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Research Article

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¿Las pandemias afectan negativamente los negocios? El caso de Estados Unidos durante el COVID-19

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Abstract

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The economic downturn caused by the COVID-19 contingency cannot be denied. Many authors have studied the effects of the sanitary emergency on labor force and the demand and supply of goods and services. This paper aims to understand the consequences of the shock to the economy caused by the pandemic, measured through mobility restrictions, in the business context. Using Google Mobility and The New York Times report, stay-at-home orders were used as a proxy for mobility restrictions. The effect of said restrictions on initial unemployment benefit claims and new business applications provides an insight into the change in people's livelihoods. The difference-in-differences and event study methodologies were applied with data from 2010 to the third week of August 2020. The results indicate that the restrictions on mobility had a significant impact on both outcome variables. The effect on unemployment claims was still present at the time of this paper, while the behavior of new business applications was mostly affected for the first few weeks and then had a quick rebound.

Resumen

No se puede negar el deterioro económico causado por la contingencia del COVID-19. Diversos autores han estudiado los efectos de la emergencia sanitaria en la mano de obra y la demanda y el suministro de bienes y servicios. Este

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artículo pretende entender las consecuencias del impacto en la economía de la pandemia a través de las restricciones de movilidad en el contexto de los negocios. A través de Google Movilidad y el reporte de The New York Times se usan las ordenes de quedarse en casa como sustituto de las restricciones de movilidad. El efecto de dichas restricciones en las solicitudes iniciales de subsidio por desempleo y las solicitudes de nuevos negocios proporcionan una perspectiva del cambio en los medios de subsistencia de las personas. Se usaron las metodologías de diferencias en diferencias y estudio de evento con los datos desde el 2010 hasta la tercera semana de agosto de 2020. Se encuentra que las restricciones de movilidad tuvieron un impacto significativo en las dos variables de resultado. El efecto en las solicitudes de subsidio por desempleo aún estaba presente al momento de escribir este artículo, mientras que el comportamiento de las solicitudes de nuevos negocios estuvo particularmente afectado durante las primeras semanas y luego se recuperó rápidamente.

1. Introduction

The World Health Organization declared the COVID-19 a pandemic on March 11, 2020, and with seemingly no cure for the disease that has now taken countless lives, governments across the globe scrambled to find policies that could prevent the spread. These measures varied from the closure of schools and social distancing to imposed curfews, but they can be summarized as mobility restrictions. The disturbances in people's lives cannot be quantified entirely, but mobility restrictions can be used as a proxy for the vast changes suffered in March 2020. Said restrictions, or anti-contagion policies, were essential when the Center for Disease Control (CDC) estimated that over 2 million people were at risk of getting the disease in the United States ([CDC, 2020](#)).

In the United States, mobility mandates were dictated state-by-state as no national requirements were made. These decisions were first taken in the second week of March, with California becoming the first state to issue stay-at-home orders. As of October, all but five states (Arkansas, Iowa, Nebraska, North Dakota, and South Dakota) declared different restrictions. By the first week of April, the lives of almost the entire population of the United States had changed (see [Figure 1](#)). Under mobility restrictions, only essential businesses were allowed to operate. This led to strenuous effects on the labor market due to an extremely high shock that affected both demand and supply.

It is also important to note that this is not the first time the world has seen restrictions in mobility caused by disease. The most remembered are SARS in 2003, the AH1N1 virus in 2009, and Ebola in 2014. The restrictions to prevent these diseases were not even that successful and still had many problems. While restricted mobility might prevent person-to-person contagion, they do not have a significant effect on the overall size of the epidemic ([Espinoza, Castillo-Chavez, & Perrings, 2020](#)). Other effects were seen, for example, in 2009, with AH1N1, Mexico saw a 40% decrease in air transport, where tourism is a big part of GDP, but no effective containment was achieved by the mobility restrictions ([Bajardi et al., 2011](#)).

Even more specifically, in the labor market, mobility restrictions cause problems, even if they have nothing to do with an epidemic. In the West Bank, when Israel declared conflict-related restrictions on mobility, the effects on the labor market were clear. There was a decrease in employment, wages and days worked, and an increase in the number of hours worked per day ([Calí & Miaari, 2013](#)).

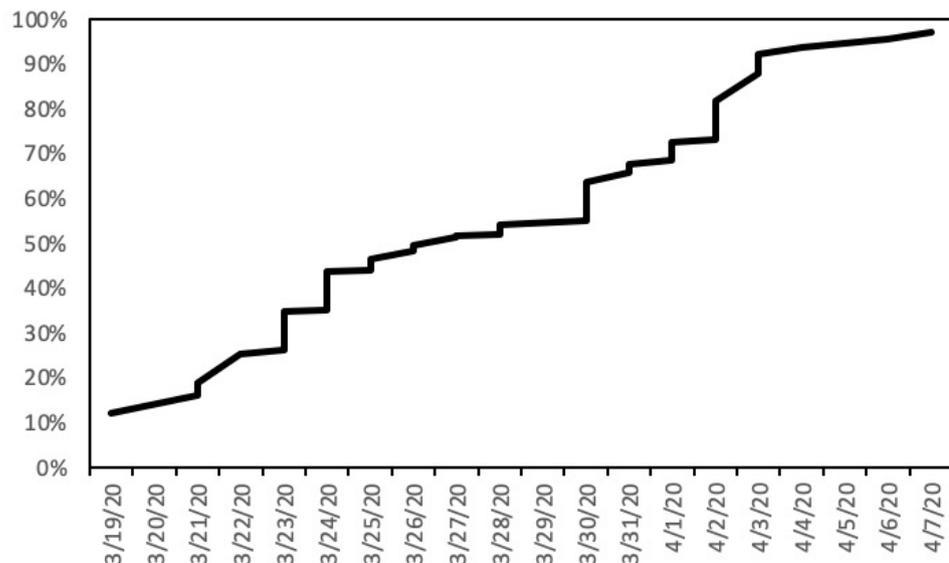
The restrictions implemented this year were extremely effective in containing the spread of disease; even so, that [Hsiang et al. \(2020\)](#) found that these types of interventions by the government

of 6 countries (China, South Korea, Italy, Iran, France, and the United States) prevented over 61 million confirmed cases that could have eventually led to 495 million total infections. Still, the restrictions did not come without their consequences. The income and wealth of individuals decreased, while aggregate consumer spending dropped thirty-one log percentage points (Coibion, Gorodnichenko, & Weber, 2020). In another study, Baker, Bloom, Davis, & Terry (2020) calculated economic uncertainty measured by stock market volatility, newspaper-based economic uncertainty, and subjective uncertainty in business expectation surveys to determine the mountainous effect that this will have on the economy (they expect a contraction of real GDP of around 11%).

As previously mentioned, this had a significant effect on the labor market, where the restrictions created a shock of contact-intensive goods and services that eventually propagated to all sectors via general equilibrium (Faria-e Castro, 2020). In a more specific approach, Baek, McCrory, Messer, & Mui (2020) find that stay-at-home orders increased a state's unemployment claims relative to other states. In a very interesting paper, back-of-the-envelope calculations suggest that for every life saved due to shelter-in-place orders, about 400 jobs were lost (Friedson, McNichols, Sabia, & Dave, 2020).

The effects on people's daily lives have not gone unnoticed by restricting mobility. The levels of unemployment, informality, savings, consumption, income, and even more have been affected significantly. In this sense, Bonaccorsi et al. (2020) study the economic and social effects of mobility restrictions in Italy. When studying the effects at the municipality level, they find that the restrictions have a greater effect in municipalities with high fiscal capacity and that there is a segregation effect in terms of income per capita. In this way, it is clear that the pandemic and its consequences have altered people in an incredibly uneven way. While unemployment has skyrocketed for people with little education in the United States, the savings rate is also at its highest level (DOL, 2020). The people least affected by mobility restrictions are those who can adapt their work to do it from home, those who can move safely, and those who have better housing, work, and savings conditions. Although the effects have been uneven, the consequences at the national level affect all inhabitants in one way or another.

Figure 1. Cumulative Population of the US Under Mobility Restrictions



Source: The New York Times and Google Mobility

The importance of this topic becomes clear when analyzing some of the surveys performed by the US Census Bureau. In the Household Pulse Survey, designed to measure the social and economic effect of the pandemic, close to a quarter of US households expected a loss in income from employment. Even more importantly, one third of households had difficulty paying for usual household expenses, and over 10% faced food scarcity ([Census, 2020b](#)). It is abundantly clear that the effects of stay-at-home orders cannot simply be measured in terms of the disease but also the effects on people's lives and their livelihoods. The question becomes a trade-off between combating the pandemic or worsening the economic recession.

The aim of this paper is to demonstrate, through high-frequency data, that the mobility restrictions imposed because of COVID-19 had a detrimental effect on unemployment and new business creations. The literature is evident in understanding the effects on the economy have been innumerable, but this study aims to concentrate on the specifics of initial unemployment claims for benefits and new business applications. The study includes the 50 states in the United States with data from 2010 to August 2020. This paper focuses on two variables that affect the labor market, enterprises, and the overall business environment. The main contribution of this paper to the literature is that it specifies the effects to be studied. It provides a perspective on the impact of mobility restriction on one of the most important aspects of people's lives: their livelihoods. Though many papers have used the initial unemployment claims data, the addition of business applications will provide a better understanding of unemployment and sources of income as many people that are fired could turn to other ways of obtaining means through new business applications. Hence, the effect of mobility restrictions on both variables provides an outlook on a more general aspect of people's lives.

It is important to note that these mobility restrictions were not the only effect of the pandemic as other factors also changed people's lives, such as fear of contagion or sudden changes in family and economic dynamics. Mobility restrictions are used because they are measurable and differ for each state, like the outcome variables.

The first specific variable to study is unemployment. In the United States, the unemployment rate went from 3.5% to 13.3% in just three months ([Bureau of Labor Statistics, 2020](#)). When the fiscal response to the crisis passed as a law, unemployment insurance was approved at a historical level, which is why this high number of people who receive a stipend from the government affects all citizens. Unemployment benefits are a necessary cost to all taxpayers and should be of interest to everyone in the United States. Applications to receive these benefits have reached over 1 million weekly, from March to July. These applications are at the state level as well as the quarantine measures, so it is believed that there must be a relationship between businesses with permission to operate and unemployment claims.

During the quarantines, consumption has had a very marked decrease. There was a minimum in March, which increased almost 20% in May, and it was only in July that pre-pandemic levels were reached ([Census, 2020a](#)). Furthermore, consumer confidence is currently at its lowest level in recent history, mainly due to the instability of the labor market and the expiration of government aid. This is why business creation will also be measured. In the United States, a measure called "Business Applications" could be affected because of the negative economic outlook created by the pandemic as well as the shock in demand and the issues with supply chains.

While the expected effects on unemployment claims are an apparent increase, the effects on new business applications are a little bit more ambiguous. On the one hand, the negative economic sentiment might lead people away from creating new businesses, as this negative economic outlook has never been seen before. On the other hand, while a recession has come, it is very unconventional as banks, the stock market, and the Federal Reserve have maintained a somewhat healthy stance. The mobility restrictions have created a complicated situation, but finding financing for a business is not as complicated as, for example, during the Great Recession in 2008. For this reason, the effect on unemployment will be much more significant and evident, however, the effect on new business will probably be negative at first but will flatten out quickly over time as people who lost their jobs try to create new companies or creative ideas arise for new businesses.

So the question becomes: What is the effect of mobility on the economic variables of the work environment? This paper aims to determine the effects of mobility restrictions on unemployment, business creation and people's perception of the crisis. This will be done through a difference-in-differences model and an event study. Thus, the study has the main objective of understanding the impact of health emergencies and their eventual restrictions on mobility, labor and business trends with the purpose of adapting disease contingency measures to a possible "second wave" or different disease and creating support policies for people who have been affected.

The structure of this paper is as follows: the data used is presented in the next sections. Then, the two methodological processes used are in the third section, The fourth section presents the results, and the fifth section has a conclusion and discussion.

2. Data

2.1 Mobility and Stay-at-Home Orders

The governor of each state was responsible for creating and implementing any mandate to contain the spread of the disease, and most of them turned to stay-at-home orders. The first one was issued in the Bay Area of California, and then California became the first state to implement state-wide orders. South Carolina became the last state to do it on April 7, while Arkansas, Iowa, Nebraska, South Dakota, and North Dakota never issued orders.

These orders varied slightly by state, as each governor deemed different types of essential businesses and managed the transportation and implementation of the measures differently. However, most consisted of school closures, work-from-home policies, and social distancing guidelines. In order to maintain a similar understating of the mobility restrictions and measure them in the same way, the data from The New York Times was used ([Jasmine C. Lee & Matthews, 2020](#)). Starting on March 24, the newspaper started tracking all policies related to mobility restrictions issued by governments. Some of these measures started within cities or countries or only for specific businesses, which is why a unified source was essential.

Knowing when the stay-at-home orders were implemented is essential to this study, but measuring how much said restrictions really affected mobility is also important. For this goal, Google Mobility data was used. The COVID-19 Community Mobility Report by Google was launched to provide insights to public health officials regarding the response to policies that affect mobility trends in specific geographical areas. In order to compare mobility, they use a baseline day, which is the median value of

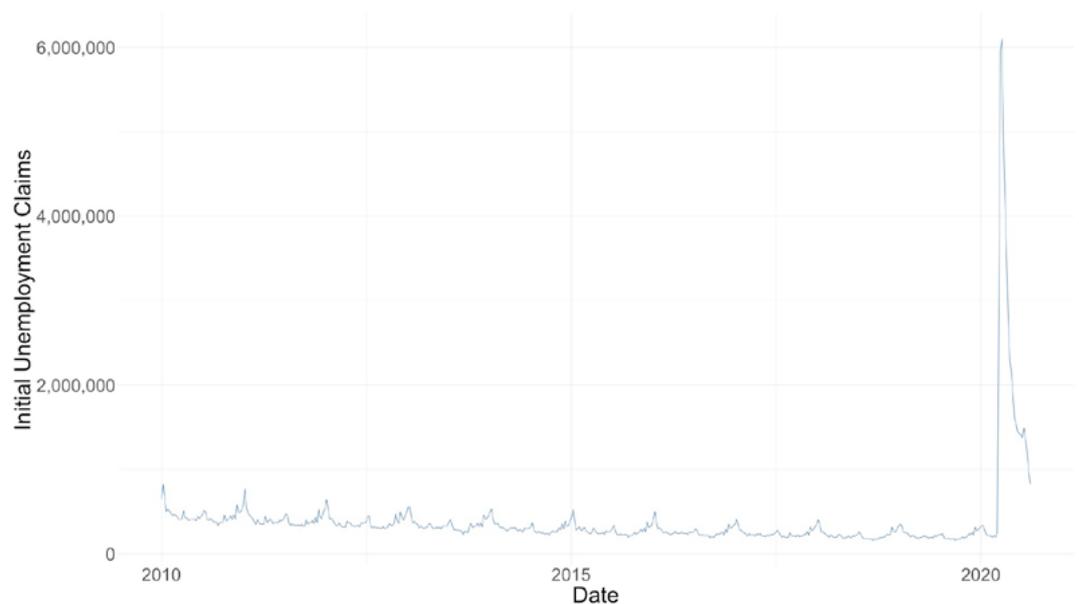
the first five weeks of 2020 (Google, 2020). The reports can be divided into categories such as home, work, parks, health, public transport, and grocery and pharmacy. For this study, the most relevant category is work-related mobility, as it differentiates between essential and non-essential mobility, those who were unrestricted, and it relates most to the outcome variables in this paper.

For reference, the home and work mobility plots by state are presented in [Appendix C](#).

2.2 Outcome Variables

The first outcome variable is initial unemployment benefit claims. The Department of Labor widely distributes this data every week, so it becomes a real-time measure of the labor market. The specific variable used in this paper is Initial Unemployment Claims; these initial applications reached a record-setting level of 3.3 million in the week of March 21. In the following three weeks, the number reached 17 million applications. This data has certain characteristics that are very valuable to analyze. The accuracy of the high-frequency data has been admired by many as the federal response to unemployment benefits affects each state differently, but the national data is very accurate. It has actually become a proxy for economic recovery as markets fluctuate and professionals analyze the meaning of the numbers published every Thursday.

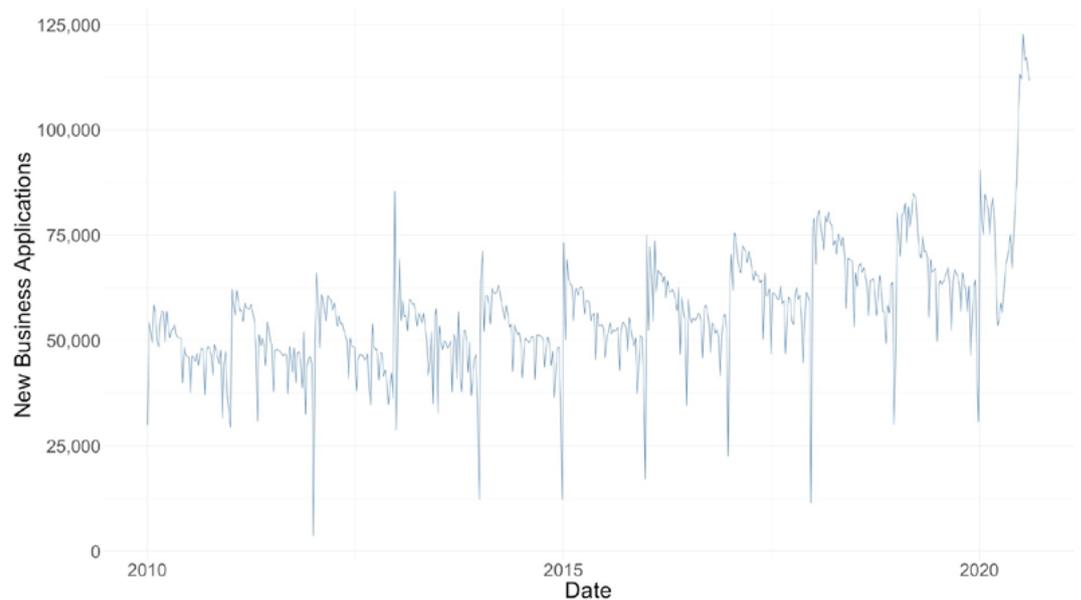
Figure 2. Time Series of Initial Unemployment Claims



Source: US Department of Labor

The second variable studied is the new business applications published by the US Census Bureau. The data consists of applications to the Internal Revenue Service (IRS) for an identification number to be able to receive payments. The data is also published weekly and by state, which is essential to this study. The differentiation in the data is the kind of business that is hoping to get registered, but in the case of this study, the total aggregate non-seasonally adjusted number will be used. This is because the methodology will factor in weekly trends in the data. For example, there is a difference between high propensity businesses and small enterprises, but as this study aims to find the effects on the overall business environment, other data specifics are not studied.

Figure 3. Time Series of New Business Applications



Source: US Census Bureau

From the time series, it is easy to tell that initial unemployment claims have been somewhat stable throughout the years compared to the incredible spike in 2020 (Figure 2). Even though the peak has slowed a little, weekly claims are still much higher than their norm. Averaging 7,588 a month and with a substantial standard deviation (over 19,000), it becomes clear that this variable was highly affected by the health contingency and its consequences. Regarding the following outcome variable (Figure 3), new business applications seem to be very cyclical with an increasing trend over time. This seasonality will be considered by using weekly factors as well as yearly and state specifying characteristics. A small drop can be seen at the beginning of 2020, but there is a bug regaining that is still going on in August. This might be because of what was previously mentioned that people might look for other sources of income, but the data has a lot more to show.

The data is collected from 2010 to the third week of August 2020. The reason is to be able to get factors concerning these years and create a baseline scenario with enough data. The time frame was selected to evade the shocks created by the Great Recession and have enough weeks for the event study. This will be enough to establish the trends throughout the years on the different outcome variables to create the best possible counterfactual.

Table 1. Descriptive Statistics

	2020		2010-2019		T-test p-value	
	Unemployment	Business Applications	Unemployment	Business Applications	Unemployment	Business Applications
Mean	32,171	1,604	6,031	1,082	< 2.2e-16	< 2.2e-16
Sd	67,560.7	2,142.7	8,807.0	1,372.8		
Min	159	60	81	10		
Max	1,058,221	14,310	114,793	10,520		

Source: Own calculations based on the US Census Bureau and the US Department of Labor

[Table 1](#) presents the descriptive statistics for the data between 2020 and 2010-2019. This makes it clear that there are significant changes between these two periods. The mean almost quintupled for unemployment claims, and the standard deviation increased. The most significant change is the maximum; there was a 721% increase. For new business applications, changes are present, albeit smaller. The mean, standard deviation, and max increased but in much smaller increments. When using a more methodological approach, a T-test proved that the difference between initial unemployment claims and new business applications in 2020 and from 2010 to 2019 is statistically significant¹.

3 Methodology

The main methods used in this study are a difference-in-differences model and an event study. First, it is necessary to create a counterfactual or a basis. This would be the United States without a pandemic, but as this situation did not happen, it needs to be recreated. In order to be able to answer what is the effect of the mobility restriction on initial unemployment claims and new business applications, it is crucial to have a comparison scenario. Then, it is possible to approximate the answer to this question by comparing the current situation in the US to an alternate scenario that approximates the situation that would have happened had COVID-19 not been present. The better the counterfactual, the better and more precise the result.

In order to build this alternate scenario, data from 2010 onwards was obtained for the outcome variables. With this, observed tendencies that were happening pre-pandemic can be obtained. These tendencies help estimate the results in unemployment claims and new business applications after March if COVID-19 had not happened. For these tendencies to be more approximate, they are adjusted for seasonality based on the different weeks (as counted by the IRS) and a year and state factor.

The first method used is a difference-in-differences to identify any causal effects. For this method, there will be two groups, control and treatment. The control group consists of the weekly trends of unemployment claims and new business applications by state from 2010 to 2019. The treatment group is made up of the data in 2020, after the day that there is at least a 30% drop in work-related mobility as measured by Google data. This specific week changes for every state and correlates significantly to when every governor dictated the stay-at-home orders.

From this, the first equation arises:

$$y_{s,t,y} = \beta D_{s,t,y} + \gamma_{s,t} + \rho_t + \epsilon_{s,t,y} \quad (1)$$

¹For unemployment claims, the test showed a p-value of < 2.2e-16 and for business applications the result was p-value < 2.2e-16

Where there is differentiation by week (t) and state (s), and the variable y corresponds to the outcome variable studied, being the case of business creation applications or applications for unemployment subsidy. D is the treatment variable that is composed as a “dummy” with a value of 1 when the specific state is under orders to stay at home or 0 when not, and the β is the average change in the trends of the outcome variable once the health emergency started, meaning when D is equal to 1. The other variables are state fixed effects γ and weekly ρ and ϵ is an error term.

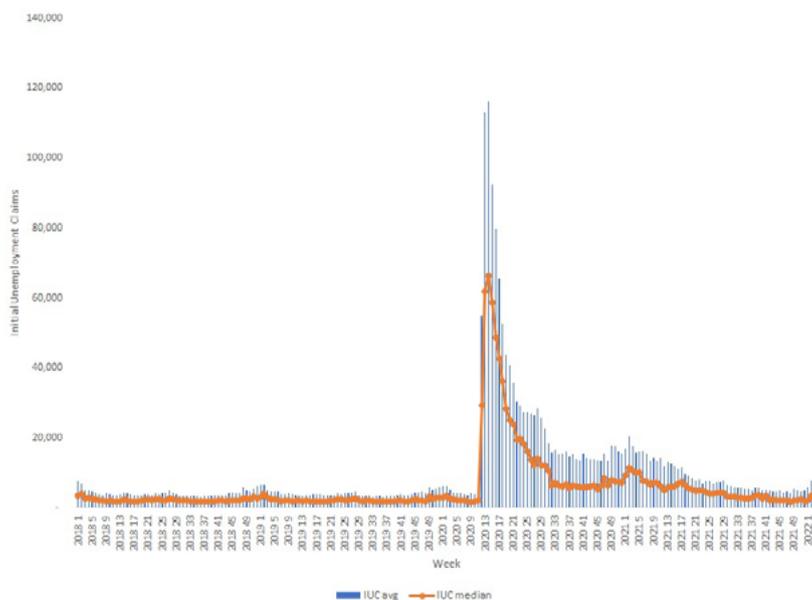
The next step in the methodology is the event study, where the treatment becomes dynamic. This methodology has two main objectives. First, it allows the assumption of parallel trends of the outcome variables for the empirical study, that is, there are no systematic differences in the unemployment claims and business application patterns in the periods before confinement. The second reason is that it allows studying how patterns change over time in the periods following confinement by COVID-19. The event study is done on a bi-weekly basis. The equation for this method is:

$$y_{s,t,y} = \sum_{k=-T}^{-2} \beta_k D_{s,t,y}^k + \sum_{k=0}^R \beta_k D_{s,t,y}^k + \gamma_{s,t} + \rho_t + \epsilon_{s,t,y} \quad (2)$$

The change between the two previous equations is given in the term D . In the periods $k = 1, 2, \dots, R$ is going to have the effect of the mobility restrictions on the result variable in each week k relative to the week prior to the restrictions, where R is given by the availability of the data (33 weeks in this case). The k values between $-T$ and -2 are used to test the assumption of parallel trends, which is fundamental in this type of impact evaluation study.

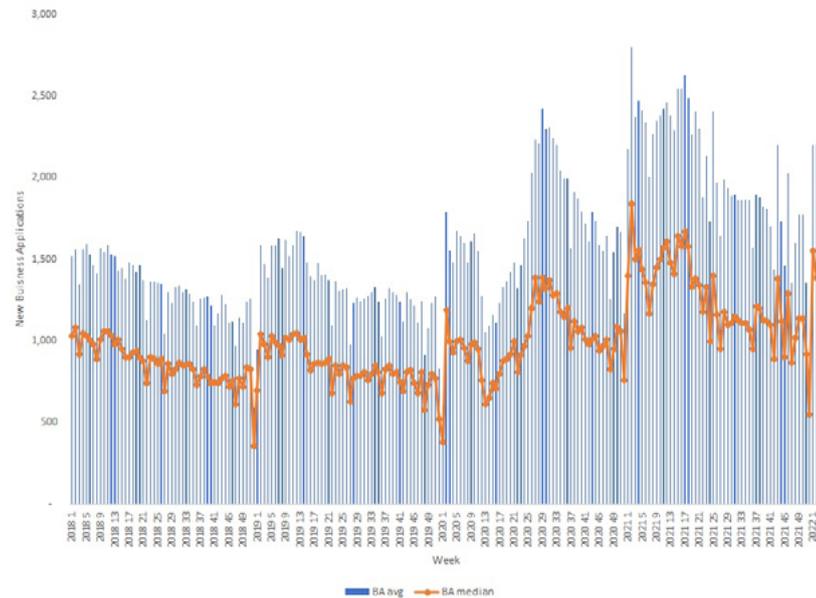
The identification strategy can be observed in the following figures, where weekly average initial unemployment claims and new business applications are grouped by state. In the unemployment figure, the variation is evident around the time mobility restrictions and COVID-19 spread throughout the country, with a considerable increase. The identification variation is a bit more blurry in new business applications, as around weeks 12-15 of 2020, there was a drop in the data, followed by an increase until new applications level out.

Figure 4. Weekly Average of Initial Unemployment Claims



Source: US Census Bureau

Figure 5. Weekly Average of New Business Applications



Source: US Census Bureau

4 Results

The results for the difference-in-differences model are seen in [Table 2](#) for the 50 states. The first results of column one estimate the effect of the health emergency on the average number of applications for unemployment benefits and the second column of applications for new businesses. The first row corresponds to the coefficient, the second row to the standard error of that coefficient, and the third row to the magnitude of the coefficient relative to the average number of the respective variable between January 1, 2010, and December 31, 2019 (reported as a percentage change). All estimations include week fixed effects, state and year fixed effects, and clustered errors to the state level. These are used to control the idiosyncratic characteristics.

Table 2. Difference-in-Differences Results

	Unemployment	Business Applications
	(1)	(2)
Treatment	68,436.89***	-550.7953***
	(11,402.51)	(116.30)
	1,134%	-50.9%
Observations	28,254	28,254
States	50	50
Week FE	Yes	Yes
State x Year FE	Yes	Yes

Note: The percentage change is calculated from the weekly average between 2010-2019. The estimation includes state-year and week fixed effects as well as robust standard errors. In the table, asterisks indicate that the result is statistically significant at 90% confidence (*), 95% confidence (**), and 99% confidence (***).

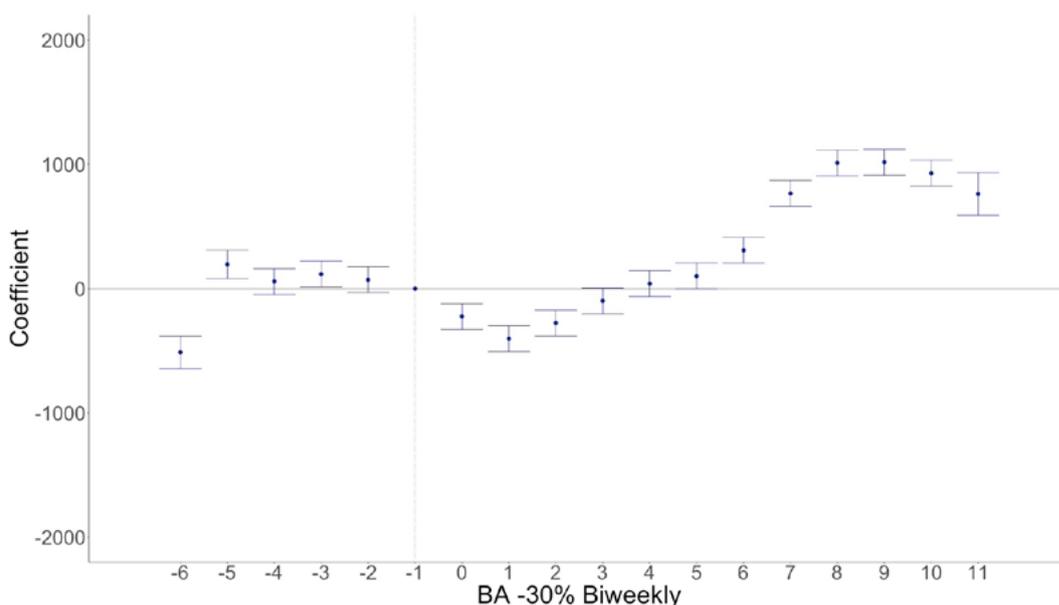
These numbers show that the effects on unemployment and business applications are more than significant. Once the pandemic set in with all its effects and mobility restrictions were put in place, initial unemployment claims increased by over 68,000 weekly while new business applications dropped over 500, all relative to the week before stay-at-home orders were issued. In relative terms, this indicates a 1,100% increase in unemployment claims compared to the average of 2010-2019, and for business applications, the results show a -50.9% drop.

In [Appendix A](#), the results with unclustered errors are reported, with an OLS and Poisson estimation. The changes are minimal, meaning the results hold and are significant for the estimation. These results also have week and state-year fixed effects. The [table](#) is constructed in the same way as [Table 2](#), where the main takeaway is that the coefficient relative to the previous average is the same for OLS and is still very significant for the Poisson estimation.

The results of the event study are shown in the following figures. In terms of business applications, the results indicate a fall in the first two months after the pandemic began and then an increase. This is because as people suddenly lost their jobs, many turned to other sources of income, such as entrepreneurship or small independent businesses. As discussed in the literature review, this has been a differentiating characteristic of this economic recession.

According to [Figure 4](#), relative to the last two weeks before mobility restrictions, new business applications fell by over 200 applications in the first weeks, even going as far as reaching a 400 drop in the subsequent month. Compared to the last nine years, the first two weeks showed a 20% drop in applications. This is a very considerable and quick drop, but the recovery momentum is even more surprising, where the increase reached an astounding 1,000 plus applications in two weeks, meaning around a 50% increase.

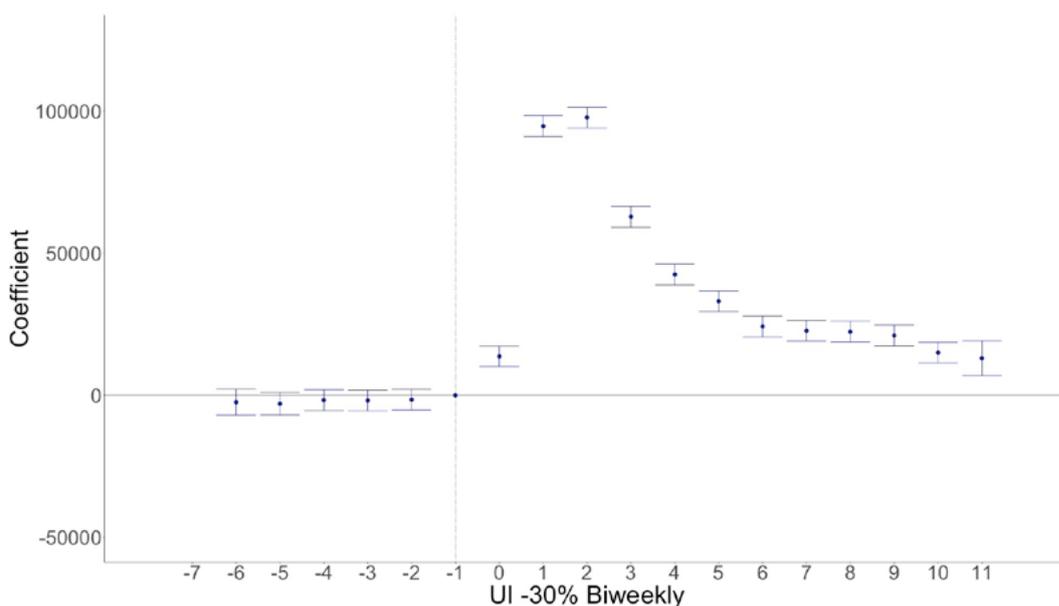
Figure 6. Event Study of New Business Applications



Note: Event study calculated with data from Google Mobility and US Census Bureau. It includes week and state-year fixed effects. The band represents a 95% confidence interval.

The event study plot for unemployment claims is even more drastic (Figure 5). In the month following the mobility restrictions, initial unemployment claims rose to levels never reached before. In the first two weeks, claims reached an increase of 13,700 more applications even when considering all fixed effects. In the next two weeks, that number climbed to 94,000 and even 97,000. For that month, it means an increase of over 700% relative to the biweekly average of claims from 2010 to 2019. As of the third week of August, claim applications did not return to their pre-pandemic level, and that does not seem to be happening anytime soon. Even without federal aid, which ran up in July, state unemployment claims will continue to rise even more now. With a second, and even third wave coming in the winter, unemployment claims will at least continue steady at 800,000 weekly for the following months.

Figure 7. Event Study of Initial Unemployment Claims



Note: Event study calculated with data from Google Mobility and US Department of Labor. It includes week and state-year fixed effects. The band represents a 95% confidence interval.

[Appendix B](#) shows the event study for a 20% drop in mobility, where results hold and are still significant. As in all estimations, the magnitude of the significance is greater for unemployment claims but still present for new business applications.

5 Conclusion

The aim of this study was to find a causal effect between the mobility restrictions caused by the COVID-19 pandemic and initial unemployment benefit claims and new business applications. Mobility restrictions were one of the most prominent effects of the pandemic that have been correctly quantified. There were many other effects of the disease and many other reasons for the changes in the livelihood of people, but mobility restrictions are a good representation of regulatory implementations that people were obliged to follow. Therefore, these results are useful for understanding some effects of the pandemic because they encompass the exogenous disturbance that happened in March 2020. While many studies have dove into different effects of the disease and its economic consequences, this study aims to emphasize the effect on the business environment through causal inference methods. The importance of this is evident as the labor market and enterprises are essential to economic recovery, now more than ever, given the future second and third waves of contagions. The data used for this study was obtained from different sources. For mobility, stay-at-home orders were grouped and organized by The New York Times, while the proxy for the restrictions was the work mobility data obtained from the Google Mobility Report. The outcome variable data was all federal for the United States from 2010 to the third week of August 2020. For unemployment claims, the US Department of Labor publishes weekly data, while business applications are issued by the US Census Bureau.

The methods used were a difference-in-differences method and an event study. The paper finds that the effects are very significant for both outcome variables. Compared to a relative baseline of an average of the variables between 2010-2019, unemployment claims increased by over 1,000%, while business applications decreased by 50%. Then, compared to the baseline two weeks before the pandemic, the results were also sustained at an increase of over 90,000 unemployment applications and a decrease of over 400 new business requests.

From all this information, it becomes clear that stringent mobility restrictions might not be the perfect answer to prevent the spread of the disease. Regarding unemployment, the restrictions on mobility had a directly harmful effect. When people could not leave their homes, and non-essential businesses had to close, many lost their jobs. The federal unemployment benefits that were put in place from March to July were a great help to people as they were able to sustain their lives somehow, but that has changed. The unemployment rate will take a long time to return to the pre-pandemic level, and claims will remain high for a long time. While from 2010 to 2019, the weekly average was around 6,000, the last reported data on October 24 was still 751,000.

In terms of new business applications, the effect was significant but did not persist much in time. In the first two months after the pandemic, applications dropped to lower levels because of a terrible economic outlook and the actual restriction on mobility because people were afraid of not having customers, have interrupted supply chains, or many other concerns. As the pandemic progressed, the number of applications increased. This is probably due to the lack of recovery in employment and job openings. Thus, people turned to other sources of income, such as creating their own companies. This economic crisis has been one of the worst in history, but it has certain exceptions. The Fed and the government worked very hard for liquidity to be available in the economy, and it shows as people can have easier access to financing needs. Also, as life was turned upside down, people came up with new business ideas or even turned hobbies into money-making companies.

Some possible limitations of this study are based on the methodology and data. The causal inference models rely on the construction of a viable counterfactual to be able to obtain better results. The scope of this study aimed to create the most accurate counterfactual attainable, but it is never possible to predict what the world would have been like without COVID-19. Of course, mobility restrictions were not the only economic or institutional change at the time. Therefore, it would be bold to assume that these effects would be replicable in another pandemic. Still, as mobility was one of the most considerable effects and very well measured, it can be used as a proxy for the exogenous shock suffered by all. In terms of the data, there are particular challenges. The measurement of restriction mobility used with Google data may not be perfect as it is an opt-in service for Google users. This may not seem like much, but considering that there are over 1.5 billion Gmail accounts, it is probably a good sample of the US population. The difference between orders within states was also complex as some governors relied on mayors, others did it by themselves, and others waited for federal orders that never came. This is why The New York Times data was used, but it is still not perfect. Some possible future improvements could be factoring in other data such as political parties as the handling of the pandemic became very politicized or taking into account counting claims and high propensity or different kinds of new business applications.

As a second and third waves are already happening worldwide, the policy implications of this cannot be ignored. It is essential to protect citizens from the disease, but mobility regulations might be very restrictive. Other alternatives may be better as other variables come into play, such as vaccines, previous infections, and polarizing politics. For example, measures like those implemented in October in France might be more useful. The only workplaces that have to close are those that cannot work remotely, so there is a smaller chance of employers closing or firing employees. Also, schools and transportation are still open, interrupting life a little less and allowing people to live a more seemingly “normal” life. Even though no clear path is paved and finding a balance between health and the economy seems impossible, it is very important for policymakers to understand that such restrictions have long-lasting negative effects.

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Appendices

A Estimations with Unclustered Errors and Poisson Model

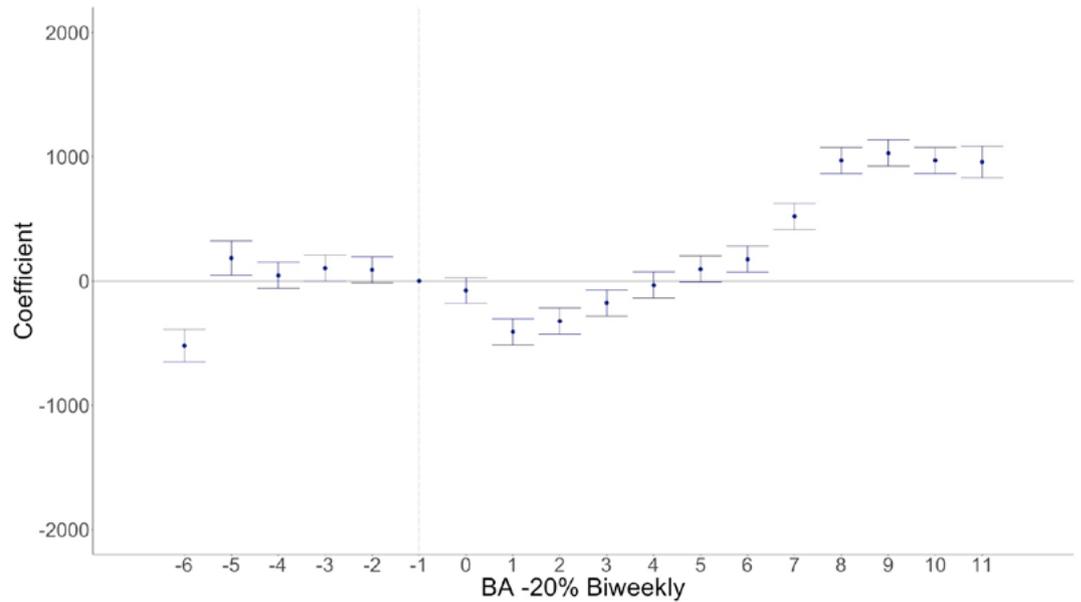
Table A.1. Difference-in-Differences Results with Unclustered Errors and Poisson Model

	Unemployment		Business Applications	
	OLS	Poisson	OLS	Poisson
	(1)	(2)	(3)	(4)
Treatment	68,436.89	1,269	-550.795	-0.342
	(1,020.13)	(0.001)	(22.071)	(0.002)
	1,134%	256.1%	-50.9%	-28.9%
Observations	28,254	28,254	28,254	28,254
States	50	50	50	50
Week FE	Yes	Yes	Yes	Yes
State x Year FE	Yes	Yes	Yes	Yes

Note: The percentage change is calculated from the weekly average between 2010-2019. The estimation includes state-year and week fixed effects as well as robust standard errors. In the table, asterisks indicate that the result is statistically significant at 90% confidence (*), 95% confidence (**), and 99% confidence (***)

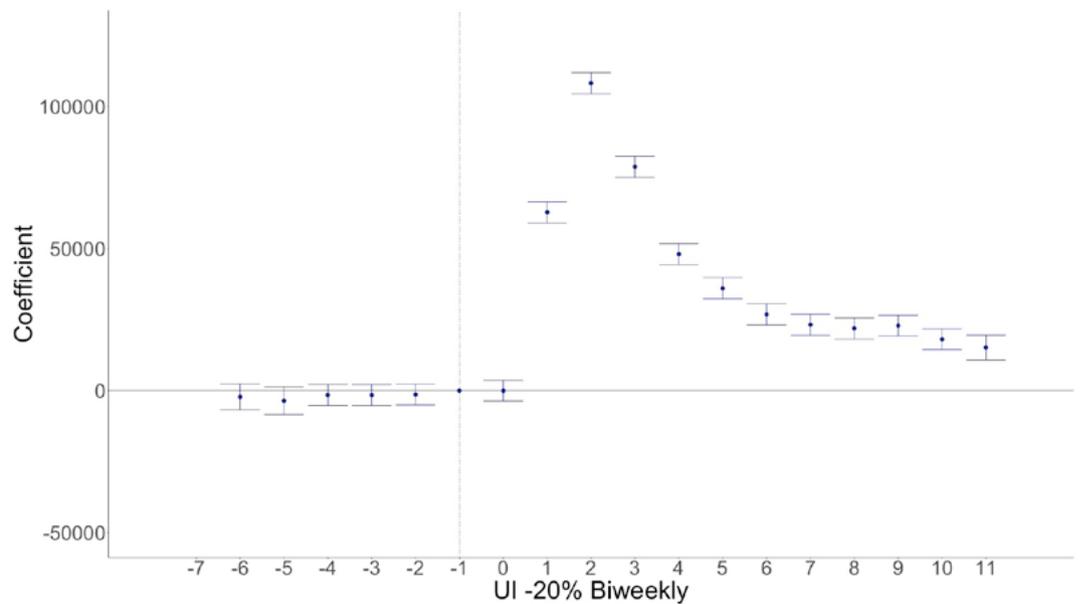
B Event Study Plots (20% Mobility Reduction)

Figure B.1. Event Study of New Business Applications



Note: Event study calculated with data from Google Mobility and US Census Bureau. It includes week and state-year fixed effects. The band represents a 95% confidence interval.

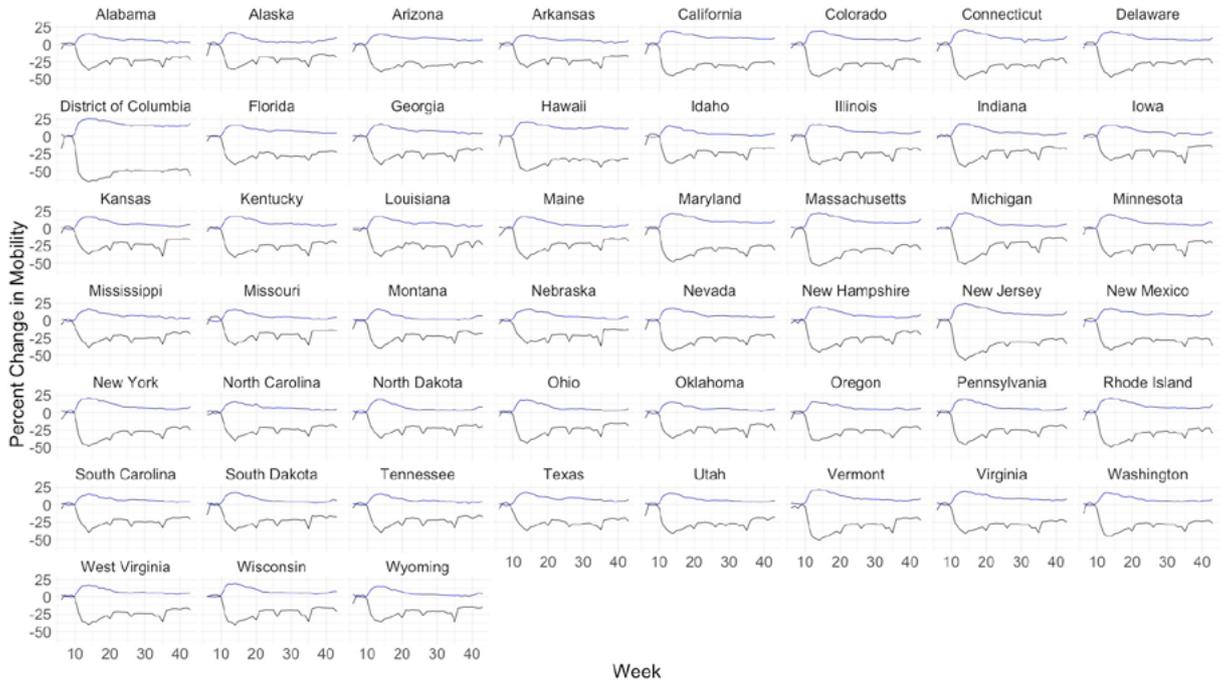
Figure B.2. Event Study of Initial Unemployment Claims



Note: Event study calculated with data from Google Mobility and US Department of Labor. It includes week and state-year fixed effects. The band represents a 95% confidence interval.

C Home and Work Mobility Plots

Figure C.1. Mobility changes by state



Note: The black line represents changes in mobility to workplaces and the blue one mobility changes in housing facilities.

Source: Google Mobility