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Bachelor Thesis [International Bachelor Economics and Business Economics (IBEB)]

Title thesis: Examining the impact of employee status classification changes on firm hiring behaviour.

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I. INTRODUCTION

The work landscape has evolved, leading to the "gig economy" phenomenon. The gig economy is also known as the sharing economy, crowd-working economy, or on-demand economy (Kalleberg & Dunn, 2016). There are various definitions; however, the gig economy can be interpreted as a set of markets that connect suppliers and customers on a gig (or job) basis to promote on-demand trade (Donovan, 2016). In this study, we use the terms gig worker and independent contractor interchangeably but define a gig worker as an incorporated self-employed individual. Given numerous interpretations and definitions of the gig economy, specific aspects of gig employment distinguish it from traditional labour market interactions. For example, it often depends on temporary and part-time roles performed by independent contractors and freelancers rather than full-time permanent workers who enjoy flexibility and freedom but have little or no job security (Investopedia Team, n.d.). However, just like the inability to accurately define gig work, it is with defining a gig worker under most legal frameworks for employees. Thus, as legal institutions are trying to resolve the issue of gig worker status, the implications of these decisions extend to impact the strategies and behaviour of firms and not just the "gig workers". Thus, this study explores how firms respond to labour legislative changes in worker classification.

The gig economy has experienced significant growth in recent years, which has disrupted the traditional view of employment. In the United States, the gig economy comprises freelancers (one-third of workers) who act as independent contractors lending their services via work on-demand apps and platforms (Sprague, 2015). In addition, the number of freelancers in the United States (US) is expected to increase from 57 to 86 million by 2027; with this growth comes the issue of the classification of gig workers as either independent contractors or employees (Broda, 2021). This is further emphasised by Stefano (2015), who states that one of the critical legal difficulties, which has already resulted in significant litigation in the gig economy, is the designation of the persons engaged as employees or independent contractors. However, one of the biggest problems that has resulted from this classification discrepancy is the need for more access to benefits that would have been available if gig workers were recognised as employees. According to Broda (2021), 54% of gig workers cannot access employer-based benefits. Such legal disputes have arisen and consequently triggered a change in labour laws surrounding employee classification.

However, the success of companies such as Uber makes the gig employment model more appealing to businesses. According to Lavri (2023), many businesses see temporary contracts with freelancers with specialised talents as a more realistic long-term approach for meeting shifting market demand than regularly retraining permanent workers. Furthermore, it enables enterprises to reduce transaction costs and market friction (Stefano, 2015). For gig workers, the gig economy allows them to take advantage of career possibilities that they may not have had access to otherwise and operate on a flexible schedule, allowing them to balance work with other personal activities (Stefano, 2015).

California has a long history of misclassifying class actions due to many sharing economy companies with deep roots in the state and global recognition, such as Uber, Lyft and Airbnb (Morgan, 2018). Moreover, the first lawsuit against the company Uber was filed in northern California, a state with a broad legal definition of employees and potentially sympathetic judges and juries, according to Dubal (2017). Consequently, in April 2018, the California court, in response to the case of Dynamex Operations West Inc vs Superior Court, announced a new method to classify workers called the ABC test. According to this test, a person is regarded as an employee unless the hiring entity can demonstrate that all three criteria have been met: (A) the worker is free from the hiring entity's control and direction; (B) the worker performs work outside the hiring entity's ordinary course of business; and (C) the worker is engaged in an independently established trade, occupation, or business.

Dynamex Operations, Inc. is a nationwide courier and delivery business where customers would contact the firm directly, and rates for its services are determined or negotiated by the company (Burdick, 2019). The drivers were paid a fixed charge or a portion of the agreed amount, depending on the conditions. Before 2004, all Dynamex drivers were recognised as workers and paid following state wage rules. However, the corporation chose to designate drivers as independent contractors in 2004 to save money. In April 2005, Charles Lee filed a complaint alleging Dynamex misclassified employees as independent contractors, dodging its duties under the California Labor Code and wage orders. At the time, the Californian courts used three main methods to classify workers: the modified Common Law Test, the economic realities test, and the three alternatives test (Morgan, 2018).

According to Morgan (2018), the modified common law test is a multi-factor test that mainly focuses on the extent to which a firm has control over how their workers perform their tasks but also considers other factors such as the degree of supervision required, the worker's integration into the business, the necessity of the worker's services for the business and the method of payment. On the other hand, the economic realities test, which is most used in California and popular nationwide, is a five-part test that considers factors such as the company's degree of control, the worker's opportunity for profit or loss, the worker's investment in the business, the long-term nature of the working relationship, and the level of skill required for the job. The main difference between the modified common law and economic realities test is that it considers the worker's actual economic situation and allows for more subjective judgements. Lastly, the three alternatives test considers a person an employee if (1) the business exercises control over wages, hours, or working conditions, (2) the business permits an individual to suffer or permit to work, or (3) the business engages the worker to work.

Initially, the California supreme court tried to use the three alternatives test based on the condition of "suffer or permit to work", meaning that if the employer knows or has reason to know that work is being performed, the worker is considered an employee. However, the court recognised that conventional independent contractors, such as plumbers and electricians, should not be deemed employees. As a result, the court used the "ABC" test to separate these genuine independent contractors. According to the court, the "B" element of the "ABC" test's commonality of interest requirement supported the class certification for Dynamex drivers. Given that Dynamex provided delivery services, the question of whether delivery drivers performed work outside the scope of their regular duties came up frequently. Due to this, after years of litigation, the court also recognised the drivers as employees in April 2018, announcing that the ABC would be the new standard for classifying workers.

Furthermore, Assembly Bill 5 (AB-5) was enacted into law in September 2019 and went into effect in January 2020 (Win, 2020). The ABC test overturned the widely recognised system for categorising workers, which calls for a judge to consider a long list of criteria before deciding whether to categorise a person as an employee or an independent contractor (Morgan, 2018). Instead, the court declared that all workers are believed to be employees, and it is the employer's responsibility to prove the existence of an independent contractor relationship.

Given the significance of the case and the popularity of the gig economy, this paper seeks to understand how such a legislative change would impact employers' hiring behaviour. Although the bill was effective in 2020, this paper will focus on the initial responses from firms following the announcement of the use of the ABC test. Therefore, the research question is as follows:

How did the legal re-classification of employee status affect the hiring patterns of gig workers in California?

The ABC test is stricter form of employee classification so you would expect more workers to identify as employees as a share of the labour force because all workers are deemed employees, but the firm has the burden to prove that their workers are independent contractors. Thus, we expect the share of gig workers to reduce after the Dynamex case as there are increased costs to proving a non-employee relationship.

To address our research question, we will utilise a synthetic control approach to create a control group for California using other US states. We will examine the change in the proportion of gig workers in the labour force following the Dynamex case. Our investigation will primarily rely on the Current Population Survey conducted monthly by the US Census Bureau. By employing the synthetic control approach, our study reveals that the proportion of gig workers in California rose after the announcement of the ABC test.

The structure of the paper is as follows; in section II, we discuss existing literature concerning how firms respond to different forms of employment legislation and an insight into the dynamics of the gig economy. Section III will explain the construction of our sample after that how the synthetic control is created and used is discussed in Section IV. Sections V and VI will present the main findings from the synthetic control analysis and the robustness of our results. The paper will end by discussing the main findings and will conclude by providing ideas for future research in sections VII.

II. LITERATURE REVIEW

The gig economy is a complex part of the labour market. Consequently, it challenges the traditional employment patterns in the theoretical and empirical evidence on labour market dynamics with conventional employment relationships. Thus, this literature aims to investigate how the gig economy responds to labour policy changes. To do so, we explore how the gig economy operates and the controversial aspects of it related to labour policy. Then, to assess the potential firm behaviour in response to classification changes, we investigate firms' perspectives and responses to labour regulations such as employment protection legislation (EPL) and analyse its influence on self-employment. Additionally, we observe how firms have responded to previous labour policy changes related to worker classification in California.

For an insight into the dynamics of the gig economy, (Stefano, 2015) discusses the structure of employment relationship for gig firms in the labour market, how they operate to evade labour policies and the risks and opportunities present in this form of work. The study examines two prevalent forms of gig work – crowd work and work-on-demand via apps. The two forms operate on the internet to connect labour demand and supply via applications/platforms; however, crowd work involves tasks ranging from small and repetitive "microtasks" that require human judgment, such as tagging photos or completing surveys, to larger and more significant projects like logo design and marketing campaigns. On the other hand, work-on-demand involves traditional work activities, such as transportation, cleaning, running errands, and clerical tasks. The significant risks highlighted are the limited worker protections due to workers in these forms of work being classified as independent contractors and the lack of stability of earnings as they earn per task rather than arranged salaries. As for the main opportunities, workers gain flexibility and accessibility to various jobs. Employers benefit from labour cost savings from employing independent contractors and accessing a scalable workforce on demand. One of the key arguments in the paper is that gig work should not be viewed as its distinctive labour market but rather as a part of the general labour market. This is because gig work and traditional forms of work have overlapping characteristics and share labour issues such as income instability and employee protection. There are interconnected actors whose interactions can also be mirrored in traditional labour market dynamics.

Furthermore, the paper explains that misclassification issues arise because some companies in the gig economy will add enhanced independent contractor clauses in their contracts to assert self-employment relationships. Other clauses that impede the employer–employee relationship are "representation and warranties", which aim to make workers acknowledge that they are indeed working as independent contractors. Courts use the "right of control" mainly to justify employee classification. However, gig platforms impose policies and instructions on the drivers and monitor their actions, which contradicts the notion of complete independence for independent contractors.

Using the right of control as a criterion to classify workers is a clear impediment for courts and firms to classify workers appropriately. Thus, the ABC test from the Dynamex case serves as a transformative move in labour classification policies, so how firms respond to such a legislative change is essential to study. Given the structure of clauses and innovative business models, such a policy change can impact firm behaviour, creating more reason for us to explore this research question. Employee classification policies are designed to identify persons entitled to legislative employee protection rights and benefits mandated by the state and federal state for firms to uphold. Although there is a lack of empirical literature assessing the effect of classification policies on firm hiring behaviour, we can observe how firms respond to labour policies such as employee protection legislation (EPL) which, just like classification policies, if adjusted affect labour costs and are both designed to protect employees. The main form of response critical to this paper is that of the employment patterns of gig workers. Therefore, we need to learn how firms respond to EPLs.

To learn how firms respond to EPLs, we study Pierre and Scarpetta (2006), which examines how businesses in 140 countries both perceive and react to the strictness of EPL using a generalised ordered logit model and a bivariate probit model. The EPL studied are on notice periods, severance payments and dismissal requirements/procedures. The data on firm response, perception and EPL strictness is sourced from the World Bank's Doing Business Database and the World Bank's Investment Climate Survey. The paper's main argument is that the impact of EPL is contingent on the company's characteristics and performance. Smaller businesses may go undetected by regulators and investors, but larger corporations can reduce recruiting and firing costs. Medium-sized companies, on the other hand, have more challenges since they cannot avoid regulations owing to regulator visibility and lack the flexibility to transfer personnel.

The findings of the paper offer insight into the various effects of EPL on businesses' perceptions and behaviour regarding labour standards. According to the results, older and larger companies are more likely to view these restrictions as barriers, whilst younger and smaller businesses are less concerned. Furthermore, enterprises engaged in innovation frequently identify employment regulations as a key hindrance. Thus, it should be noted that firm behaviour towards the Dynamex case ruling may vary depending on the size of firms and the economic climate in which they operate. Although we do not delve deeper into the mechanisms by which firm behaviour comes about, we can make assumptions about why we observe the results from this paper. In addition, the authors find that businesses generally respond to strict employment regulations by investing more in training and using temporary workers. However, this response is most significant among medium and large-sized companies. In contrast, smaller-sized firms depend on temporary workers more, whereas innovative firms will rely on training than temporary employment.

Given that some gig work can be classified as temporary employment, it is plausible to assume that California's stricter labour classification law led to an increased number of gig workers (restricted to those who work under temporary employment). However, this conclusion is flawed, as temporary employment is a very restrictive form of gig work, and some parts of temporary jobs are not necessarily considered gig work. As we have defined gig workers as unincorporated self-employed individuals, we need to understand firm responses along the margins of self-employment.

Firstly, to understand the relationship between the strictness of EPL and self-employment, we study Robson (2003). The paper's primary purpose is to examine whether stricter EPL on regular, temporary, and overall employment incentivises firms to contract out to self-employed individuals. The sample is from OECD countries, and the analysis is done using panel data from the OECD with an index on the level of strictness. It covers 13 countries from the 1960s to the mid-1990s in seven five-year periods. They also use other data from OECD about the incidence of EPL measures by regular employment, temporary employment, and collective dismissals. They used a simple OLS regression with no controls and found a positive association between overall EPL strictness and self-employment. However, the correlation was negative when using country-specific fixed effects, even with some controls for labour market structure and dynamics. Upon examining the impacts on self-employment of regulations relating to regular employment contracts and regulations governing the use of temporary employment with fixed effects, the author finds that all these types of EPL reduce the incidence of self-employment. The paper highlights that a similar study was conducted by the OECD but found a positive relationship; however, the dependent variable used was the share of self-employed, so they claimed the results to be non-robust.

Given the ambiguity in the results about the direction of the effect of EPL on self-employment, we cannot determine the expected impact on the proportion of gig workers in California following the legislative change. However, the paper does not distinguish the type of self-employment. In the following paper, we can separate the kinds of self-employment that firms may contract out so we can isolate the possible effects on gig workers.

Román, Congregado, and Millán (2009) study two types of self-employments and the effect that strictness on EPL has on them. The first is dependent self-employment (DSE), and the other is independent self-employment (ISE). In the paper context, DSE refers to self-employed workers who are employed with the same tasks by the same employer for whom they previously worked as employees. In contrast, ISE refers to entrepreneurship driven by recognising a business profit opportunity, where individuals transition from formal or informal labour relationships with their previous employer to establish their self-employment venture. The study conducted a binary logit model using individual-level panel data from the European Community Household Panel (ECHP) for the periods 1994 – 2001 only for EU-15 countries. The EPL measures are derived from the OECD with strictness evaluated on regular and temporary employment regulations. The study's findings suggest that EPL strictness has opposite effects on DSE and ISE – EPL strictness on regular and temporary employment is likely to increase DSE but reduce ISE. However, the authors also find that economic conditions play a role in these effects' likeliness. Thus, in seasons of economic decline, transitions from paid employment to DSE are more probable, while ISE likelihood decreases. On the other hand, in seasons of economic growth, the change to ISE is more probable, while DSE transitions are likely to drop.

The paper is the first attempt to investigate the phenomenon of firms employing DSE models to evade EPL regulations. DSE models resemble independent contractor models used by famous gig firms like Uber regarding the right of control being with the employer and workers having to meet working conditions and requirements of the employer although working by contract as a self-employed individual. These transitions are critical to study the idea of firms using the gig work model in their business structure to evade labour regulations such as employment benefits and union rights. This is important considering the rise in litigation in misclassification cases because firms exploit this model to classify workers as independent contractors rather than employees. These results suggest that stricter labour regulations incentivise firms to employ the DSE model rather than have paid employment. The papers above have studied the labour market dynamics in response to labour regulations in the form of EPL on regular and temporary employment. However, we also need to understand how firms are likely to respond in the case of changes in classification regulations.

Dubal (2017) explores the aftermath of famous misclassification cases in California that resulted in state-level regulation changes in how workers could be determined as employees or independent contractors. This study analyses the qualitative effects of three successful misclassification cases that instigated legislative reform on the parties involved in the cases over time using pre- and post-litigation interviews. The lawsuits called into question the status of independent contractors of taxi drivers (Tracy v. Yellow Cab co, Friendly Cab v. NLRB) and truck drivers (Alexander v. FedEx Ground Packaging System Inc.). In each case, the plaintiffs prevailed, securing net safety benefits (Tracy), secure earnings (Alexander), and collective bargaining rights (Friendly Cab). As a result of the Tracy case, the companies responded by restructuring, such that the taxi drivers were then classified as independent contractors. In addition, they did not provide the insurance benefits the court gave them and used deceptive tactics to prevent workers from claiming their benefits.

On the other hand, the Alexander case highlighted that plaintiffs often do not recognise themselves as employees due to the restrictions of work law, rather than the employee status they sought to be seen as mistreated independent contractors. However, FedEx also retaliated by changing its business model to maximise profits. Rather than adhering to court decisions and demands, Friendly Cab used its political and structural power to refrain from complying.

The paper highlights firms' significant response: restructuring the business to exploit the independent contractor classification to minimise labour costs or exploit employee status but changing the business model such that income increases. This would prove the assumption under Román, Congregado, and Millán (2009) about firms' incentive to adopt DSE models (a form of restructuring the employment relationship) to evade labour regulations. Thus, we would expect that the Dynamex ruling triggered companies to restructure. They may have their workers not classified as employees or keep them on as employees but change the working conditions to maximise profits. However, the latter poses an indirect disadvantage for misclassified workers who gain following the Dynamex case, as their workload may be compromised to meet profit targets, as is the claim with FedEx.

The papers above show mixed results about the overall effect of labour policies on firm hiring behaviour. Furthermore, we cannot identify the direct impact of classification policy changes on firm behaviour. Thus, this paper is a steppingstone to give a general understanding of how firms would respond to such forms of employment regulation. Furthermore, we also observed from Dubal (2017) and Román, Congregado, and Millán (2009) that we can expect to find firms still employing workers under the guise of self-employment/ independent contractor relationships. Given that the purpose of the outcome of the Dynamex case was to discourage firms from misclassification practices, this paper seeks to explore the employment patterns of individuals classified as gig workers following the case.

III. DATA

The primary data source is the Current Population Survey (CPS), a survey conducted to gather information about households and individuals in the United States. It uses a multi-stage selection procedure to achieve national representation using a probability-selected sample of over 60,000 occupied homes from various states. The survey obtains cross-sectional data about household and demographic information, labour force information, and additional information regarding an individual's well-being that month (U.S. Census Bureau, 2018). The survey is restricted to those aged 16 and above, with no maximum age limitations, and the data is weighted to ensure that the results represent the U.S. population. Consequently, because of its representativeness in capturing the U.S. population and consistency in defining "gig workers" during our study period, the Current Population Survey was chosen as the data source for this research.

The data obtained is from January 2014 until June 2020. The monthly data is aggregated into quarterly data to make 26 quarters. As the treatment period is April 30th, 2018, we merge it into a quarter with May and June 2018 since we do not expect an immediate response from firms as they would need an adjustment period.

In CPS, workers are classified as government (federal, state, or municipal), private (for-profit or non-profit), or self-employed (incorporated or unincorporated). It allows us to confine our definition of gig workers to self-employed unincorporated individuals ("Current Population Survey (CPS)," n.d.). Individuals who work for themselves in different legal formations, such as sole proprietors of firms or independent contractors, are considered self-employed and unincorporated (Startup 4, 2013). The Census Bureau defines self-employed unincorporated employees as those who worked for profit or fees in their unincorporated firm (Bureau, n.d.-a). However, this is a limited definition of gig workers since it only includes people who work for themselves within other legal companies. The gig economy, on the other hand, is a more extensive phrase that encompasses a variety of independent contractual arrangements, such as temporary employees and freelancers (Oyer, 2020). Defining and quantifying the gig economy is difficult since there is no universally accepted definition or simple mechanism for classifying employees or jobs as "gig" or "not gig" (Burdick, 2019; Oyer, 2020). However, many gig workers satisfy the Census Bureau's definition of non-employers, self-employed persons who manage small, unincorporated firms with no paid employees (Bureau, n.d.). Thus, this paper defines a gig worker as an individual who classifies themselves as a self-employed unincorporated worker.

Our sample over the 26 quarters contains information on over 3 million workers in the United States, of whom roughly 6% are gig workers. In California, Figure 1 shows us the distribution of the proportion of gig workers in the labour force across the 26 quarters. The distribution is skewed to the right, with a high frequency for the proportion 7.5% to 8%. On the other hand, Figure 2 displays the between-state variation in the average proportion of gig workers across the 26 quarters. Gig workers account for roughly 3% to 9% across the US, with most states in our sample having approximately 5% and above.

From the CPS, we also obtain information about the class of the worker, the state they work and live in (they must be working and living in the same state), their sex and age, the highest level of education attained and their ethnicity. This information can show us differences or characteristics between gig and non-gig workers in our sample, as shown in Table 1. There are no drastic differences in observable characteristics between the two groups. However, gig workers, relative to non-gig workers, are older, with a lower proportion of females and a higher percentage of white people. But both groups have the highest level of education, a high school diploma or GED.

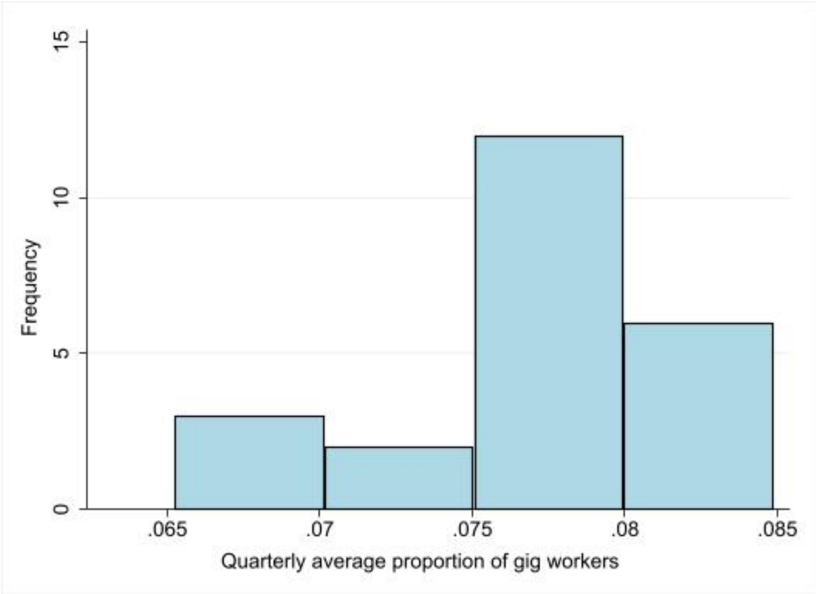

Figure 1. Distribution of the average proportion of gig workers in California

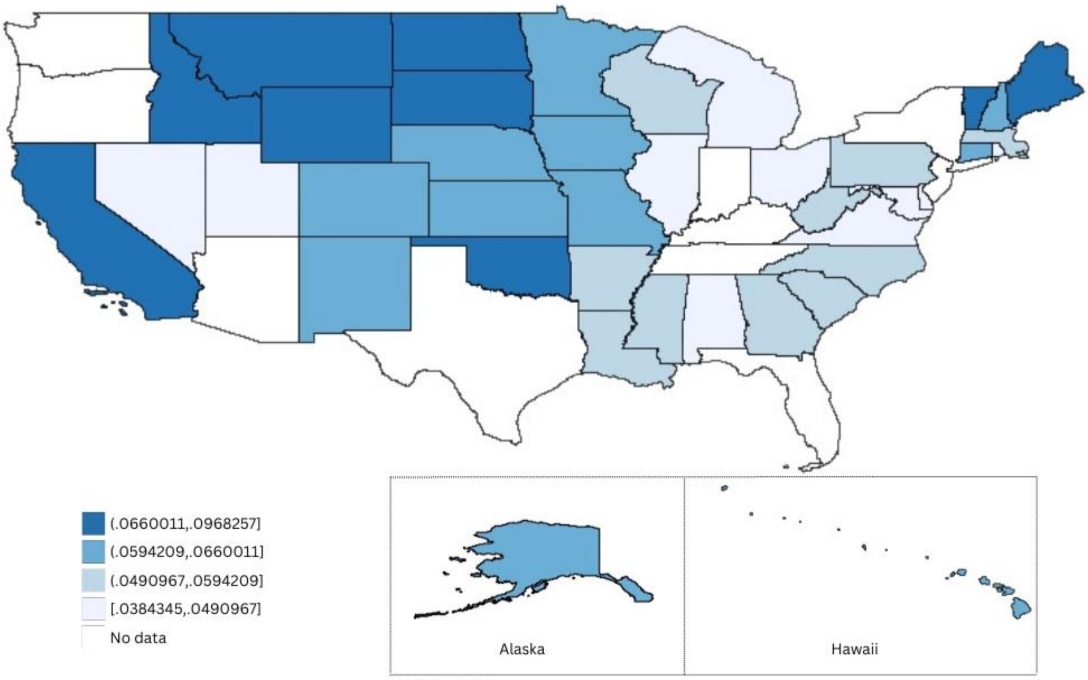

Figure 2. The average proportion of gig workers across the US.

Note. The US states with no data are states that are excluded from the sample as will be explained in the methodology.

Table 1. Characteristics of the gig and non-gig workers

Characteristics	Gig workers	Non-gig workers
Proportion of females	0.482	0.409
Proportion of white people	0.811	0.860
Average age	41	46
Highest level of education	High school diploma/GED	High school diploma/GED

Note. The table shows the mean values of observable characteristics between gig workers and non-gig workers over all the 26 quarters. The highest level of education is a categorical variable of which both groups had the highest majority count of 39 which represents high school diploma or GED.

We also utilise data from The Bureau of Economic Analysis (BEA) for additional statistics on quarterly GDP per capita by state. BEA is a US Department of Commerce institution that generates financial account data that allow government and corporate decision-makers, scholars, and the American public to track and analyse the performance of the nation's economy (Bureau of Economic Analysis, n.d.).

IV. METHODOLOGY

To conduct the empirical analysis, we transform the individual-level data into state-level data. So first, we aggregate the variables sex, ethnicity, and proportion of gig workers as the average values of individuals from that respective state. The proportion of gig workers is calculated by summing the number of individuals classified as self-employed incorporated and dividing that by the total number of workers in that state. As for education, we deduce the majority count of the highest level of education obtained from the sample of individuals working in that state in that month. The highest majority count is used because, in the CPS data, the level of education is a binary indicator for each level of education completed. In addition, we derive the proportion of males in the state's workforce and the proportion of people with a white ethnicity in that state. These monthly variables are then for each quarter added together and divided by three to become quarterly averages. There are five main independent variables and 26 quarters from January 2014 to June 2020. The dependent variable average proportion of gig workers (Lagged).is derived using the lagged quarterly average proportion of gig workers.

To answer the research question, a synthetic control approach will be employed. Courthoud (2022) asserts that synthetic controls assemble untreated units in such a way that they most closely resemble the behaviour of the treated unit without the treatment and then utilize this "synthetic unit" as a control. In order to create a synthetic control unit for California (synthetic California), weights need to be assigned to the dependent values of the other U.S. states that we choose to use in the control group. These weights will enable us to construct a pre-intervention trend for synthetic California that resembles California's. Then the difference between the trends post-intervention will represent the treatment effects of the Dynamex case ruling. In this paper, the intervention is the Dynamex case ruling about the change in the classification of workers.

To compile the appropriate sample, we restrict the CPS monthly data to include only those in the labour force who are working and between the ages of 18 and 64. Although the legal working age for California is 15 to 64, we exclude those between 15 and 18 because we would like to focus on the labour outcomes of adults and exclude teenage labour dynamics. In addition, to construct an appropriate donor pool (states from which weights will be assigned to the synthetic control), we must leave out states that experienced idiosyncratic shocks during and after the Dynamex verdict. Therefore, we leave out Massachusetts since it had already adopted a similar ABC testing scheme before and after the Dynamex decision and enacted legislation comparable to California's. In addition, in 2019, New Jersey, New York, Oregon, and Washington passed similar laws.

In contrast, Arizona, Florida, Indiana, Kentucky, Tennessee, and Texas all passed rules or legislation making it more challenging to classify gig workers as employees and will thus be excluded (Matsumura, 2020). Finally, because the District of Columbia is not a state, it is not included in the control units. As a result, the remaining states will serve as the control group: Alabama, Alaska, Arkansas, Colorado, Connecticut, Delaware, Georgia, Hawaii, Idaho, Illinois, Iowa, Kansas, Louisiana, Maine, Maryland, Michigan, Minnesota, Mississippi, Missouri, Montana, Nebraska, New Hampshire, New Mexico, North Carolina, North Dakota, Nevada, Ohio, Oklahoma, Pennsylvania, Rhode Island, South Carolina, South Dakota, Texas, Utah, Vermont, Virginia, West Virginia, Wisconsin, and Wyoming. The synthetic control can be built from a weighted combination of control states based on pre-treatment variables like the lagged average proportion of gig workers before the Dynamex ruling, GDP per capita, and demographic characteristics (average share of females, average share of whites, average age, and the average majority count of highest level of education attained).

Following the synthetic control approach presented in Abadie, Diamond, and Hainmueller (2015), our sample consists of $J + 1$ units (in this case, states) indexed by j. Thus, assuming that $j = 1$ is the state of interest (also known as the treatment unit) and $j = 2 \; to \; j = J + 1$ are the comparable states (also referred to as the donor pool). Since, we transformed the data into panel data, we also have time periods $t = 1, \ldots, T$. In this case, t refers to the quarters 1 to 26. We also assume that the sample has a positive value for pre-intervention periods T_0 and a positive value for post-intervention periods T_1 such that $T = T_0 + T_1$. Thus, a state is exposed to the Dynamex case ruling during the periods $T_1 + 1, \ldots, T$ (quarters 18 to 26) and the case ruling has no effect during the pre-treatment periods $1, \ldots, T0$ (quarters 1 to 17). A synthetic control is defined as the weighted average of the units in the donor pool which can be represented by a vector of weights $W = (w_2, \ldots, w_{J+1})'$, with $0 \leq wj \leq 1$ for $j = 2, \ldots, J$ and $w_2 + \cdots + w_{J+1} = 1$. Given that X_1 contains the values of the pre-intervention characteristics of the treated unit that we aim to match and X_0 represents the values of the same variables but for the units in the donor pool, the difference between the pre-intervention characteristics of California and synthetic California is represented by: $X_1 - WX_0$. For m = 1, …, k, let X_{1m} and X_{0m} be the value of the mth variable for the treated unit and the donor pool respectively i.e., X_{1m} could be the value for the share of females in the labour force in California in the quarters 1 to 17. Thus, we choose W* as the value of W that minimises:

$$\sum_{m=1}^{k} \mu_m \left(X_{1m} - X_{0m}W\right)^2 \tag{1}$$

where μ_m is a weight that reflects the relative importance that we assign to the m^{th}variable when we measure the difference between X_1 and X_0W. However, in this case, we have no reason to believe from our set of varibales that any has more or less relative importance so these is kept equal for all varibales. Assuming that Y_0 contains the pre-intervention values of the outcome for a state and Y_1 contains the post-intervention values of the outcome for the treated state, then the synthetic control estimator of the effect of the treatment is given by the comparison of postintervention outcomes between the treated unit, which is exposed to the intervention, and the synthetic control, which is not exposed to the intervention: $Y_1 - Y_0W^*$. That is, for a post-intervention period t (with $t \geq T_0$), the synthetic control estimator of the effect of the treatment is given by the comparison between the outcome for the treated unit and the outcome for the synthetic control at that period:

$$Y_t - \sum_{j=2}^{J+1} w_j^* Y_{jt}. \tag{2}$$

When we compare the pre-intervention trends in the average proportion of gig workers in California to the other U.S. states in the sample, we see that in Figure 3, the combined use of these states cannot be comparable to California. There are drastic differences in the pre-trend lines for California and synthetic California; thus, we need to estimate weights to get the trend lines to resemble each other to deduce the treatment effects. Therefore, we construct our synthetic control using the weights in Table 2. Weights are built using all the lagged average proportion of gig workers for the quarters (5 to 17) and the variables GDP per capita, average proportion of females, average proportion of white people, and the majority count highest level of education. Table 2 shows that only three states are assigned weights, with North Dakota having the highest. In the following section, we will discuss the results of this synthetic control and the derived treatment effects.

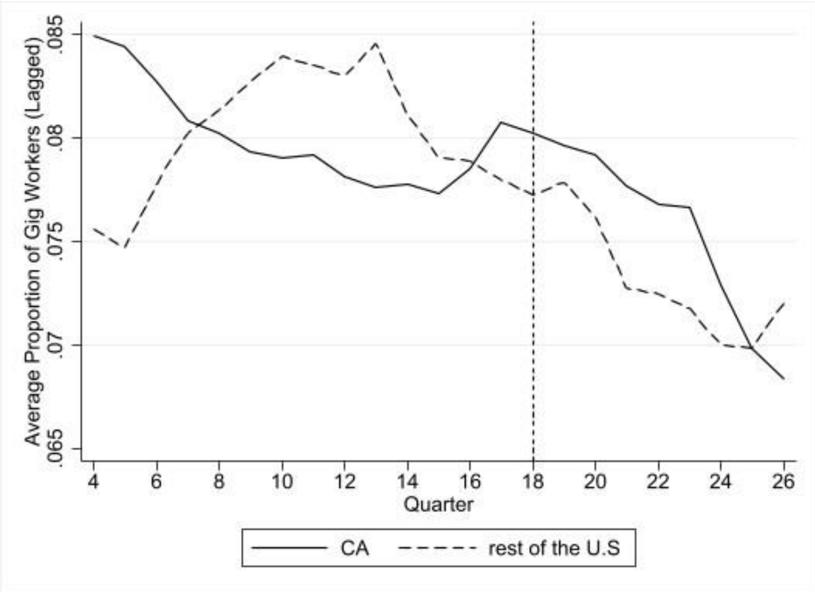

Figure 3. Trends in the average proportion of gig workers for California versus the rest of the U.S

Table 2. Synthetic control weights for synthetic California

State	Weight	State	Weight	State	Weight
Alabama	0	Massacheusets	0	Ohio	0
Alaska	0	Maryland	0	Oklahoma	0
Arkansas	0	Maine	0	Pennsylvania	0
Colorado	0	Michigan	0	Rhode Island	0
Connecticut	0	Minessota	0	South Carolina	0
Delaware	0	Mississippi	0	South Dakota	0
Georgia	0	Montana	0	Utah	0
Hawaii	0	North Carolina	0	Virginia	0
Idaho	0	North Dakota	0.554	Vermont	0.139
Illiniois	0	Nebraska	0	Wisconsin	0
Iowa	0	New Hampshire	0.306	West Virginia	0
Kansas	0	New Mexico	0	West Virginia	0
Louisiana	0	Nevada	0	Wyoming	0

Note. Table shows the weight assigned to each state in the synthetic control group for California.

V. RESULTS

This section discusses the results of using a synthetic control using the weights in Table 2. From the donor pool, only New Hampshire, North Dakota and Vermont contribute to the construction of the synthetic control. The weights from these three states are used to construct California's synthetic control, as shown in Figure 4. The figure shows the quarterly average proportion of gig workers for

California and the US states in the donor pool from January 2014 to June 2020. As observed, the weights and predictors could construct a synthetic California that closely reproduces the average proportion of gig workers for California before the ABC test was announced. However, around quarter 15, before the verdict, there was a sharp increase in the proportion of gig workers, likely due to an anticipation effect since the case was ongoing for decades. However, this is unlikely given that case rulings are unknown until they are announced, and the legal change announcement was made when the verdict was given; thus, it is not plausible to assume that there was an anticipation effect from firms or individuals.

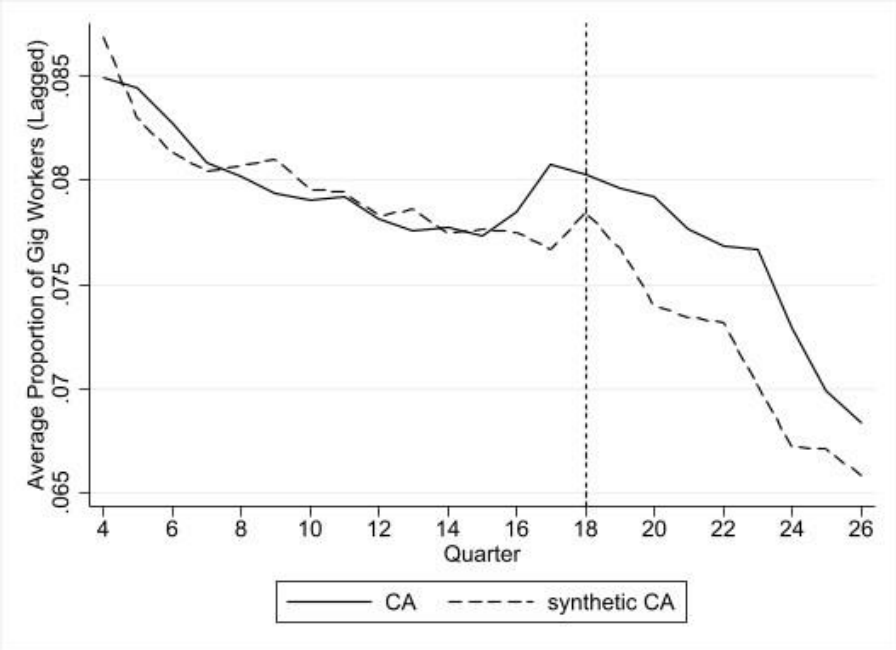

Figure 4. Trends in the average proportion of gig workers for California versus Synthetic California.

Note. The solid line represents observed average proportion of gig workers (lagged) in California for the 4th to 26th quarter; the dashed line represents the synthetic control. The vertical dashed line represents the quarter in which the Dynamex case ruling occurred (quarter 18).

The treatment effect of the Dynamex case ruling on the average proportion of gig workers in California is given by the difference between the actual California and synthetic California, which can be visualised in Figure 5. Over the post-Dynamex case period, the magnitude of the treatment is roughly 0.004 percentage points which is very close to zero. Thus, the effect holds little economic significance. This suggests that the change in worker classification ruling needs to be more relevant in impacting the proportions of individuals identifying as gig workers.

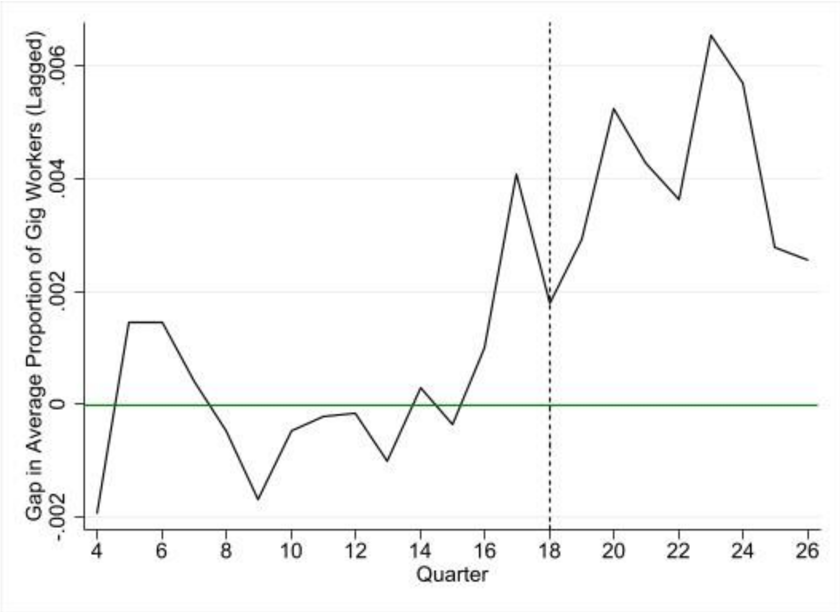

Figure 5. Average proportion in gig workers gap between California and Synthetic California.

Note. The solid line represents the difference between average proportion of gig workers (lagged) in California versus synthetic California for the 4th to 26th quarter; the green line represents the synthetic control. The vertical dashed line represents the quarter in which the Dynamex case ruling occurred (quarter 18).

The root mean square prediction error (RMSPE) measures the difference between the outcome in the treated unit and the synthetic control (Abadie, Diamond, & Hainmueller, 2015). To deduce the viability of our synthetic control, we thus need to calculate the ratios of the post-intervention RMSPE to the pre-intervention RMSPE. Figure 6 displays the ratios of post-intervention RMSPE to pre-intervention RMSPE for all states in the sample. California's ratio is around the middle compared to the sample's other states. Additionally, the weighted states used to construct the synthetic control lie around the same ratio as California. Thus, we were able to build a suitable synthetic control that mimics changes in California without the ABC test introduction.

To evaluate the credibility of our results, we conduct a placebo test where the Dynamex case verdict is assumed to have taken place in quarter 12 and not in quarter 18. Using the same predictors used to construct the synthetic control in Figure 4 and the intervention period as quarter 12, we obtain the trends in California and synthetic California observed in Figure 7. Like before, we can construct similar pre-intervention trends. Although previously, we saw a considerable divergence between the synthetic control and California in quarters 16 to 18, in Figure 7. However, we see the same divergence but slightly larger. In addition, the trend in the synthetic control from quarters 12 to 18 is different. However, we still observe the same effect size and movement. These divergences in the synthetic control trend from that observed in quarter 12 to quarter 18 suggest that the treatment effects we observed earlier may not be valid.

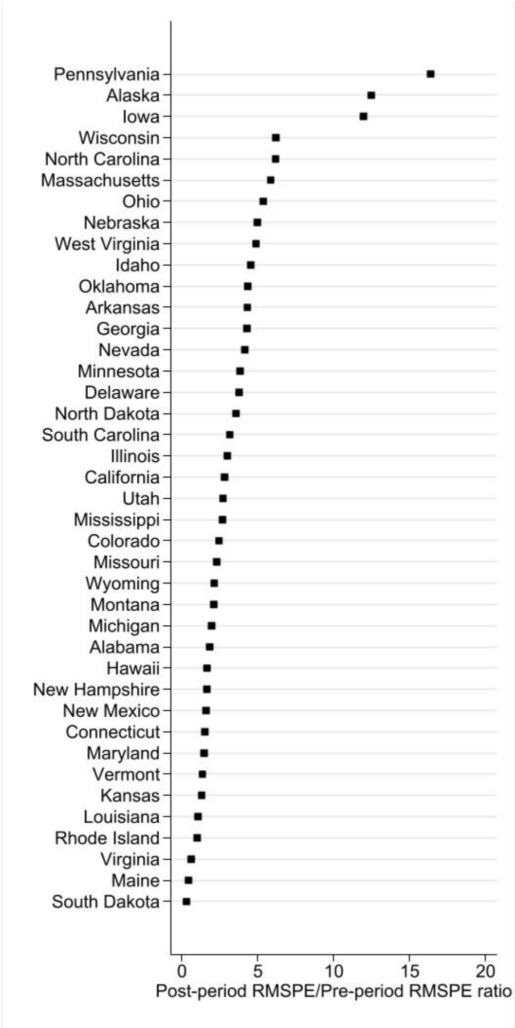

Figure 6. Ratio of Post-Dynamex RMSPE to Pre- Dynamex RMSPE

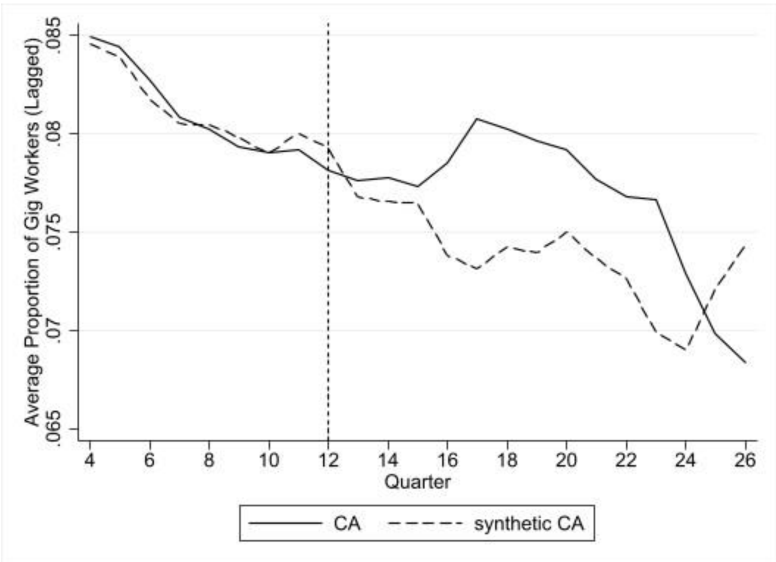

Figure 7. Placebo in-time: Trends in the average proportion of gig workers for California versus Synthetic California.

Note. The solid line represents observed average proportion of gig workers (lagged) in California for the 4th to 26th quarter; the dashed line represents the synthetic control. The vertical dashed line represents the in-time placebo quarter in which the Dynamex case ruling occurred (quarter 12).

VI. ROBUSTNESS

In this section, we will run a series of robustness checks and sensitivity analyses to test the sensitivity of our main results. Firstly, we conduct a robustness check to test the sensitivity of our main results to changes in the state weights. This is done by excluding the states allocated positive weights in Table 2 to see whether a particular state drives our results. When we exclude New Hampshire and Vermont, as seen in Figures 8 and 10, the pre-trend and post-trend are like that observed in the main results. However, In Figure 9, we follow slightly different pre-trend and post-trend in the synthetic control when North Dakota is excluded. This is especially visible after quarter 24, where the treatment effect becomes negative. However, with these exclusions, the synthetic control pre-trend almost closely follows that of California, and all show similar though slightly higher or lower treatment effect sizes to those observed in the main results.

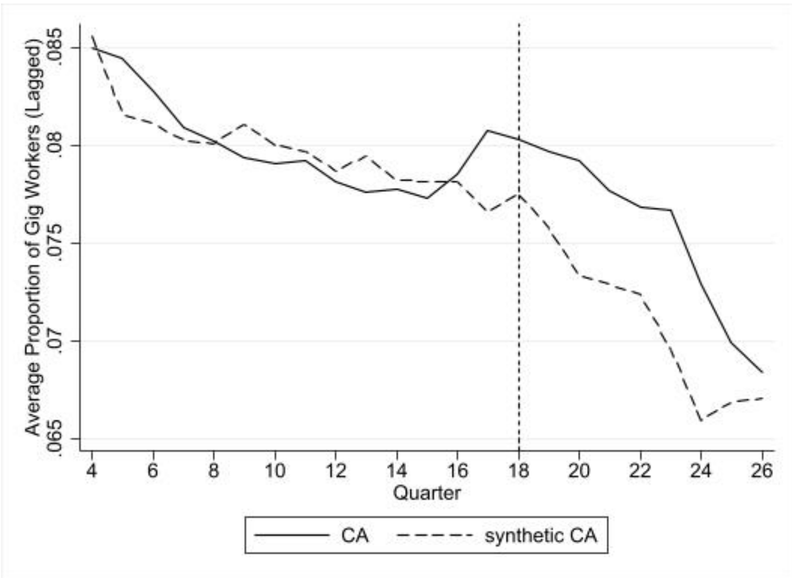

Figure 8. Synthetic control trend without New Hampshire in donor pool

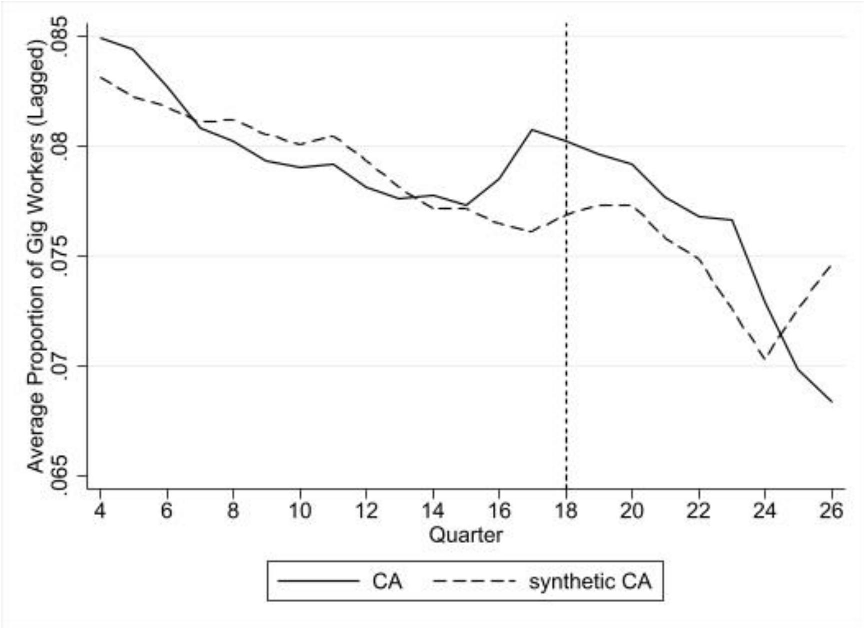

Figure 9. Synthetic control trend without North Dakota in donor pool

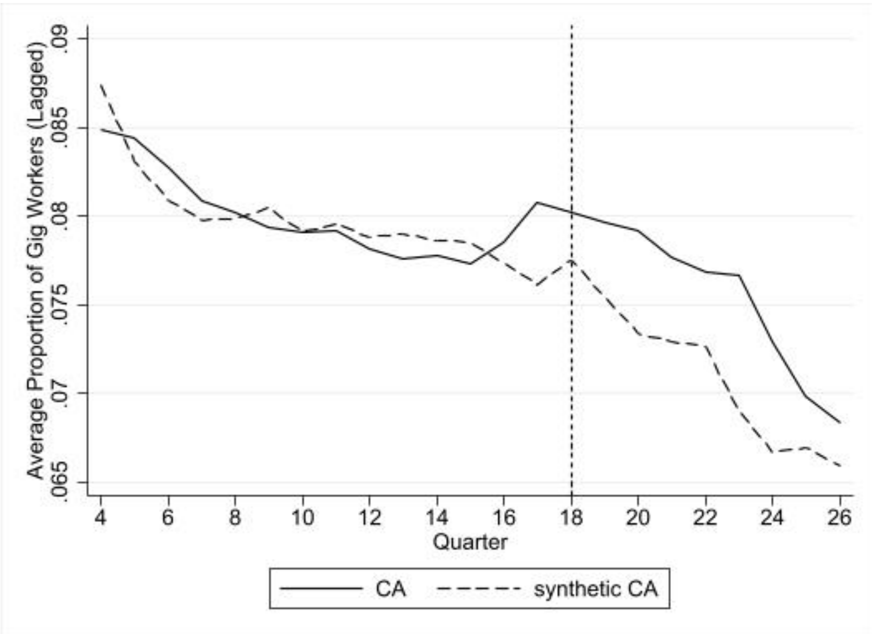

Figure 10. Synthetic control trend without Vermont in donor pool

It can be argued that the predictors used in Table 2 do not produce the closest pre-trend for the synthetic control. Thus, different model specifications can be used to get the pre-trend as close as possible. Therefore, to test this, we try different predictors and combinations of predictors. Using only the lagged average proportion of gig workers in quarters 4 to 17, we construct a synthetic California with the weights and selected countries as shown in Table 3. Compared to Table 2, the synthetic control method adds weight to Louisiana, New Hampshire, North Dakota, and Vermont. Although the weights for New Hampshire and North Dakota decrease, that of Vermont increases. But, in both specifications, North Dakota maintains the highest attached weight compared to all the other US states in the sample.

Table 3. Synthetic control weights for synthetic California using only lagged values.

State	Weight	State	Weight	State	Weight
Alabama	0	Massacheusets	0	Ohio	0
Alaska	0	Maryland	0	Oklahoma	0
Arkansas	0	Maine	0	Pennsylvania	0
Colorado	0	Michigan	0	Rhode Island	0
Connecticut	0	Minessota	0	South Carolina	0
Delaware	0	Mississippi	0	South Dakota	0
Georgia	0	Montana	0	Utah	0
Hawaii	0	North Carolina	0	Virginia	0
Idaho	0	North Dakota	0.385	Vermont	0.279
Illiniois	0	Nebraska	0	Wisconsin	0
Iowa	0	New Hampshire	0.263	West Virginia	0
Kansas	0	New Mexico	0	West Virginia	0
Louisiana	0.074	Nevada	0	Wyoming	0

Note. Table shows the weight assigned to each state in the synthetic control group for California.

Upon comparing the pre-trend between California and synthetic California before quarter 18 in Figures 4 and 11, we see that in Figure 11, the divergence between the pre-trend lines is higher than that observed in Figure 4. Thus, confirming that the model specification used to construct the weights in Table A is the most suitable.

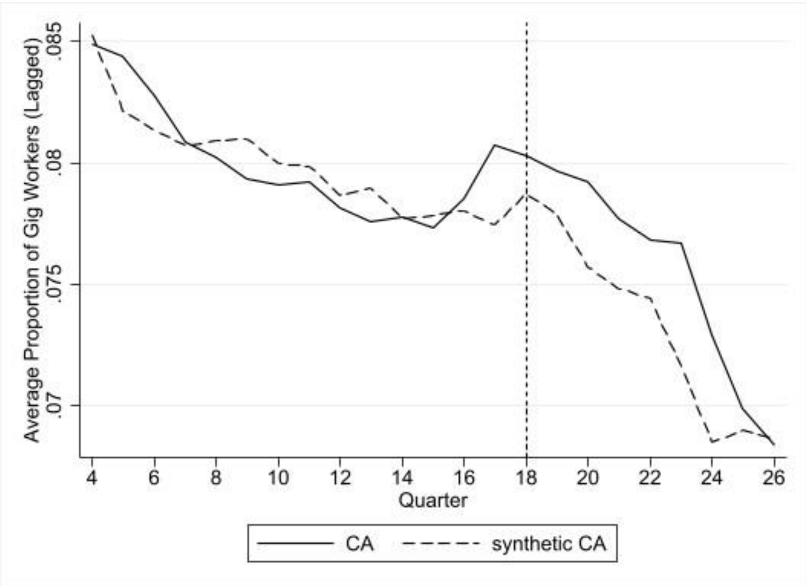

Figure 11. Trends in the average proportion of gig workers for California versus Synthetic California using only the lagged values.

Note. The solid line represents the observed average proportion of gig workers (lagged) in California for the 4th to 26th quarter; the dashed line represents the synthetic control. The vertical dashed line represents the quarter in which the Dynamex case ruling occurred (quarter 18)

In the model specifications to derive the weights in Table 2 and Table 3, the weights relied on the lagged values for almost all quarters in the pre-intervention period. However, in Table 4, the synthetic control is constructed using the lagged average proportion of gig workers for quarters (5, 6, 8, 9, 10, 11, 12, 14, 16) and the predictor variables: GDP per capita and majority count highest level of education. North Dakota, New Hampshire, and Vermont are still assigned the highest weights, with North Dakota taking the highest. However, Montana also takes weight here. From Figure 12, however, we still observe visible divergences in the pre-Dynamex case ruling trend for California and synthetic California. Thus, this model specification is also unsuitable to conclude the treatment effects of the case.

Table 4. Synthetic control weights for synthetic California using some lagged and predictor variables.

State	Weight	State	Weight	State	Weight
Alabama	0	Massacheusets	0	Ohio	0
Alaska	0	Maryland	0	Oklahoma	0
Arkansas	0	Maine	0	Pennsylvania	0
Colorado	0	Michigan	0	Rhode Island	0
Connecticut	0	Minessota	0	South Carolina	0
Delaware	0	Mississippi	0	South Dakota	0
Georgia	0	Montana	0	Utah	0
Hawaii	0	North Carolina	0	Virginia	0
Idaho	0	North Dakota	0.563	Vermont	0.083
Illiniois	0	Nebraska	0	Wisconsin	0
Iowa	0	New Hampshire	0.282	West Virginia	0
Kansas	0	New Mexico	0	West Virginia	0
Louisiana	0	Nevada	0	Wyoming	0

Note. Table shows the weight assigned to each state in the synthetic control group for California.

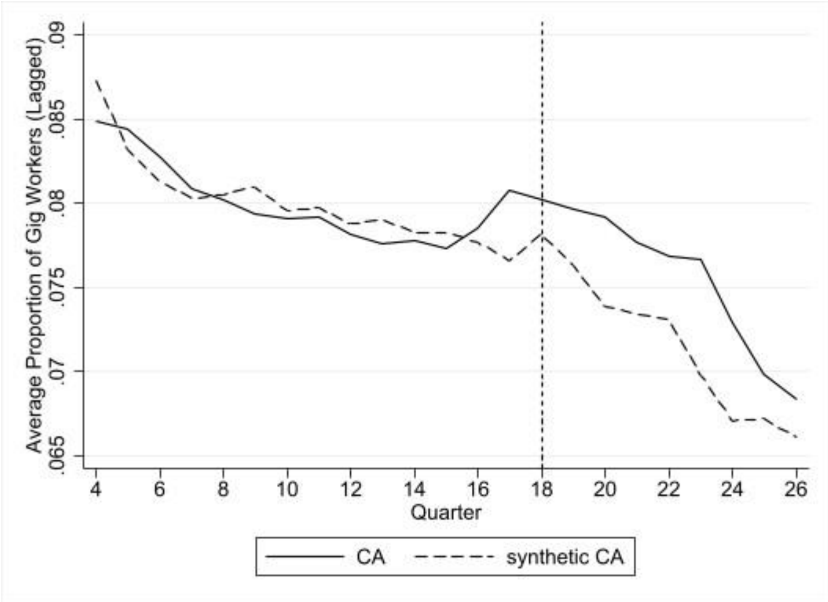

Figure 12. Trends in the average proportion of gig workers for California versus Synthetic California using some lagged and predictor variables.

Note. The solid line represents the observed average proportion of gig workers (lagged) in California for the 4th to 26th quarter; the dashed line represents the synthetic control. The vertical dashed line represents the quarter in which the Dynamex case ruling occurred (quarter 18).

VII. DISCUSSION & CONCLUSION

The main objective of our study was to examine how legal changes impact firm hiring behaviour, specifically how the changes in the employee classification laws impacted firm hiring behaviour. We employed a synthetic control approach to construct a synthetic California that closely matched the pre-intervention average proportion of gig workers. Our results showed that this legislative change increased the proportion of gig workers in the Californian labour force. Initially, we expected that such a legislative change would reduce rather than increase the proportion of gig workers because the criterion to prove a non-employee relationship is stricter. From the literature, however, we found that firms will respond to labour policies by utilising temporary employment or DSE models. These responses suggest that the change in employee classification laws could lead to an increase in gig workers rather than the decrease we initially expected. This also depends on the firm size and characteristics we discussed from Pierre & Scarpetta (2006). Although we can assume that the increase in the proportion of gig workers is via the implementation of DSE models, we cannot distinguish the type of self-employment category that the gig workers in our sample predominantly fall under. In addition, we discussed earlier that this ABC test posed a threat to a firm's labour costs; however, if the proportion of gig workers increased, we could also assume that the cost of proving a non-employee relationship is not higher than the cost of having firms' workers classified appropriately as employees.

This is a policy concern because the legislative change needed to incentivise firms to classify their workers correctly. However, we also found that the magnitude of the effect was not substantial enough to deem the legal change to affect firm behaviour.

However, it is vital to acknowledge the limitations of our study. Although our findings demonstrated an increase in the proportion of gig workers following the Dynamex case ruling before the verdict, synthetic California did not closely reproduce the average proportion of gig workers for California, as seen in Figure 4. Therefore, the divergence observed between the actual California and the synthetic California after the case cannot be interpreted as a treatment effect. Our findings were not robust from the robustness checks when we carried out the in-time and in-space placebo tests.

Another limitation was that our identification strategy for gig workers depends on individuals' self-perception of their work rather than a universal set criterion to classify a person as a gig worker correctly. The share of gig workers in our sample may be less than or more than what is shown in the CPS for each state because it is confounded by all people who may engage in any unincorporated business activity. However, they are not necessarily the contemporary gig worker.

While we employed robustness checks and synthetic control methodology, endogeneity issues will still likely arise. One is that there may still be unaccounted factors that could contribute to the observed changes in gig worker proportions. Not accounting for these unobservable factors will lead California and synthetic California to have different patterns in the proportion of gig workers before the Dynamex case verdict came out. Consequently, the estimated treatment effect we observed might not be reliable. This makes it difficult to determine whether the treatment caused the observed outcome difference.

Another source of endogeneity comes from the synthetic control, assuming that the treatment effect is constant over time. However, a policy change like the ABC test will likely have a varying treatment effect at different times. For example, we have focused on the firm responses after announcing the new classification measure. Still, there could also be a varying effect on the proportion of gig workers when it was enacted (quarter 25) and the ability of firms to adjust at different points in time following the Dynamex case. These dynamic treatment effects cannot be observed with our methodology and thus leading to biased results.

In conclusion, our findings suggest that introducing the ABC test increased the share of gig workers in California. While these results can contribute to our understanding of the dynamics of firm behaviour in response to classification policies, it is essential to interpret them cautiously, given they were not robust. Future research should use data with a standard criterion for gig workers under the contemporary understanding of gig work or analyse the employment effects on specific firms that primarily use the gig work model following such cases to see the hiring behaviour before and after the policy changes.

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