on average, workers from California have increased monthly earnings, stemming from both increases in daily earnings and the number of working days in a month. Although our findings might not apply to all gig workers, such as app-based ridesharing and delivery service workers that are exempted by California Proposition 22, our research does provide initial evidence that the impact of this legislation is stronger for more experienced workers on online gig platforms. This result suggests the effect is mainly driven by demand for the talent pool provided by online gig platforms, i.e., employers are willing to pay more for highly experienced workers.

Practically, our results speak to the important debate on how to effectively regulate the gig economy by providing much-needed empirical evidence of the impact of one such regulation. This exemplary regulation can guide the development of similar regulations in other states and legislation at the national level. The results show that regulations on gig employers provide protections for gig workers and attract highly qualified workers. This change might facilitate the transformation of the gig economy from mainly providing access to low-cost labor to providing access to the global talent pool on demand.

In addition, our results provide implications for gig economy platforms. Although there are persuasive reasons to believe that the regulations might negatively impact the gig economy platforms, our empirical evidence suggests that the regulations actually benefit these platforms by attracting higher-quality workers and thus promoting the long-term growth of these platforms.

[4] https://www.mediaservices.com/blog/ab5-style-laws-could-come-to-your-filming-state-next/ Last accessed April 28, 2022

2. Related Work and Research Questions

The literature studying the gig economy has grown on several fronts. A large number of studies have focused on the social and economic impacts of the gig economy (Cramer and Krueger 2016; Edelman et al. 2017; Han et al. 2021; Greenwood and Wattal 2017; Zervas et al. 2015), such as the impact of sharing economy platforms on incumbent industries. For example, Zervas et al. (2015) examine the impact of Airbnb's entry on the hotel industry, finding strong evidence of cannibalization. Similarly, Cramer and Krueger (2016) find cannibalization of the traditional taxi industry resulting from the entry of Uber and Lift. One stream of research that has received significant attention investigates the spillover effect of the gig economy, such as disturbing residential areas, increasing the cost of housing, and the use of unsafe and uninsured cars. For example, Chen et al. (2022) found that the reduction of Airbnb listings reduced rents as well as home values. Han et al. (2021) found that the removal of professional hosts from home-sharing platforms reduced crime rates in certain areas. Greenwood and Wattal (2017) found the entry of Uber reduced the number of drunk driving-related fatalities. Closely related to our work, a handful of studies have examined the relationship between wages and labor supply in the gig economy (Chen and Sheldon, 2015; Angrist et al., 2017).

A growing number of studies have also investigated the ethical and moral issues in the gig economy, such as the lack of legal protection for gig workers (Malhotra and Van Alstyne, 2014; Westerman, 2016). The regulatory issues have been discussed, including the misclassification of workers, wage and benefit protections, safety issues, and discrimination, among others. Scholars pointed out that in the sharing economy, employers set worker rates and the terms of their work and unilaterally terminate workers while reducing labor costs through misclassification, and gig workers have to bear all the risks (Dubal, 2002). These studies discuss the need and possible ways to regulate the gig economy; however, as regulations are yet to catch up with the development of the gig economy, empirical work that examine the impact of regulations is lacking. The signing of Ab5 into law provides a unique natural experiment setting that can facilitate our understanding of the impact of such regulations.

2.1. Gig Economy and Labor Cost

Since signed into law in September 2019, a major press has reported various protests against AB5 as gig workers "losing jobs."[5,6] AB5 is a legislation intended to protect the benefit of workers. Why might workers from California receive fewer job offers and lower income after the AB5 is signed into law? One of the reasons could be that employers are unwilling to hire workers from California with the increasing costs.

Research suggests that the growth of the gig economy might be driven by companies' preference for workers with lower wages and benefit costs (Friedman 2014). The sharing economy rose during a period of heightened unemployment and distrust of government. These platforms capitalized on the public appetite for easy access to jobs (Dubal, 2022). As a result, a growing share of the workforce is no longer employed in jobs with long-term stable connections with an organization; instead, they are hired through "flexible" arrangements, working only to complete some tasks for a defined time, and this arrangement may not align with the well-being of the workers (Friedman, 2014). With the advancements in communication technologies, the barriers to delivering work remotely and finding workers on demand have been greatly reduced; thus, organizations can hire gig workers at a lower cost not only from other states but also overseas. Indeed, research shows that online gig workers are facing greater competition from workers from lower-income countries (Kanat et al., 2018) as employers from developed nations access freelancers in low-income counties through digital gig platforms (Beerepoot and Lambregts, 2015). From worker's perspective, the features of gig work, such as flexible hours, low or no training costs, and generally lower barriers to entry, enabled gig workers to generate new income or supplement their primary incomes during difficult times in a strained job market (Dokko et al., 2015). Significant evidence can be found in prior literature that supports this view. For example, Huang et al. (2020) found a positive and significant association between local unemployment in the traditional offline labor market and the supply of online workers. Thus, during economic downturns, gig workers emerged because better employment options were not available for these workers, and gig work provided "bridge employment" during the recession (Donovan et al., 2016). Similarly, Burtch et al. (2018) found that gig economy platforms predominately reduce lower-quality entrepreneurial activity by

[5] https://www.cnbc.com/2022/07/20/trucker-protests-over-gig-worker-law-shut-port-of-oakland-terminals.html

[6] https://www.cwsl.edu/news/newsroom/campus-news/2020/03/12/the-unintended-consequences-of-ab5

offering employment to the unemployed and underemployed.

Based on prior evidence, we argue that organizations could be deterred by regulations such as AB5, where higher wages and overhead costs, such as benefits, unemployment compensation, and even penalties, would incur. Even if hired gig workers would not be classified as employees in accordance with the law, the complexity and nuance of the law impose an additional burden on human resources and percurrent departments of organizations. As a result, employers might simply hire workers from less regulated states and countries to lower their costs. Therefore, it is possible that regulations like AB5 would drive employers away from hiring gig workers from regulated areas, thus reducing the employment opportunities and/or income for these workers.

2.2. Gig Economy and Talent on Demand

Another stream of research has focused on the economic benefits that the gig economy may produce, such as flexible employment, increased productivity, and individual innovation and entrepreneurship (Sundararajan 2014). This research suggests that the growing number of gig workers reflects a culture shift fostered by technological advancement where many jobs now can be completed remotely; thus, more and more workers today prefer the flexibility provided by gig work over a 9 to 5 job (DeMartino and Barbato, 2003), and many of the best and the brightest workers turn to gig for their primary employment (Roy and Avinash, 2020). This shift has led to changes in employment models. For example, the future of work is becoming more flexible, and location is no longer a constraint to acquiring capable talent. Employers also increasingly prefer to use the gig economy to fill their talent gaps (Balakrishnan, 2022), as gig platforms allow them to find immediate talent with the most recent and relevant expertise without the need to maintain a long-term workforce.

Practically, in the earlier phases, typical gig work might be labor intensive and require lower skills, such as cleaning, shopping, driving, landscaping, and so on (Dokko et al., 2015). Only bootstrapping start-up companies, cash-strapped ventures, and small businesses would hire online freelancers (Roy and Shrivastava, 2020). With the evolution of the gig economy, the scope of gig jobs has significantly expanded. According to Stephane Kasriel, CEO of Upwork, one of the key factors of increased freelancing activity is hiring from big companies, and 30% of the Fortune 500 companies are now using top freelancing platforms (Pofeldt,2019).

The passage of AB5 protects workers' benefits, and therefore, gig jobs would become more attractive to workers, especially higher-quality workers with alternative employment options. Thus, after the law is implemented, there might be an increase in the availability of higher-quality workers in regulated areas, and we may observe an increase in gig workers' average income in these areas driven by skilled workers partaking in more work on these platforms.

In sum, the presence of persuasive theoretical arguments on both sides of the possibilities reveals a compelling tension. In the following session, we rely on our empirical analyses to determine the predominant effect of the regulation.

3. Research Context

On September 18, 2019, California enacted Assembly Bill 5 (AB5).[7] AB5 codifies the ABC test after it was used by the California Supreme Court in Dynamex.[8] 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 this paper, we use this event as a shock of a natural experiment to investigate the impact of gig economy regulations.

Due to the complexity and ambiguity of the law, including the ABC test, AB5 imposes additional challenges for employers. To help employers navigate the space, leading online freelancing sites such as Upwork have provided services to streamline the hiring and compensation process to ensure that the workers are correctly classified in accordance with the law.[9]

3.1. Data

Our research context is an industry-leading online labor market (upwork.com) that connects gig workers and clients. Upwork has the largest and most active user base among all the online freelancing marketplaces. The platform classifies gig workers into

[7] See supra notes 7-8 and accompanying text. California's AB5 statute was enacted to give more workers in its labor force certain state labor law protections. App-based and other workers are being misclassified as independent contractors and are thereby being exploited through a lack of employment law protections: minimum wage, overtime, workers' compensation coverage, and unemployment compensation coverage.

[8] Dynamex, 416 P. 3d 35-42.

[9] https://support.upwork.com/hc/en-us/articles/360001662868-Working-Through-Upwork-Payroll

12 categories, including Accounting & Consulting, Admin Support, Customer Service, Data Science & Analytics, Design & Creative, Engineering & Architecture, IT & Networking, Legal, Sales & Marketing, Translation, Web, Mobile & Software Dev, and Writing. It is worth noting that, with the passage of Proposition 22, ride-sharing companies, such as Uber and Lyft, as well as app-based deliver services, such as Instacart and DoorDash, are exempt from AB5. Thus, AB5 mainly covers workers such as the ones using upwork.com for freelancing. Therefore, Upwork is an ideal platform for investigating our research questions.

We collect all workers' profiles from this platform, and our dataset contains 47,537 gig workers across all categories. Specifically, we collect the worker's earnings for each job, the rating given by the client for each job, job duration, user's geographical location, user's total earnings to date, the total number of jobs, total working hours, education, and employment history. Figure 1 presents a screenshot of a worker's profile. Note that the dataset spans more than ten years, but over 80% of the observations are from 2018 to 2021. Therefore, we shorten the time window to include the year 2018-2021 (48 months) only, which covers the event (Sep 2019) of interest.

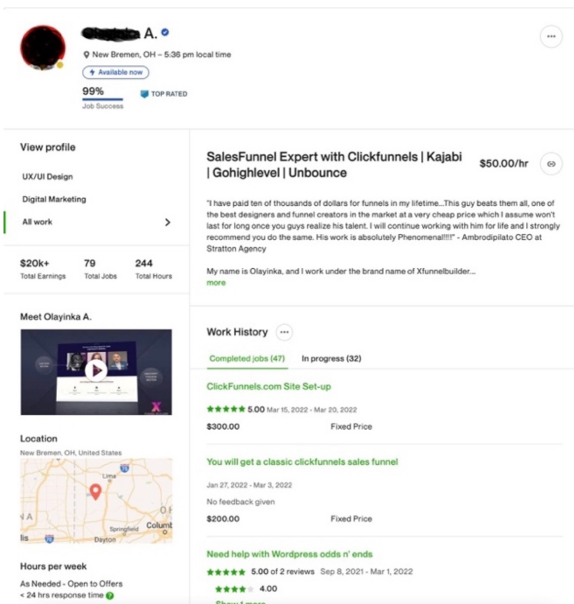

Figure 1. A Screenshot of an Upwork worker profile

3.2. Variables

Keeping the natural experiment design in mind, we construct a worker-month panel where we aggregate workers' information at the monthly level. The outcome of interest is workers' monthly earnings. Furthermore, we use a worker's geographic location to determine if a worker resides in California or other states, which enables us to create a dummy variable for the treatment/control group. Following prior studies in the gig economy research (Huang et al. 2020), we control for several factors found to be associated with the state-level labor force, including the state-level unemployment rate and median individual income.

4. Empirical Analysis

4.1. Identification strategy

The introduction and signed-in of the AB5 in California but not in any other states offer a natural experimental opportunity to examine the impact of the law. Our empirical strategy is the standard DID approach, capitalizing on the law insofar as the law was only effective in California. This identification strategy has been widely implemented in IS research (Chen et al. 2022; Kuang et al. 2019; Ozer et al. 2022). Equation (1) presents the estimation specification:

$$y_{it} = \beta_0 + \beta_1 \times Post_t \times Treat_i + \beta_2 \times X_{it} + \gamma_t + \delta_i + \varepsilon_{it} \quad (1)$$

where y_{it} is the dependent variable (i.e., monthly earnings). i denotes the user, t denotes the month, X_{it} is a vector representing several state-level control variables, including the unemployment rate and median income, and population. γ_t is the time-fixed effect including a set of monthly time dummies that control for time trends, δ_i is the user-fixed effect that captures the time-invariant characteristics of user i, and ε_{it} is the error term. The dummy variable Post equals one if month t occurs after the AB5 was signed into law, i.e., September 2019, and zero otherwise. Its main effect is absorbed by the time-fixed effects. *Treat* is a dummy variable, which is set to one if the observations belong to the state of California, and zero if the observations belong to other states. Its main effect is absorbed by the user-fixed effects. We are interested in the estimated coefficient β_1, which estimates the effect of AB5 on the outcome of interest in California relative to that in other states after the AB5 was signed into law.

4.2. Main Results

As preliminary model-free evidence, Figure 2 visualizes the monthly trends in gig workers' monthly earnings from January 2018 to December 2021. The vertical line represents September 2019, which is the month AB5 was signed into law. We can observe that the gap in monthly earnings between the two groups increases after the lockdown, suggesting there is a general post-AB5 increase in monthly earnings for individuals in California.

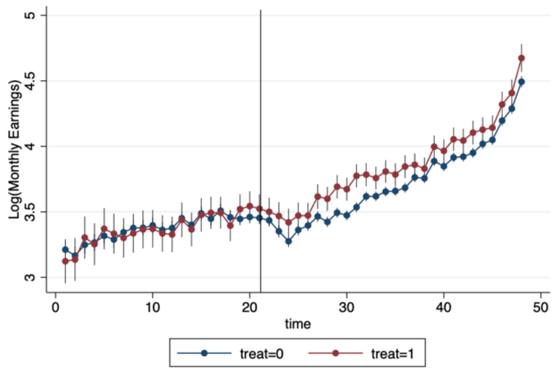

Figure 2. Trends of Monthly Earnings

Table 1 reports the estimated effect of the AB5 on gig workers' monthly earnings using equation (1). The results reveal a significant increase in gig workers' monthly earnings. Specifically, we estimate that after the AB5 law, there is a 3.8% increase in monthly earnings in California relative to other states.

Table 1. Impact of AB5 on gig workers' monthly earnings

Variable	DV = Monthly Earnings
Post × Treat	0.128*** (0.02)
Unemployment Rate	0.003 (0.009)
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	559,146
No. of Users	41,945

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

4.3. Robustness Checks

4.3.1. Relative Time Model.

We test the parallel trends assumption by performing an analysis following Cui et al. (2022) and Greenwood & Wattal (2017), where we expand specification (1) to estimate the treatment effect month by month before and after the shock. Specifically, we replace $Post_t$ in the specification (1) with month dummy variables, indicating the relative month to the shock. The model is presented in equation (2).

$$y_{it} = \beta_0 + \beta_1 \times MonthDummy_t \times Treat_i + \beta_2 \times X_{it} + \sum MonthDummy_t + \delta_i + \varepsilon_{it} \quad (2)$$

Figure 3 illustrates the coefficients of the interaction terms, verifying the parallel assumption.

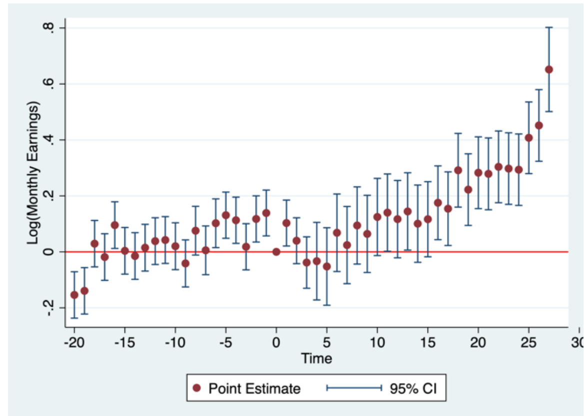

Figure 3. Relative Time Model Estimates

4.3.2. COVID. Since the time AB5 was signed into law (September 2019) was close to that of the COVID outbreak in the US (March 2020), the DID estimation might be biased due to the shock of state-wide lockdown orders across the nation. To mitigate this concern, we carried out an additional analysis where we trimmed our time window to exclude the periods after February 2020 and re-run our model. Table 3 presents the results, which are qualitatively consistent with our main analysis.

Table 3. Impact of AB5 on gig workers' monthly earnings controlling for COVID

Variable	DV = Monthly Earnings
Post × Treat	0.111*** (0.021)
Unemployment Rate	-0.007 (0.009)
Median Income	-0.000 (0.000)
Population	0.000 (0.000)
Constant	3.353*** (0.612)
Month Fixed Effects	Yes
User Fixed Effects	Yes
No. of Observations	232,322
No. of Users	16,314

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

4.3.3. PSM + DID. One of the concerns raised in the main analysis is that the users in the treatment group could systematically differ from those in the control group. Therefore, in this robustness check, to make the samples in the two groups more comparable, we constructed matched samples before conducting the empirical analyses. We matched the samples at the user level; that is, for each user in the treatment group, we identified a similar user in the control group. In

Table 4. Summary Statistics of Control and Treat Group Before and After Matching

Variable	Before Matching (N = 41,945)				After Matching (N= 1,576)			
	Mean (Treated)	Mean (Control)	t	p-value	Mean (Treated)	Mean (Control)	t	p-value
Job Days	17.991	18.378	-0.93	0.351	18.013	18.234	-0.4	0.686
Rating	4.8697	4.864	0.45	0.652	4.8695	4.8722	-0.16	0.869
Age	31.262	31.6	-1.29	0.197	31.28	31.419	-0.39	0.694
Gender	0.55387	0.50387	2.59	0.01	0.5533	0.53426	0.76	0.448
Race	1.1166	0.79695	6.82	0.00	1.1142	1.1459	-0.48	0.632
Education	0.36375	0.3613	0.11	0.911	0.36294	0.35279	0.35	0.725

particular, we adopted the propensity score matching approach to balance the observed characteristics between the treatment and control groups. We calculated the propensity score using logit regression with an indicator of being treated (user in California) as a dichotomous outcome and a set of observed characteristics as covariates. The covariates primarily include the users' job-related characteristics prior to the treatment, including the number of working days in a month, their job rating; and user-related characteristics such as education level, gender, race, and age. Then, based on the propensity scores, we matched users between the treatment and control groups by applying the one-to-one nearest-neighbor matching without replacement.

Table 4 presents the summary statistics of the treated and control groups before and after matching. The t-tests and p-values confirm that the means of the two groups are more similar after matching. Figure 5 presents the distribution of propensity scores for the treatment and control groups for both unmatched and matched samples. This figure indicates that the matched control group users have a propensity score distribution more similar to those in the treated group than those in the unmatched control group. These checks validate that the matching method is appropriate for producing similar groups. Based on the matched sample, we re-run the DID estimation, and the results (reported in Table 5) are qualitatively consistent.

4.4. Synthetic Control Method

Proposed by Abadie et al. (2010), synthetic control method has been used in many IS studies (e.g., Li et al. 2022; Kim et al. 2022). The idea of the synthetic control method is to use data-driven procedures to select synthetic comparison units in comparative case studies (Abadie et al. 2010), and the rationale is that a combination of units usually

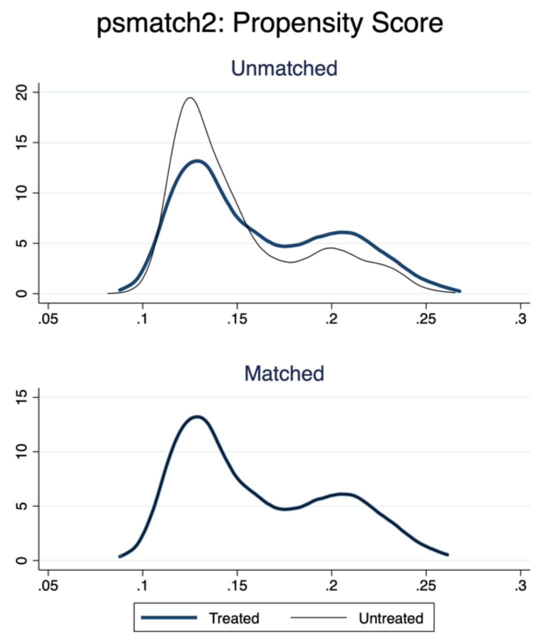

Figure 5. Distribution of Propensity Scores for Treatment and Control Groups (Both Unmatched and Matched).

Table 5. Impact of AB5 on gig workers' monthly earnings (matched sample)

Variable	DV = Monthly Earnings
Post × Treat	0.279*** (0.072)
Unemployment Rate	-0.024 (0.02)
Median Income	-0.000 (0.000)
Population	0.000 (0.000)
Constant	5.299** (1.432)
Month Fixed Effects	Yes
User Fixed Effects	Yes
No. of Observations	45,053
No. of Users	1,505

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

provides a better comparison for the treated unit than any single unit alone. Applying the synthetic control method in our case is appropriate as our context is similar to that of Abadie et al. (2010). In that research, they studied the impact of Proposition 99, a large-scale tobacco control program that California passed in 1988, on tobacco consumption. They constructed a synthetic California that mirrors the values of the predictors of cigarette consumption in California prior to the passage of Prop 99. They then estimated the effect of Prop 99 on cigarette consumption as the difference in cigarette consumption levels between California and its synthetic versions after Prop 99 was passed. In our research, we follow Abadie et al. (2010) and construct a synthetic California based on the predictors of earnings before the passage of AB5.

Since the synthetic control method is only applicable when there is a single treatment unit, we aggregate our data into a state-month panel where only California was exposed to the treatment. Specifically, our predictors of earnings are the unemployment rate, median personal income, Gini index, Asian population, white population, and the number of working days. Figure 6 plots the trend of monthly earnings for both treated and synthetic control groups. Using the "synth_runner" command in Stata, we are able to estimate the post-treatment effect and their standard p-values. Based on Table 6, starting from post-period 4, we see a significant effect (at p=0.1) of the AB5 on monthly earnings, which is consistent with our main analysis.

Table 6. Impact of AB5 on gig workers' monthly earnings (synthetic control)

Months	estimates	p values	Months	estimates	p values
Post_1	39.15	0.06	Post_15	61.62	0
Post_2	6.60	0.82	Post_16	80.81	0
Post_3	28.70	0.2	Post_17	69.24	0
Post_4	36.96	0.08	Post_18	39.20	0.02
Post_5	44.66	0.04	Post_19	20.96	0.3
Post_6	9.39	0.58	Post_20	21.68	0.28
Post_7	47.61	0.02	Post_21	32.14	0.08
Post_8	43.86	0.06	Post_22	9.72	0.62
Post_9	74.77	0	Post_23	-10.99	0.48
Post_10	44.09	0.04	Post_23	6.80	0.72
Post_11	70.69	0	Post_25	42.54	0.06
Post_12	77.97	0	Post_26	54.13	0.06
Post_13	69.56	0	Post_27	40.68	0.16
Post_14	85.56	0	Post_28	43.06	0.12

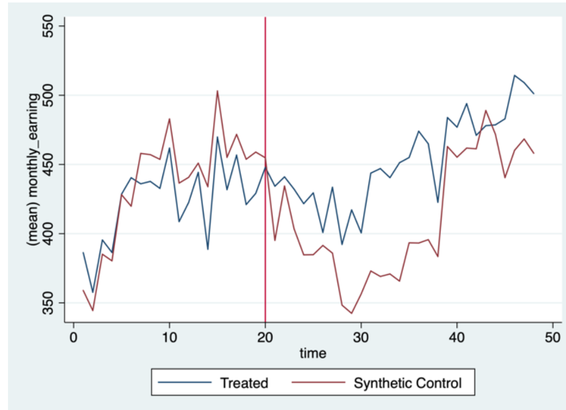

Figure 6. Trends in monthly earnings

4.5. Underlying Mechanism

In this section, we explore the mechanism that could lead to the main effect, i.e., the positive impact of AB5 on California gig workers' monthly earnings. Specifically, we consider two related variables, namely the number of working days per month and average daily earnings, and we provide the rationale below. In the main analysis, we observe monthly earnings increased; however, we are not able to tell if it was because the workers worked more (worked more days a month) or because the workers were paid more per time unit (more daily earnings). Therefore, we carried out two additional analyses where we replaced the dependent variables in equation (1) with job days and daily earnings and re-ran the model. Table 7 and Table 8 present the results, respectively. We found that California workers' job days and daily earnings both increased after AB5 compared to other states' workers. These results enable us to understand the nuances behind the main results.

Table 7. Impact of AB5 on gig workers' number of working days per month

Variable	DV = Job Days
Post × Treat	0.06*** (0.011)
Unemployment Rate	0.004 (0.004)
Median Income	0.000 (0.000)
Population	0.000 (0.000)
Constant	1.791*** (0.301)
Month Fixed Effects	Yes
User Fixed Effects	Yes
No. of Observations	559,146
No. of Users	41,945

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

Table 8. Impact of AB5 on gig workers' daily earnings

Variable	DV = Daily Earnings
Post × Treat	0.063*** (0.013)
Unemployment Rate	0.001 (0.005)
Median Income	-0.000 (0.000)
Population	0.000 (0.000)
Constant	1.513*** (0.371)
Month Fixed Effects	Yes
User Fixed Effects	Yes
No. of Observations	559,146
No. of Users	41,945

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

4.6. Additional Analysis

4.6.1. Was the (state-level) number of gig workers impacted by AB5?

Our main findings show that gig workers' monthly earnings increased in California after the AB5 was signed into law, indicating that at the micro-level, California gig workers were paid more because of the AB5 law. A natural follow-up question would be, will the AB5 also impact the total number of gig-workers at the macro-level (i.e., state level)? To answer this question, we aggregate our data into a state-month panel where we have 51 states, each having 48 periods. We then estimate equation (1), with the dependent variable being the total number of workers for state i at time t. We control for COVID-related variables and only include pre-COVID observations. Table 9 presents the results, based on which we find that after the AB5 law, there is a 2.6% increase in the number of workers in California relative to other states.

Table 9. Impact of AB5 on the total number of gig workers

Variable	DV = No. of Worker
Post × Treat	0.023* (0.01)
Unemployment Rate	-0.038 (0.021)
Median Income	0.0001 (0.000)
Constant	2.432 (0.513)
Month Fixed Effects	Yes
State Fixed Effects	Yes
No. of Observations	1,326
No. of States	51

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

5. Conclusions and Future Research

In this paper, we empirically investigate the impact of gig economy regulations on gig workers. Using the passage of AB5 in California as a natural experiment, we found that after the passage of the law in California, both the number of workers and the earnings of gig workers significantly increased compared to other states. In future research, we plan to explore the heterogeneity of these impacts by investigating how the legislation impacts the wages and working days of workers with different levels of education and experiences, as well as the impacts on different categories of jobs, such as high-tech jobs versus jobs with lower entry barriers. This paper will contribute to the literature studying the gig economy and its practice by furthering our understanding of the regulations' effect in this novel labor market.

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