Are Pandemics Bad for Business? Evidence From the US COVID-19 Experience

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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 the labor force, demand, and supply of goods and services. This paper aims to understand the consequences of mobility restrictions caused by the pandemic on the business environment. Through the use of Google Mobility and The New York Times report, I use stay at home orders 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. I use Difference in difference and event study methodologies on data from 2010 to the third week of August 2020. I find 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 application was mostly affected for the first few weeks and then had a quick rebound.

Key Words: Mobility Restrictions, Unemployment Claims, Business Applications, Causal Inference, COVID-19

JEL Codes: J64, J65, G14

1 Introduction

The World Health Organization declared SARS-Covid-19 a pandemic on March 11th 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, social distancing, to imposed curfews, but they can be summarized as mobility restrictions. Said restrictions, or anti-contagion policies, were essential at a time when the Center for Disease Control (CDC) estimated that over 2 million people were at risk of getting the disease in America (CDC, 2020).

In the United States, specifically, mobility mandates were dictated on a state by state basis 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 4 states (Arkansas, Iowa, Nebraska, North Dakota, and South Dakota) declared different restrictions. By the first week of April, the lives of almost the whole 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. Those that are most remembered are SARS in 2003, the AH1N1 virus in 2009, and Ebola in 2014. The restrictions put in place to prevent these diseases were not even that successful but 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, like 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).

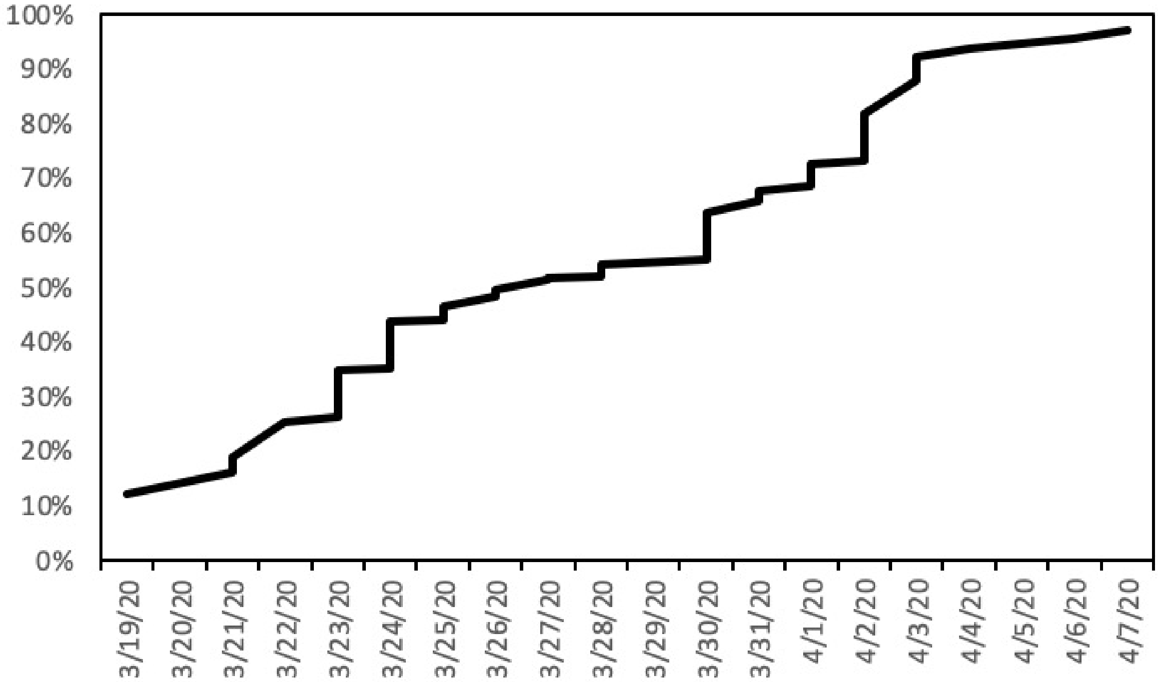
Even more specifically in the labor market, mobility restrictions cause problems, even if they have nothing to do with an epidemic. In the West Bank, when Israel declared conflict-related restrictions on mobility, the effects on the labor market were clear. There was a decrease in employment, wages and days worked, and an increase in the number of hours worked per day (Calì & 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 31 log percentage points (Coibion, Gorodnichenko, & Weber, 2020). In another study, Baker, Bloom, Davis, and 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 in the economy (they expect a contraction of real GDP of around 11%).

As previously mentioned, this had a great effect on the labor market, where the restrictions created a shock of contact-intensive goods and services that eventually propagate to all sectors via general equilibrium (Faria-e Castro, 2020). In a more specific approach, Baek, McCrory, Messer, and 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).

By restricting mobility, the effects on people's daily lives have not gone unnoticed. The levels of unemployment, informality, savings, consumption, income, and even more have been affected in an incredible way. 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 also find 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 who are 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 U.S. households expected a loss in income from employment. Even more importantly, a 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, in terms of 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 clear in understanding that the effects in the economy have been innumerable but this study aims to concentrate on the specifics of initial unemployment claims for benefits and new business applications. I will conduct the study for the 50 states in the United States with data from 2010 to August 2020. The specific scope of this paper is on two variables that affect the labor market, enterprises, and the overall business environment. This is the main contribution of this paper to the literature as it specifies the effects to be studied. It will contribute a look into the consequence of mobility restriction into 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 not only unemployment but also sources of income as many people that are fired or let go, could turn to other ways of obtaining means through new business applications, so an effect of mobility restrictions on both of these variables really provides an outlook on a more general aspect of people's lives.

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 responses to face the crisis passed as a law, unemployment insurance was approved at a historic level, which is why this high number of people who receive a stipend from the government affect all citizens. Unemployment benefits are a necessary cost to all taxpayers and therefore should be of interest to all Americans. Applications to receive these benefits have reached over 1 million weekly, from March to July. These applications are at the state level, and the quarantine measures are also, 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, 2020b). 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, there is a measure called "Business Applications" that could be affected because of the negative economic outlook created by the pandemic as well as the shock in the demand and the troubles with supply chains.

While the expected effects on unemployment claims are a clear increase, the effects on new business applications are a little bit more ambiguous. On one hand, the negative economic sentiment might lead people away from creating new businesses, as this negative economic outlook is a kind that has never been seen before. 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 restrictions in mobility have made for a complicated situation, but one in which finding financing needs for a business are not as complicated as say during the Great Recession in 2008. For this reason, the effect in unemployment will be much greater and clear, but the effect on new business will probably be negative at first but will flatten out quickly over time as people who lost their jobs look to create new companies, or creative ideas arise for new businesses.

So the question becomes: What is the effect of the mobility on economic variables of the work environment? What I want to achieve is to determine the effects of mobility restrictions on unemployment, business creation and people's perception of the crisis. This is going to be done through a difference in difference 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, on labor and business trends. This is done with the idea of adapting disease contingency measures for a possible 'second wave' or different disease and to create 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 consists of the results found 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 7th, while Arkansas, Iowa, Nebraska, South Dakota, and North Dakota never issued orders.

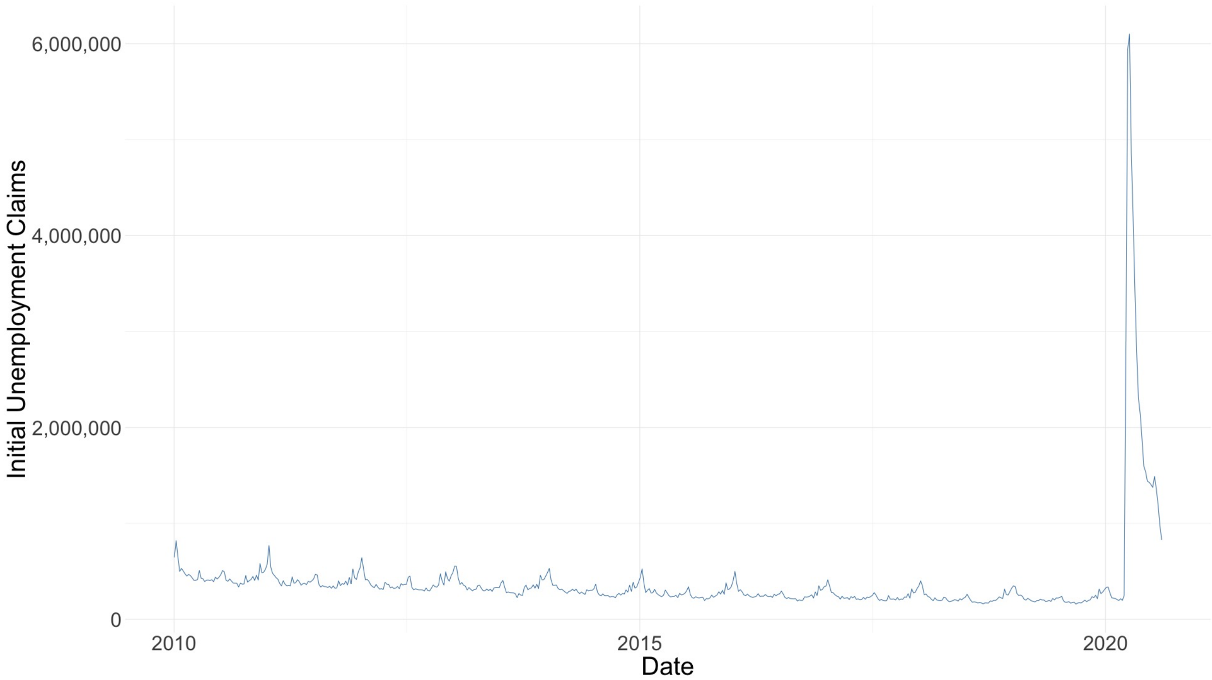
These orders varied a little by state, as each governor deemed different types of businesses essential and managed transportation and implementation of the measures in a different way. They mostly consisted on closure of schools, work from home policies, and social distancing guidelines. In order to maintain a similar understating for 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 24th, the newspaper started tracking all policies related to mobility restrictions that were issued by governments. Some of these measures started within cities or countries, or only for specific kinds of businesses, which is why a unified source was very important.

Knowing when the stay at home orders were implemented is essential to this study, but it is also important to have a way of measuring how much said restrictions really affected mobility. For this goal, I use Google Mobility data. The COVID-19 Community Mobility Report by Google launched as a way to provide insights to public health officials, specifically for 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 5 weeks of 2020 (Google, 2020). The reports also break down into different categories such as home, work, parks, health related, public transport and grocery and pharmacy. For the purpose of this study, the most relevant category is work related mobility as it differentiates between essential and non-essential mobility, it differentiates 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 insurance claims. This data is widely distributed by the Department of Labor on a weekly basis, 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 21st, which was only the beginning of what was to come; in the following 3 weeks the number reached 17 million applications. This data has certain characteristics that make it very valuable to analyze. The accuracy of the high-frequency data has been admired by many as the federal response of unemployment benefits affects each state differently, but the national data is very precise. It has actually become a proxy for economic recovery as markets fluctuate and professionals analyze the meaning of the numbers published every Thursday.

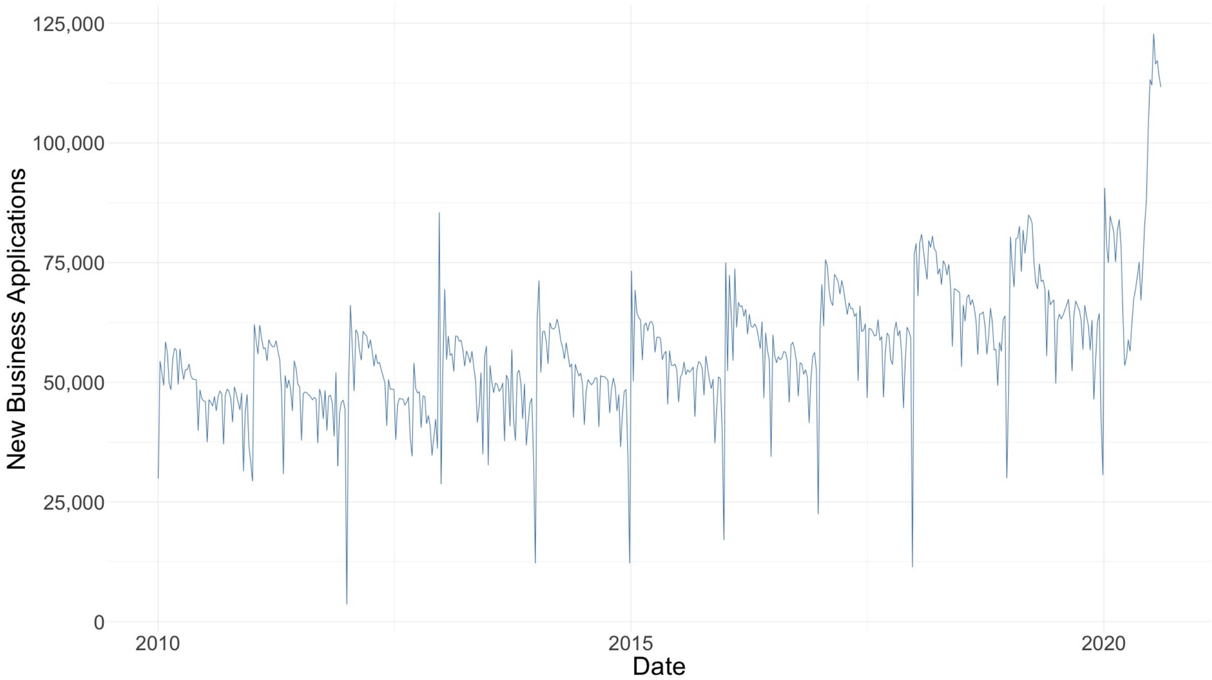
Figure 2. Time Series of Initial Unemployment Claims



Source: U.S. 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 present in the data is the kind of business that is hoping to get registered, but in the case of this study,I will use the total aggregate non-seasonally adjusted number. This is because the methodology will factor for weekly trends in the data. For example, there is a difference between high-propensity business and small enterprises, but as this study aims to find the effects on the overall business environment, other specifics of the data are not studied.

Figure 3. Time Series of New Business Applications



Source: U.S. 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 from their norm. Averaging 7,588 a month, and with a huge standard deviation (over 19,000), it becomes clear that this variable was extremely affected by the health contingency and all its consequences. On to the next outcome variable, Figure 3, new business applications seem to be very cyclical with an increasing trend over time. This seasonality will be taken into account 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 is still very interesting to dig deeper into.

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

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 U.S. Census Bureau and the U.S. Department of Labor

variables as to create the best possible counter factual.

Table 1 presents the descriptive statistics for the data separated between 2020 and 201-2019. This makes it very clear that there a significant changes between these two time periods. For unemployment claims, the mean almost quintupled and the standard deviation increased highly. The biggest change is the maximum, there was a 721% increase. For new business applications that changes are present, albeit smaller. The mean, standard deviation, and max all 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 are statistically significant[1].

3 Methodology

The main methods I use in this study are a difference in difference model and an event study. To begin, it is necessary to create a counterfactual or a basis. This would mean 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 important to have a comparison. I can then 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, then the better and more precise the result.

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

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 what the results in unemployment claims and new business applications would have been after March if COVID-19 had not happen. For these tendencies to be more approximate, I adjust them for seasonality based on the different weeks (as counted by the IRS) and a year and state factor.

The first method I use then, is a difference in difference in order 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 2010-2019. 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 is very correlated to when the stay at home orders were dictated by every governor.

From this, the first equation arises:

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

Where there is differentiation by week (t) and state (s) and the variable y corresponds to the outcome variable studied, be it the case of business creation applications or applications for unemployment insurance. D is the treatment variable that is composed as a 'dummy' that takes 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 a 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 empirical study the assumption of parallel trends of the outcome variables, that is, that there are no systematic differences in the unemployment claims and business applications 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 then is:

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

The change between the two previous equations is given in the term D. In the periods $k = 1,2$,...,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.

4 Results

The results for the difference in difference 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 application for new businesses. The first row corresponds to the coefficient, the second row to the standard error of that coefficient, and the third row 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 and state and year fixed effects and clustered errors to the state level. These are used to control for the idiosyncratic characteristics.

Table 2. Difference in Difference Results

	Unemployment (1)	Business Applications (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 (***).

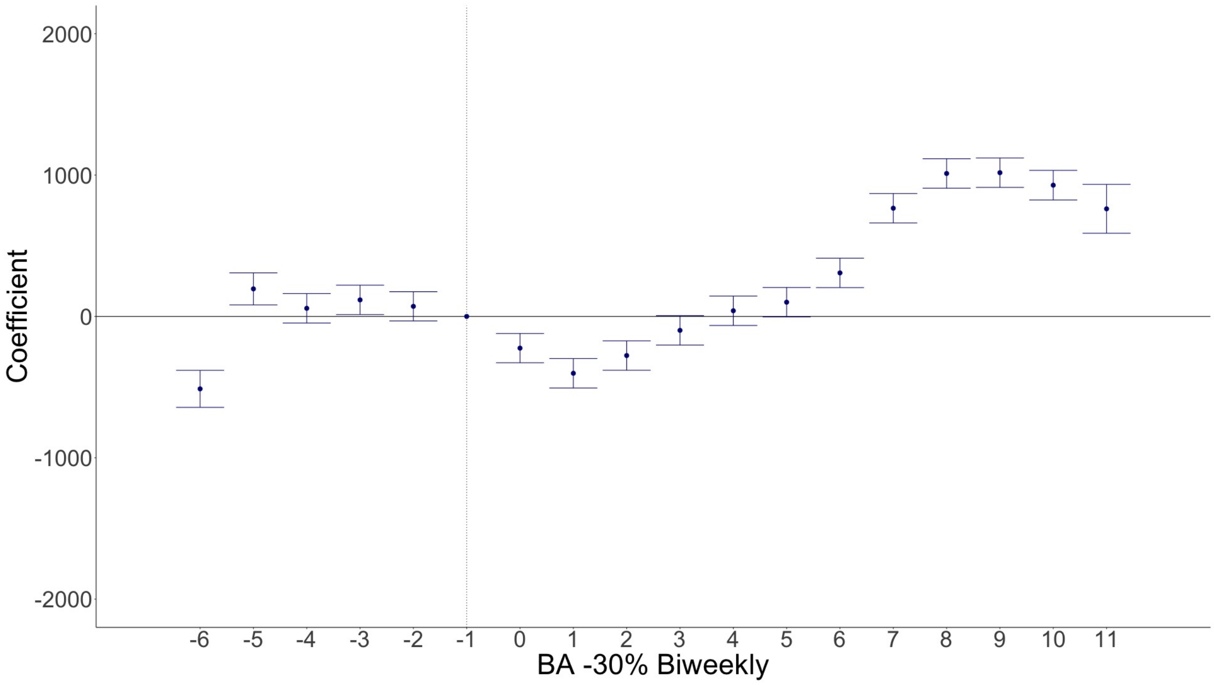
These numbers go to show that the effects on both unemployment and business applications are more than significant. Once the pandemic set in and mobility restrictions were put in place initial unemployment claims increased in over 68,000 on a weekly basis while new business applications dropped over 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 both an OLS and Poisson estimation. The changes are minimal, which means that 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 3 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 for 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. In relative terms compared to the last 9 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 application in a span of two weeks, meaning around a 50% increase.

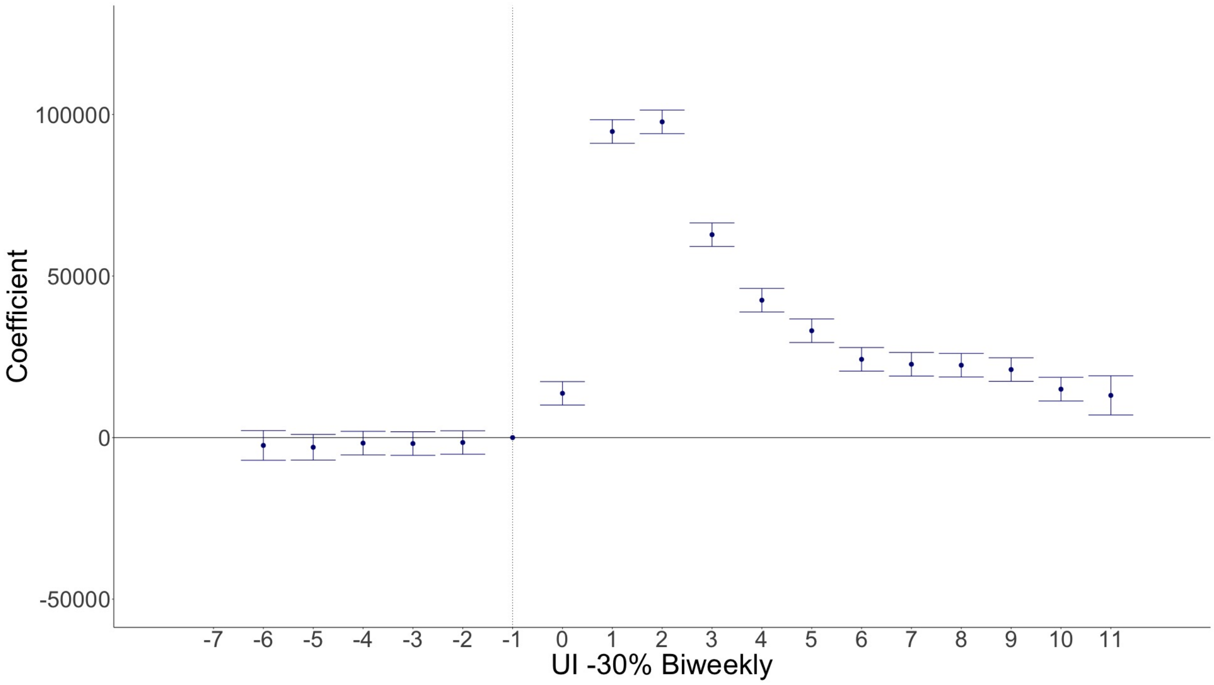
Figure 4. Event Study of New Buisness Applications



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

The event study plot for unemployment, Figure 5, insurance claims is even more drastic (Figure 5). In the month following the mobility restrictions, initial unemployment insurance claims rose to levels never reached before. In the first two weeks, claims reached an increase of 13,700 more applications even when taking into account 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 have not returned to their basis 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 5. 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 represent 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 restrictions in mobility caused by the COVID-19 pandemic and initial unemployment benefit claims and new business applications. 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 clear as the labor market and enterprises are essential to economic recovery, now more than ever given the coming 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 that I used 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 202. For unemployment claims, the US Department of Labor published weekly data while business applications are issued by the US Census Bureau.

The methods used were a difference in difference method and event study. Through this, 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 over 1,000% while business applications decrease 50%. Then, compared to the baseline of the two weeks before the pandemic, the results were also sustained at an increase of over 90,0000 unemployment applications and a decrease of over 400 new business requests.

From all of this information, it becomes clear that very strict mobility restrictions are not the perfect answer to prevent the spread of the disease. In terms of unemployment, the restrictions in mobility had a directly harming effect. When people couldn't 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 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 24th was still 751,000.

In terms of new business applications, the effect was very significant but did not persist that 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 to not have customers, have interrupted supply chains, or many other concerns. As the pandemic progresses, the number of applications actually increased. This is probably due to the lack of recovery in employment and job openings so 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 counter factual 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. In terms of the data, there are certain 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 taking into consideration 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 complicated 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 wave are already happening around the world, the policy implications of this cannot be ignored. It is important to protect citizens from the disease, but such strict restrictions should not be put in place again. Instead, measures such as those implemented in France in October 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 which interrupts life a little less and gives people the possibility 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.

References

Baek, C., McCrory, P. B., Messer, T., & Mui, P. (2020). Unemployment effects of stay-at-home orders: Evidence from high frequency claims data. *Institute for Research on labor and employment working paper*, 101–20.

Bajardi, P., Poletto, C., Ramasco, J. J., Tizzoni, M., Colizza, V., & Vespignani, A. (2011). Human mobility networks, travel restrictions, and the global spread of 2009 h1n1 pandemic. *PloS one*, *6*(1), e16591.

Baker, S. R., Bloom, N., Davis, S. J., & Terry, S. J. (2020). *Covid-induced economic uncertainty* (Tech. Rep.). National Bureau of Economic Research.

Bonaccorsi, G., Pierri, F., Cinelli, M., Flori, A., Galeazzi, A., Porcelli, F., ... others (2020). Economic and social consequences of human mobility restrictions under covid-19. *Proceedings of the National Academy of Sciences*, *117*(27), 15530–15535.

Calì, M., & Miaari, S. H. (2013). *The labor market impact of mobility restrictions: Evidence from the west bank*. The World Bank.

CDC. (2020). *The true burden of covid-19 in the us* (Tech. Rep.). Center for Disease Control.

Census. (2020a). *Business formation statistics* (Tech. Rep.). U.S Census Bureau.

Census. (2020b). *Household pulse survey data* (Tech. Rep.). U.S Census Bureau.

Coibion, O., Gorodnichenko, Y., & Weber, M. (2020). *The cost of the covid-19 crisis: Lockdowns, macroeconomic expectations, and consumer spending* (Tech. Rep.). National Bureau of Economic Research.

DOL. (2020). *Unemployment insurance weekly claims data* (Tech. Rep.). U.S Department of Labor.

Espinoza, B., Castillo-Chavez, C., & Perrings, C. (2020). Mobility restrictions for the control of epidemics: When do they work? *Plos one*, *15*(7), e0235731.

Faria-e Castro, M. (2020). Fiscal policy during a pandemic. *FRB St. Louis Working Paper*(2020-006).

Friedson, A. I., McNichols, D., Sabia, J. J., & Dave, D. (2020). *Did california's shelter-in-place order work? early coronavirus-related public health effects* (Tech. Rep.). National Bureau of Economic Research.

Google. (2020). *Covid-19 community mobility reports* (Tech. Rep.).

Halford, E., Dixon, A., Farrell, G., Malleson, N., & Tilley, N. (2020). Crime and coronavirus: social distancing, lockdown, and the mobility elasticity of crime. *Crime science*, *9*(1), 1–12.

Hsiang, S., Allen, D., Annan-Phan, S., Bell, K., Bolliger, I., Chong, T., ... others (2020). The effect of large-scale anti-contagion policies on the covid-19 pandemic. *Nature*, *584*(7820), 262–267.

IMF, I. M. F. (2020). World economic outlook update, june 2020: A crisis like no other, an uncertain recovery. *Wolrd Economic Outlooke*.

Jasmine C. Lee, Y. A. B. H., Sarah Mervosh, & Matthews, A. L. (2020). See how all 50 states are reopening (and closing again). *The New York Times*.

McWilliams, T. P., & McWilliams, V. B. (2000). Another look at theoretical and empirical issues in event study methodology. *Journal of Applied Business Research (JABR)*, *16*(3).

Mohler, G., Bertozzi, A. L., Carter, J., Short, M. B., Sledge, D., Tita, G. E., ... Brantingham, P. J. (2020). Impact of social distancing during covid-19 pandemic on crime in los angeles and indianapolis. *Journal of Criminal Justice*, 101692.

Morales, L. F., Bonilla-Mejía, L., Pulido, J., Flórez, L. A., Hermida, D., Pulido-Mahecha, K. L., ... others (2020). *Effects of the covid-19 pandemic on the colombian labor market: Disentangling the effect of sector-specific mobility restrictions* (Tech. Rep.). Banco de la Republica de Colombia.

Appendices

A Estimations With Unclustered Errors and Poisson Model

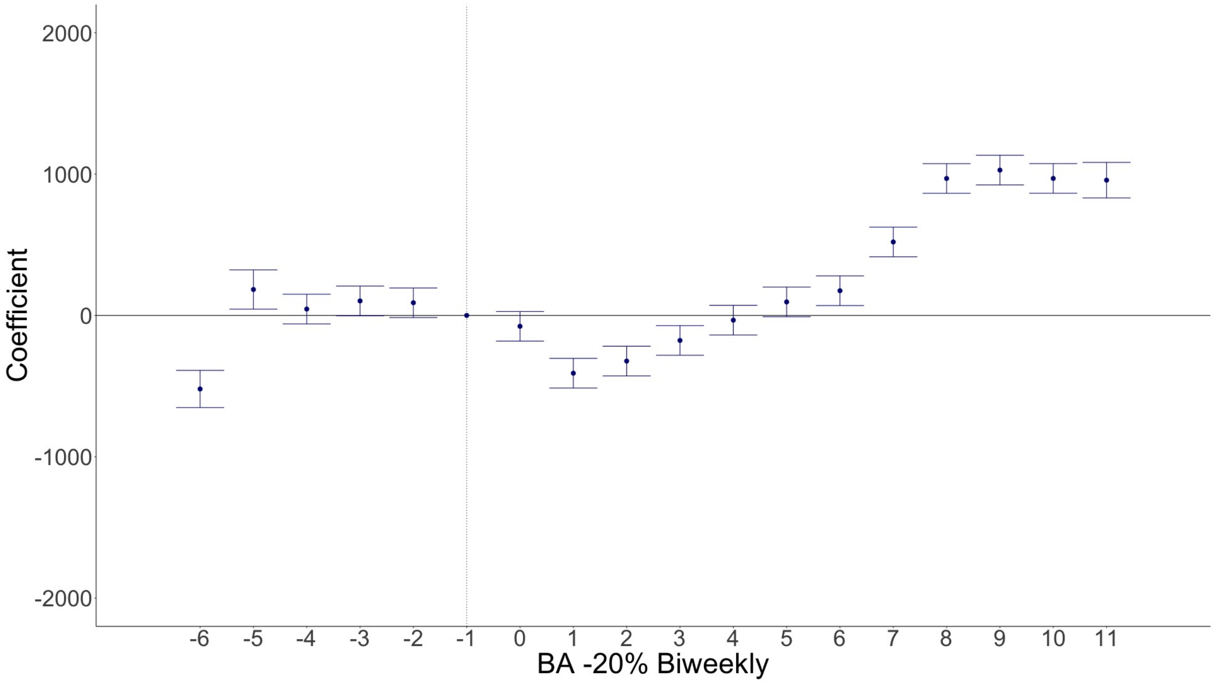
Table A.1. Difference in Difference Results With Unclustered Errors and Poisson Model

	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 (***).

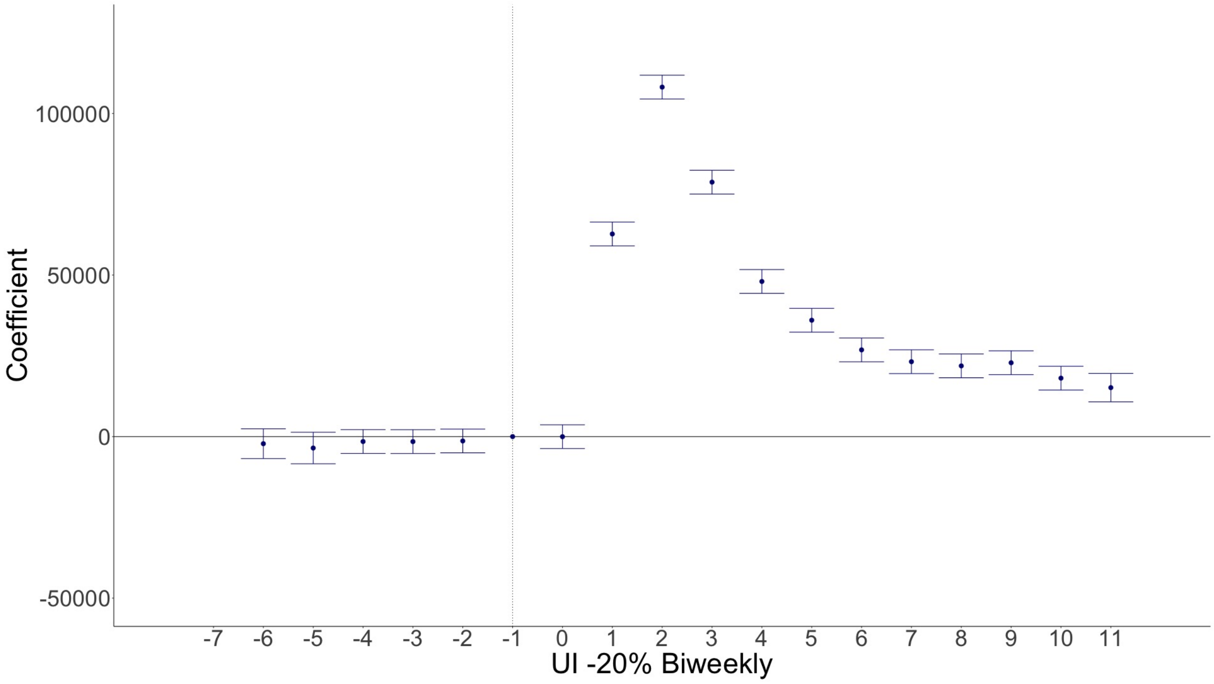
B Event Study Plots (20% Mobility Reduction)

Figure B.1. Event Study of New Buisness Applications



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

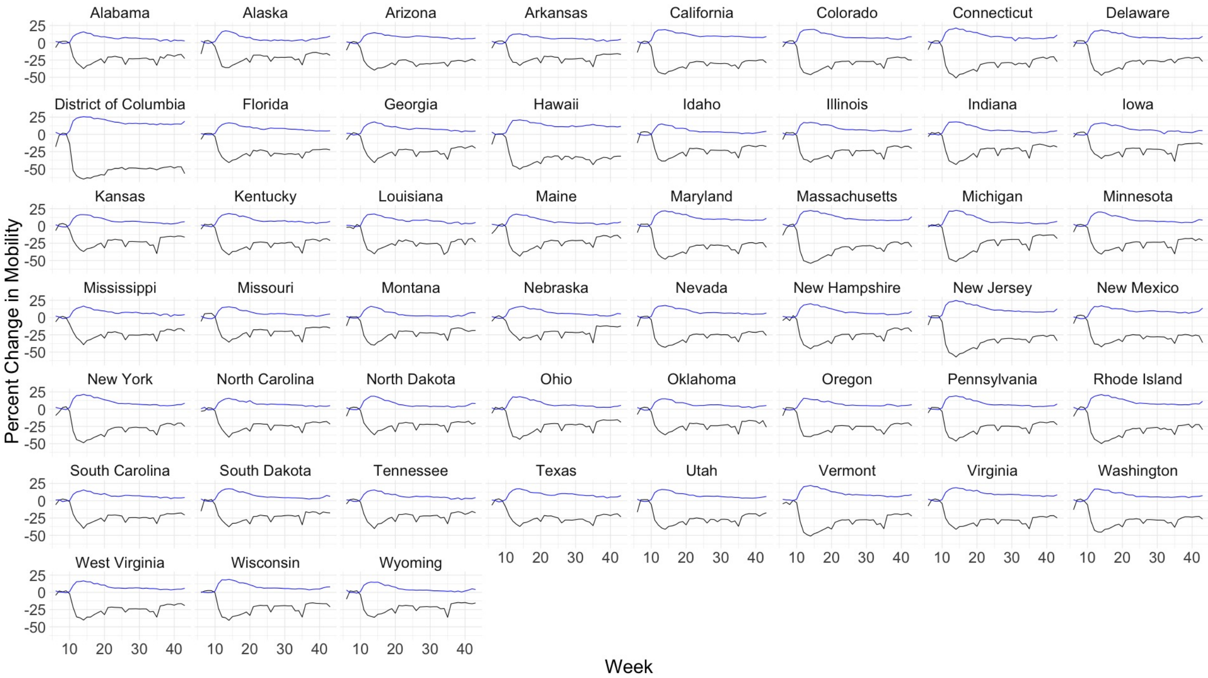
Figure B.2. Event Study of Initial Unemployment Claims



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

C Home and Work Mobility Plots

Figure C.1. Mobility changes by State



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

Source: Google Mobility