Effects of COVID-19 Lockdown Duration on Business Start-ups: U.S. Analysis

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Abstract

This paper examines the dynamic impact of COVID-19 lockdown durations on High Propensity Business Applications (HPBA) across the 50 states of the US, from January 2018 to November 2020. Employing de Chaisemartin and D'Haultfœuille's difference-in-differences estimator, this study is the first to explore the state-level dynamic impact of lockdowns on High Propensity Business Applications. Results show an immediate decrease in High Propensity Business Applications post-lockdown, followed by a recovery phase, with the magnitude of these effects influenced by the lockdown duration. Additionally, extended lockdowns, particularly those lasting 3 months, result in a significant 3.07% decrease in the growth of High Propensity Business Applications. These findings underscore the need for nuanced policies that balance public health concerns with economic resilience.

JEL Codes: E24 I10 L26

Keywords: Start-ups · Lockdown · Business Formation Statistics · COVID-19

I affirm that I have held the highest principles of honesty and integrity in my academic work and have not witnessed a violation of the Honor Code.

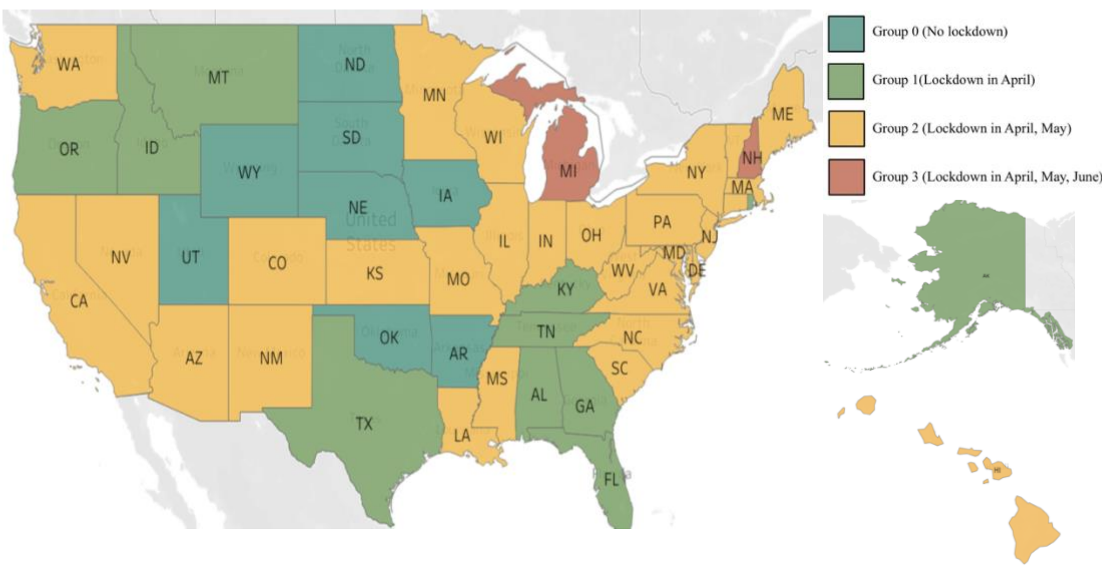
1. Introduction:

The COVID-19 pandemic, marked by over 1.1 million fatalities in the United States by January 2023, has resulted in unprecedented global challenges (CDC, 2023). States implemented lockdowns to contain the virus, inadvertently triggering economic stagnation. These restrictions, while necessary for public health, adversely impacted consumer spending and business operations, significantly affecting economic activities (Shen et al., 2020). The ensuing economic downturn not only diminished consumer demand and disrupted supply chains but also impeded the formation of new businesses—key drivers of job creation, innovation, and economic recovery (Sedlacek & Sterk, 2020).

Startups, essential for job creation, require protection and policy intervention to foster economic recovery and navigate regulatory and market challenges (Haltiwanger, et al., 2013). In order to do that, it is important to understand the link between lockdown duration in the U.S. and startup numbers, especially considering the pandemic's dynamic impact on entrepreneurship. Initially, the pandemic-induced economic uncertainty and supply chain disruptions are likely to result in a decline in business applications, as potential entrepreneurs become increasingly risk-averse (Sedlacek & Sterk, 2020). Conversely, in the long run, high unemployment may increase self-employment and startups, driven by both necessity and identification of new entrepreneurial opportunities, in line with Schumpeter's Creative Destruction theory (Fairlie, 2013; Fairlie & Fossen, 2019; Sedlacek & Sterk, 2020). Analyzing the pandemic's impact on business applications is key for developing crisis management strategies and equipping policymakers for similar crises. This study is significant, as a decline in firm creation could hinder economic recovery and lead to a missing generation of firms (Sedlacek & Sterk, 2020). In this paper, I study entrepreneurship in the 50 U.S. states during and after the first COVID-19 lockdowns. Using state-level monthly data, I measure entrepreneurship based on the number of business applications with a high propensity of turning into a business with a payroll.

In the United States, lockdowns were implemented locally in a staggered manner over time and in geographies, without national coordination (Elenev et al., 2021). Figure 1 shows the staggered lockdown adoption across U.S. states. There are 4 lockdown groups, with Group 0 being states that did not implement lockdown during the study period, Group 1 with lockdown in April, Group 2 with lockdown in April & May, and finally Group 3 with lockdown in April through June.

Figure 1. Lockdown Groups derived from Staggered Lockdown adoption, 50 U.S. States



Notes: Group 0 (No lockdown in study period) has 8 states; Group 1 (Lockdown in April) has 11 states; Group 2 (Lockdown in April, May) has 29 states; Group 3 (Lockdown in April, May, June) has 2 states. Figure generated using Tableau.
Source: Ballotpedia

Previous studies suggest that COVID-19 lockdowns caused a decrease in the number of business applications in the short-run but may have increased the rate of business startups in the long-run (Melugbo et al., 2020; Karimov, S., & Konings, J., 2021; Zhang and Huang, 2021; Nuringsih et al., 2020). These studies are conducted in the UK, China, Ecuador, and Indonesia. Some studies go further on to say that individuals may become more interested in and involved in entrepreneurship as a proactive career strategy (Akkermans et al., 2020). With all the research taking place, the answer is still unclear, especially about the overall effect of lockdown for the U.S. Although crucial, there are scant empirical studies investigating the connection between lockdown lengths and business startups. The existing literature studying the impact of COVID-19 on business startups predominantly relies on Two-way Fixed Effects approach and a few on regression discontinuity in time (RDiT) model, often focusing on countries as a whole units rather than examining subnational data (Walker and Hurley, 2021; Camino-Mogro, 2020; Brodeur et al., 2021). While these existing research offers valuable insights into the pandemic's effects on entrepreneurship, the duration of lockdown's impact on business applications remains unexplored, especially on the state level, underscoring the necessity for further investigation. These methods may also fail to capture the fact that there are different effects of lockdown on different states based on the duration of lockdowns.

In this paper, I employ de Chaisemartin and D'Haultfœuille's estimator to capture the dynamic nature of the lockdown treatment and its impact on High Propensity Business Applications (HPBA). This longitudinal study, encompassing January 2018 to November 2020, contrasts Group 0, the control group, against Groups 1, 2, and 3, the treated group, to disentangle the impact of varying lockdown durations on entrepreneurial activities in the 50 states of U.S. Through this paper, we gain insights into the short-term ramifications of lockdown measures on business activities. I also incorporate a panel first difference model to further validate my findings. Overall, this paper provides insights for policymakers who are tasked with balancing public health concerns and economic resilience.

The rest of the paper is organized as follows. In the next section, I present the data. In Section 3, I discuss the methodology. Section 4 shows results and additional analysis, while Section 5 provides the conclusion.

2. Empirical Approach

2.1. Sample Description

In this study, I investigate the relationship between COVID-19 lockdown duration and business startups using panel data consisting of monthly observations from January 2018 to November 2020 for all 50 states in the United States.

To measure entrepreneurship, I utilize the Business Formation Statistics (BFS) dataset from the United States Census Bureau, a comprehensive source of information on new business initiations. It is based on Employer Identification Number (EIN) requests within the United States, serving as identifiers for business entities, particularly for tax purposes. The BFS dataset offers a wealth of data, ranging from established to anticipated employer business establishments. It is available at various geographical levels, including national, regional, state, and county, and is categorized by 2-digit NAICS industry sectors starting July 2004.

Within the BFS dataset, I focus on High Propensity Business Applications (HPBA). High Propensity Business Applications identify formations with a high likelihood of evolving into businesses with payroll. In this study, I restricted the sample period from January 2008 to November of 2020 because I am studying the first wave of installation of lockdown and beginning December 2020, California goes into its second lockdown period. This refined time frame enables me to scrutinize recent trends in business applications, especially in the context of COVID-19. Similarly, this study employs state-level analysis as lockdown policies were predominantly state-mandated, ensuring a uniform approach within states while capturing variations across them. This level of analysis is appropriate despite a few counties in New York and California implementing independent measures, as it reflects the broader policy environment impacting business startups.

To determine the installation of lockdown in each state, I use data from Ballotpedia, a digital encyclopedia of American politics and elections. Ballotpedia has compiled data on the implementation and removal of statewide lockdown orders, including details on each state that issued an order, the respective dates of the order, and the reference to the executive order itself.

Moreover, I integrate the data on COVID-19 cases by state on a monthly basis from Our World in Data, a public data portal maintained by the Oxford Martin Programme on Global Development at the University of Oxford. This portal is a valuable resource for exploring a wide range of topics related to global living conditions.

2.2 Variables

Dependent Variable

The key outcome variable, High-Propensity Business Application, is the logarithm of the number of business applications with high propensity. It includes applications for corporate entities that indicate they are hiring employees that provide a first-wage paid date (planned wages) or that have a NAICS industry code in accommodation and food, construction, manufacturing, retail, professional, scientific, and technical services, education services and health care. The raw data of HPBA has a right-skewed distribution, where a small number of very high numbers of business applications significantly differ from the majority. I take the logarithm for HPBA to help normalize the distribution and to make it better suited for my model. This transformation aligns with the approach taken by Hean and Chairassamee (2023), the paper serving as the foundation for my HPBA data interpretation. To minimize the negative impacts on startups and promote economic recovery and stability, it is crucial to understand the relationship between lockdown durations and the number of business startups in the United States.

Explanatory Variables

My key explanatory variable, lockdown, a is a binary variable, taking on the value of 1 if the state was in lockdown in a certain month and 0 if the state did not implement a lockdown at a particular month. For the states that never installed lockdown, the lockdown variable had a value of 0 throughout the study period. The inclusion of the lockdown variable enables an exploration of the impact of lockdown measures on entrepreneurial activities during the COVID-19 pandemic.

To attribute observed changes in business applications to the lockdown, I incorporate COVID-19 cases as my control variable. I do this to control for its potential impact on both the business application and duration of lockdown and isolate the effect of lockdown policies on business applications from the direct impact of the pandemic itself. This dataset captures the number of people who tested positive for COVID-19 on a particular day. To ensure the data matches the time frame of my study, I aggregate daily cases by state for each month. Likewise, I log transform them to normalize the distribution. This is because we expect the COVID-19 cases to grow at a constant growth rate.

2.3 Descriptive Statistics

Table 1. Descriptive statistics for a panel of 50 U.S. states, January 2018 - November 2020.

Variable	Mean	Standard Deviation
High-Propensity Business Application (HPBA)	2,250.513	3,221.738
Lockdown	0.0429	0.2026
COVID-19 cases	7,090.7160	26,077.18

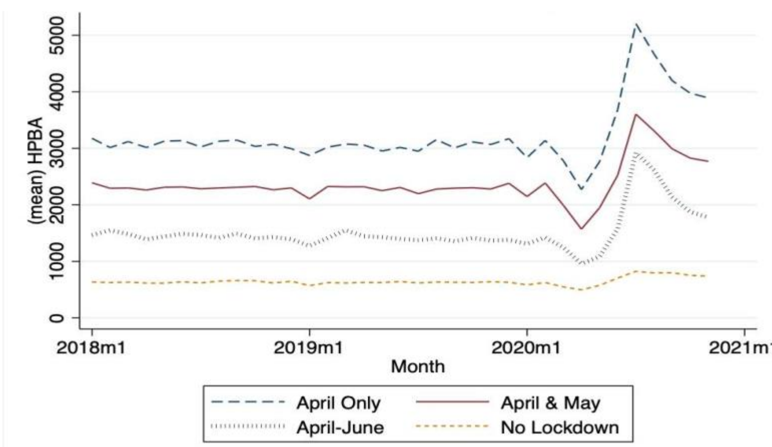
Notes: The business application variable is a monthly data. The COVID-19 cases are a daily data aggregated into monthly data.
Sources: HPBA from BFS dataset, lockdown from Ballotpedia. COVID-19 cases through Our World in Data portal.

Table 1 provides a comprehensive overview of the descriptive statistics for all 50 states in the United States, spanning the monthly period from January 2018 to November 2020. Approximately, 2,250 High Propensity Business Applications were received each month showcasing entrepreneurial activities across the US.

With different lockdown groups in mind, in figure 2, I present graphical evidence of fluctuations in the average High Propensity Business Applications across groups over time. The average number of HPBA for group 1 (lockdown in April) was fairly steady until January of 2020, decreased dramatically in February 2020 after the COVID-19 cases started skyrocketing, then trended upward from May to its peak in July. This trend is consistent for groups 2 and 3. However, the average HPBA for Group 0 (no lockdown) is pretty consistent throughout the time period we're looking at except for a slight fluctuation between January 2020 and June. These aggregate trends certainly suggest that the implementation of lockdown was associated with an increase in the HPBA. These trends, however, could be confounded by changes in other variables.

Additional feature of these data are worth mentioning. First, there are 8 states for group that did not install lockdown in the study period (baseline group), 11 states for group with lockdown in April, 29 states for group with lockdown in April & May and 2 states for group with lockdown in April through June. The different number of states in each group means variation in the number of populations, which could have affected the average number of HPBA for each group.

Figure 2. Average High Propensity Business Applications for each Lockdown Group, by Months

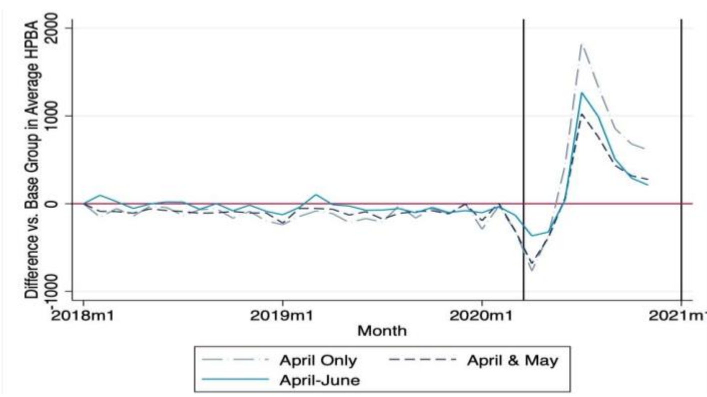


Notes: This figure depicts the average monthly count of HPBA for different lockdown durations. The trend lines represent states grouped by the extent of lockdown enforced—'April Only', 'April & May', and 'April-June' - contrasted with states that did not implement lockdown, 'No Lockdown'. The data spans from January 2018 to December 2021 for 50 states of the U.S.

2.4 Trends in Business Applications

Figure 3 presents illustrates the empirical strategy of this paper. It provides the trends in average HPBA for three lockdown groups (group 1, 2 and 3) relative to the baseline (group 0). To ensure a fair comparison, I make adjustments to account for any initial disparities among the groups prior to the lockdown. This involves calculating the difference in HPBA for each group relative to the baseline (the maximum HPBA value observed in the no-lockdown group at each time point). This step is important to standardize the starting points of the groups, making them comparable from the beginning of the analysis period (January 2018). Not only that, the adjustments are made to adhere to the parallel trends assumption, fundamental to the difference-in-differences analysis. The assumption holds that, in the absence of treatment (lockdown), all groups, including the control (no lockdown) and various lockdown groups, would have exhibited parallel trends over time. Figure 3 illustrates this assumption by showing how the average HPBA rate across all groups follows a common trend prior to the installation of lockdown; that is, it has passed the parallel trends test.

Figure. 3. Trends in average number of HPBA for Lockdown groups, by months.



Notes: Average differences in High Propensity Business Applications over time among different lockdown groups and baseline (no lockdown group) from January 2018 to November 2020. The black line in April 2020 marks the lockdown installation period.

3. Model

3.1. Regression Models

To study the impact of duration of lockdown on High Propensity Business Applications, I use the Difference-in-Difference (DID) design with multiple groups and periods designed by Chaisemartin and D'Haultfœuille.

I estimate a Difference-in-Differences model for the lockdown duration's effect on the number of High Propensity Business Application (Model 1), as follows:

$$\ln(HPBA)_{g,t} = \tau_t + \sum_{l=0}^{4} \beta_l \; Lockdown_{t-l} + \phi_1 \; Placebo_{Jan2020} + \phi_2 \; Placebo_{Feb2020} + \phi_3 \; Placebo_{Mar2020} + \Psi_g + \epsilon_{g,t} \quad (1)$$

In equation (1), $\ln(HPBA)_{g,t}$ is the natural logarithm of High Propensity Business Applications in lockdown group g at month t. $Lockdown_{t-l}$ represents the lockdown effect at time t-l (including current and past months). I estimate this parameter using the *did_multiplegt* command in Stata (De Chaisemartin et al. 2019). $Placebo_{Jan2020}$, $Placebo_{Feb2020}$, $Placebo_{Mar2020}$ represent the placebo (pre-treatment) effects in January, February, and March 2020. Ψ_s is the group fixed effects controlling for unobserved time-invariant characteristics of each group and τ_t is the time fixed effects controlling for common shocks across all groups in each month t. $\epsilon_{g,t}$ is the error term.

Due to concerned about March 2020 anticipation effect, I control for COVID-19 cases in my second (preferred) model.

In addition to the analysis conducted using the Chaisemartin and D'Haultfœuille (2022) approach, I incorporate a traditional panel first difference difference-in-differences model to evaluate sensitivity of the results to the modeling approach employed. By comparing the outcomes from both models, I can better assess the consistency and reliability of the conclusion. I estimate the panel first difference model, as follows:

$$\Delta lnHPBA_{g,t} = \sum_{j=1}^{3} \gamma_j \left(lock_{group_j} \times lockdown_{g,t} \right) + \delta\Delta \ln(Covid\ cases)_{g,t} + \tau_t + \epsilon_{g,t} \tag{2}$$

In equation (2), $\Delta lnHPBA_{g,t}$ is the first difference of the natural logarithm of High Propensity Business Applications for lockdown group g at month t. $\left(lock_{group_j} \times lockdown_{g,t} \right)$ represents the interaction between the lockdown group j and binary variable indicating whether a lockdown is in place at time t. $\Delta \ln(Covid\ cases)_{g,t}$ is the first difference of the natural logarithm of COVID-19 cases and is included as a covariate. τ_t is the time fixed effects, controlling for time varying factors that could influence growth in business applications. Finally, $\epsilon_{g,t}$ is the error term. Consequently, the model excludes state fixed effects, as sensitivity tests indicated that first differencing adequately addressed state-level heterogeneity, revealing no significant differences in HPBA growth rates across states over time.

3.2 Choice of Modeling Approach

My model, stands out for its ability to capture the dynamic nature of the lockdown treatment (see de Chaisemartin, D'Haultfœuille and Guyonvarch, 2019). This nature is characterized by states switching between treated and untreated phases over time (also called non-absorbing), an important attribute in the context of varying lockdown durations across states (Freedman, Hollingsworth, et. Al, 2023). This approach is equipped to analyze not just the immediate effects of lockdown implementations but also the subsequent economic recovery phases as lockdowns are lifted or extended. By capturing these transitions, we are at a position to gain insights into both the short-term and long-term ramifications of lockdown measures on business activities.

One additional aspect of this model is the incorporation of control variables, which helps enhance the robustness of the findings. This means I can control for factors potentially affecting HPBA, which ensures that the estimates reflect the true impact of lockdown policies.

Finally, the methodology of de Chaisemartin and D'Haultfœuille (2022) utilizes the placebo estimators to test the parallel trends assumption. These estimators compare outcome trends of switchers and non-switchers prior to any switch in treatment, providing a check on the validity of this model's assumption.

4. Results

In this section I present the result tables for the estimates between lockdown and High Propensity Business Applications.

Table 2: Effects of Lockdown on High Propensity Business Applications

	Model (1)	*Model (2)*
Contemporaneous Effect	-0.0446*** (0.1322)	-0.1158*** (0.0161)
One Month Post-Lockdown	0.0019 (0.0157)	-0.0783** (0.0260)
Two Months Post-Lockdown	0.0655*** (0.0139)	0.0009 (0.0380)
Three Months Post-Lockdown	0.1961*** (0.0281)	0.1423*** (0.0110)
Four Months Post-Lockdown	0.1466*** (0.0324)	0.0821** (0.0251)
Average Lockdown Effect	0.2046*** (0.0199)	0.0175 (0.0252)
Placebo Test (January 2020)	0.0552 (0.0092)	-0.0010 (0.0015)
Placebo Test (February 2020)	0.0301 (0.0079)	-0.0261 (0.0027)
Placebo Test (March 2020)	0.0745 (0.0069)	0.0150 (0.0194)

* Significant at 10%; ** significant at 5%; *** significant at 1%.

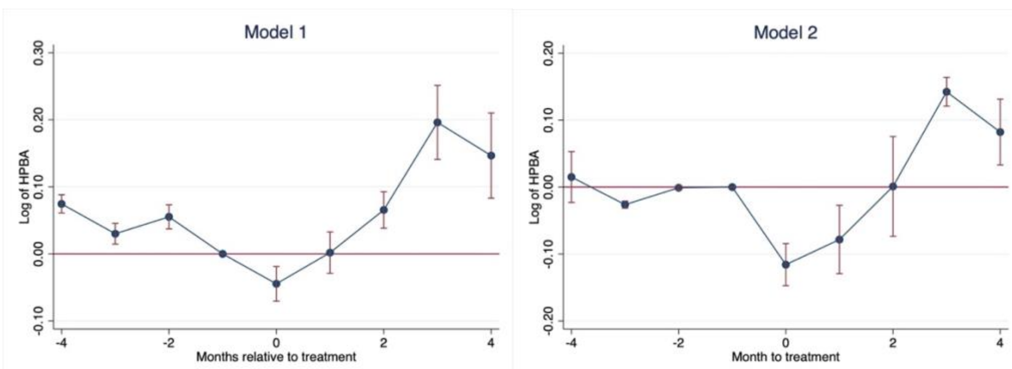
Notes: Results from the DID estimator by de Chaisemartin and D'Haultfœuille (2023) using data from Business Formative Statistics (BFS) and Ballotpedia. The table presents coefficients, accounting for the effects of lockdown durations on High Propensity Business Applications (HPBA). Standard errors (in parentheses) are robust and adjusted for clustering at the state level. Models include dynamic effects (up to 4 months) and placebo tests (up to 3 months) to check parallel trends assumptions. Control variables in Model 2 include the log-transformed number of COVID-19 cases. Observations include data from all 50 U.S. states from January 2018 to November 2020.

Table 2, model (1) shows the result from the base Difference-in-Difference model. Based on the table, there is a contemporaneous effect of 4.46% decrease ($p<0.01$) in the number of HPBA during the lockdown period. One month after the lockdown, the effect is not significant suggesting that the immediate decline was not sustained a month later. However, two months post-lockdown, there is a 6.55% increase ($p<0.01$) in the HPBA, indicating a recovery in the number of HPBA. This positive trend continues and peaks at a 19.61%

increase three months later (p<0.01), but slightly decreases to a 14.66% increase in the fourth month (p<0.01).

It is worth mentioning that the significant contemporaneous effect (Effect_0) raises a concern about businesses possibly anticipating the lockdowns and altering their behaviors even before the implementation of the policy. This is graphically shown in figure 4.This March 2020 anticipation effect can bias the estimates of the lockdown's impact, as it confounds pre-treatment trends with the actual treatment effect. Not only that, this model does not control for variables that could independently affect HPBA, which could lead to omitted variable bias.

Figure 4 & 5. Comparative Event Study Analysis of Lockdown Effects on ln (HPBA) with and without Adjusting for COVID-19 Case Growth



Notes: The event study design is implemented using the estimator designed by de Chaisemartin and D'Haultfœuille (2023) and the *did_multiplegt* Stata command. Models include dynamic effects (up to 4 months) and placebo tests (up to 3 months) to check parallel trends assumptions. Model 1 is the naïve event study while model 2 design incorporates COVID-19 cases as a covariate.

Table 2, model (2), adds COVID-19 cases as covariate in the model to account for anticipatory actions by businesses and to avoid omitted variable bias.

After controlling for growth in COVID-19 cases, I find that the contemporaneous effect of lockdown is a 11.58% decrease ($p<0.01$) in HPBA. One month post lockdown, there is a 7.83% decrease ($p<0.05$) in the number of HPBA. This means that the negative impact of lockdown continues but is slightly less severe. Two months post lockdown, we find evidence that the effect of lockdown on business applications is not statistically significant at any level, suggesting a stabilization. In contrast however, three months later, there's a notable 14.23% positive effect ($p<0.01$) on the high propensity business applications. This marks a strong rebound phase. Following that, four months past-lockdown, the positive trend continues with a coefficient of 8.21% ($p<0.05$), though the effect is less strong compared to the three-month mark.

This analysis confirms that the inclusion of COVID-19 case growth alleviates concerns about the March 2020 anticipation effect, reinforcing the immediate negative impact of lockdowns followed by a significant recovery phase. This is shown in figure 5.

The average effect here is calculated as an average of the treatment effects across all time periods and groups. I find no evidence that the lockdown had an average effect on the number of HPBA (Model 2). The non-significant average effect suggests that when considering the entire study period and all groups together, the lockdowns might not have had a strong uniform impact of HPBA. This could be a result of a mix of both negative and positive effects at different times and across different groups balancing each other out. However, it is important to realize that the average effect being non-significant does not imply that the lockdowns had no impact on HPBA, but rather that their impact was not uniform across all groups and time periods. Here, the case seems to be that the lockdown had significant immediate and short-terms effects, which were later offset by the recovery over the 4 months' time period.

I also use the Placebo test to check for parallel trends assumption, crucial in the DID analyses. None of these placebo effects are significant (Model 2), which supports the assumption that the treatment and control groups were on a similar trend before the lockdown.

Table 3 presents results from the panel first difference model. I find that being in group 1 (lockdown in April) and group 2 (lockdown in April & May) does not have a statistical effect on High Propensity Business Application (HPBA). In contrast, a more extended lockdown period, as experienced by Group 3 (lockdown from April to June), is associated with a 3.07% decrease ($p<0.05$) in the growth of HPBA. The panel first difference model shows that the duration and intensity of lockdowns have varying impacts on HPBA. While the Chaisemartin and d'Haultfoeuille's difference-in-differences model captures dynamic effects over time, the panel first difference model reinforces these findings by showing how different lockdown durations affect the change in HPBA. Likewise, the significant negative effect in Group 3 (lockdown from April to June) aligns with the dynamic effects observed in the difference-in-differences model, suggesting that prolonged lockdowns have a more pronounced negative impact. This result aligns with our expectations.

Table 3. Panel First Difference Model

Variables	Growth of HPBA
Group 1 (lockdown in April) and Lockdown (Interaction)	-0.0512 (0.0422)
Group 2 (lockdown in April, May) and Lockdown (Interaction)	-0.0217 (0.0191)
Group 3 (lockdown in April to June) and Lockdown (Interaction)	-0.0307** (0.0133)
Growth of COVID-19 cases	-0.0051 (0.0079)
Observations	1,700
R-squared	0.576

* Significant at 10%; ** significant at 5%; *** significant at 1%.

Notes: This table presents results from a panel first difference model with 1,700 observations. The model analyzes growth of High Propensity Business Applications, focusing on the impact of varying lockdown durations. Standard errors are robust & clustered by state (50 clusters) and show in parentheses. Key independent variables include interactions of lockdown groups with a binary lockdown indicator and the growth of COVID-19 cases, alongside time fixed effects. Coefficients represent the impact of lockdowns starting in April, extending through April and May, and from April to June.
Sources: HPBA from BFS dataset, lockdown from Ballotpedia. COVID-19 cases through Our World in Data portal. Standard errors shown in parentheses are clustered at the state level.

Identifying Assumptions:

1. Test for No Anticipation Assumption:

Assumption 1 requires that a group's current outcome (business applications, in my case) does not depend on its future treatments, the lockdown (De Chaisemartin and d'Haultfoeuille 2022). This assumption is essential to ensure that any observed effects during the post-treatment period are indeed due to the treatment itself and not due to anticipatory actions. As per figure 5, businesses did not alter their behavior in anticipation of upcoming lockdowns. This means that any change in the rate of HPBA immediately following the implementation of the lockdown can be attributed to the lockdown itself, rather than businesses reacting in advance. This means that the no-anticipation holds.

2. Test for Parallel Trends Assumption:

In addition to the parallel trends in the HPBA shown in section 2.4, the placebo test from difference-in-difference model (using Stata) in figure 5, indicate that the Model (2) generally supports the parallel trends assumption. This is because except for Placebo Test 2 (2 month), the other two placebo tests do not suggest significant pre-treatment effects, supporting the parallel trends assumption better.

5. Conclusion

This study uses data from Business Formation Statistics (BFS) and Ballotpedia to examine the impact of lockdown duration on High Propensity Business Applications (HPBA) in 50 states of the U.S. It reveals significant economic implications of lockdown measures on business startups, utilizing Chaisemartin and D'Haultfœuille's difference-in-difference model with multiple groups and periods. The model, incorporating COVID-19 case growth as a control variable, demonstrates a pronounced immediate effect of lockdowns on HPBA with an 11.58% decrease in HPBA post-lockdown period. This downturn diminishes to a 7.83% decrease one month later, indicating a diminishing but ongoing negative impact. By the second month, the effect neutralizes, suggesting stabilization. The recovery phase becomes evident three months post-lockdown, with a significant 14.23% increase in HPBA, followed by 8.21% increase in the fourth month, indicating a sustained yet moderating recovery trend.

Furthermore, the panel first difference analysis complements these findings by showing that prolonged lockdown durations (May to June) is associated with a 3.07% decrease ($p<0.05$) in growth of HPBA, reinforcing the notion that extended restriction had a pronounced negative effect on new business applications. However, I find no evidence that the lockdowns affected the long run number of HPBA filed. This result suggests a nuanced idea that lockdown's effects on business applications were not uniform and varied across different groups and times. The non-significant average effect indicates that while lockdowns influenced HPBAs, the effect varied across states and over time.

This study is limited by factors related to its data source. While HPBA indicates entrepreneurial intent, it doesn't guarantee the successful establishment of businesses, as various factors can influence their actualization post-application. This gap highlights the need for further research using data on actual business startups to comprehensively understand the impact of COVID-19 lockdowns on entrepreneurial activity. In the future, it would be helpful to look more closely at the industries most affected by the length of the lockdowns. This would help us understand better how the lockdowns affected business applications in different industries. This kind of detailed analysis is something we can think about doing when more specific data becomes available. Likewise, it would also be interesting to look at the county level business applications and their response to the state level lockdown installation (expect for a few counties in NY and CA where lockdowns were implemented on county level).

This study contributes to the limited literature on the impact of COVID-19 lockdowns on business startups, specifically at the state levels in the United States. It highlights the intricacies involved in assessing the true impact of policy measures like lockdowns on entrepreneurial activities. The econometric analysis reveals a clear pattern: an immediate, substantial decline in new business applications following lockdown implementations, followed by recovery, especially three months post-lockdown. The extent of these effects is closely related to the duration of lockdowns. These results suggest that while lockdowns, important for managing public health crises, initially suppress entrepreneurial activities, they also set the stage for subsequent recovery in business creation. This dynamic is essential for policymakers who are tasked with balancing public health concerns and economic resilience. Moreover, the study lays the groundwork for future research, especially in understanding the impact of lockdown on HPBA in the context of vaccine availability. Overall, this study provides important implications for policymakers as they strive to make decisions to maintain public health without undermining the health of the business ecosystem, crucial for sustained economic recovery and growth.

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