COVID-19 and layoffs in US start-ups

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Abstract

The double negative shock on supply and demand following the COVID-19 health crisis has strongly impacted the labor market with an unequal distribution. Unlike earlier empirical works that explain the unequal exposure to layoffs following the crisis by socioeconomic and geographic factors, while distinguishing between core and non-core industries, we focus our analysis on layoffs in Start-ups in the United States of America (USA) by branch of activity. We compute the probability of a start-up worker being laid off according to the branch of activity in which he or she works, using a binary logistic regression. The result shows that the health shock did not impact all the branch of activities in the same way and with the same extent. The “Media” activity is by far the most affected by the layoffs. The “Infrastructure”, “Construction”, “Transportation”, “Product”, “Support”, “Education”, “Finance”, “Travel” and “Marketing” activities were also affected, while the “Food” activity was spared due to the fact that it was maintained during the crisis.

I. Introduction

Ten years after the outbreak of the 2008 financial crisis, the world economy is hit by a new crisis of a different nature: the COVID-19 health crisis. It officially appeared in China, but has spread to all continents. This situation forced the various governments to take measures to contain its spread. Restrictions were imposed to limit the mobility of people, including the closure of borders and certain activities considered non-essential. These restrictive measures gave rise to a new kind of crisis in contemporary economies. Indeed, for the first time in history, the world economy has faced two negative shocks, one on production and the other on demand. The combination of these two shocks had important economic consequences, notably on income levels, production distribution chains and labor markets.

To analyze the economic consequences of health shocks, economic theory suggests a good understanding of the transmission channels through which they negatively impact economic activity. In this respect, the work on the impact of the COVID-19 health shock on the economy identifies three main transmission channels (Carlsson-Szlezak et al., 2020). The health shock can directly affect demand negatively, through reduced consumption of goods and services by households uncertain about the duration of the crisis. It can also indirectly depress demand through the reduction in consumption that results from the financial market shock. The COVID-19 health shock can also negatively impact supply through the disruption of supply chains or the reduction in labor demand and employment. In particular, Guerrieri et al (2020) point out that in a multi-sector model and under certain conditions, COVID-19 causes a supply shock that increases firm closures and layoffs and ultimately results in a decline in aggregate demand.

With particular regard to the latter, the first studies analyzing the impact of the crisis on the labor market show that it has amplified vulnerabilities in this market. Indeed, strong decreases in job offers and increases in unemployment are observable in all economies (Couch et al. 2020 ; Dorn et al. 2020 ; Millett
et al. 2020). Various socio-economic aspects related to social origin, education level, age, gender, type of industry and geographical location are taken into account in this work.

In this regard, Couch et al. (2020) argue that Black and Latino minorities have been more affected by unemployment than Whites in the US. Because of their low level of qualification, they are generally employed in precarious jobs that cannot be telecommuted and constitute the bulk of the unskilled labor force. Yet, according to Montenovo et al. (2022), only populations employed in core industries have been more resilient to unemployment. Geographically, Antipova (2021) explains the amplification of unemployment rate differentials by the economic marginalization of certain cities. Similarly, Mueller et al. (2021) confirm that the labor market has been more sensitive to marginalization and vulnerabilities in rural Northwest America than in urban areas.

This initial literature has therefore listed various socioeconomic and geographic channels that allow for analysis of the differential effect of the crisis on the labor market, with the aim of better informing policymakers on appropriate economic and social policy measures. However, although the importance of the type of industry is taken into account (Montenovo et al. 2022), the impact of the COVID-19 health shock on layoffs in start-ups and according to the branches of activity remains under studied in this literature. However, Gourinchas (2020) emphasizes the need to take into account the interconnectedness of different firms, financial markets, employees and many other actors, when analyzing the impact of a negative shock on the economy.

However, the situation of start-ups deserves more attention. Indeed, until 2020, they were one of the main sources of growth and net job creation in the United States (Goetz and Stinson, 2022). Unfortunately, their activity has been largely disrupted by the health crisis, in particular because of the embryonic phase in which this category of companies is in. Indeed, start-ups are particularly vulnerable to the conditions of supply and demand, and to disruptions in bank financing circuits. As Sedláček and Sterk (2020) point out, a small disruption in start-up activity can have lasting effects on employment.

This is why in this paper we analyze the effect of the COVID-19 shock on layoffs in start-ups in the US, assuming that it differs across the branches of activity. The interest of conducting this study in the US context is twofold. On the one hand, with 4.8 million start-ups, the US has the largest number of start-ups in the world today, ahead of the UK which has 845,000. Thus, the availability of data[1], especially during the COVID-19 period, allows us to understand the extent of the effects of the health crisis on American start-ups. On the other hand, the study allows the inclusion of a specific type of company, young and at the forefront of innovation, which is not sufficiently taken into account in the existing literature. Choosing the country with the largest number of companies in this category in the world could give an indication of how to better orient support measures to companies according to their specificities. Indeed, these measures should not be uniform to those of mature firms that create relatively fewer jobs.

This study follows the empirical work that focuses on the uneven distribution of COVID-19’s effects on layoffs across industries. In contrast to the approach used in previous work, which distinguishes between core and non-core industries, we retain the specific case of U.S. start-ups and analyze layoffs by branch
of activity. Specifically, we calculate the probability of a worker in a given start-up being laid off according to his or her branch of activity.

The empirical results confirm the research hypothesis. Indeed, they show that the probability of being laid off in an American start-up, following the health crisis, differs according to the branch of activity. The COVID-19 health shock did not therefore impact all industries in the same way and to the same extent. The "Media" industry is by far the most affected by the redundancies. Infrastructure, Construction, Transportation, Product, Support, Education, Finance, Travel and Marketing are also affected, but with relatively lower probabilities than the Media industry. Policies to support economic activity should therefore incorporate these disparities.

The rest of the study is organized as follows: Section 2 reviews the literature on the impact of COVID-19 on unemployment. Section 3 is devoted to the analysis of the impact of the COVID-19 on start-ups in the US by industry. Finally, section 4 concludes.

[1] Data on start-ups are available on the website https://layoffs.fyi/

ii. Covid-19 And Unemployment: Not Taking Into Account Layoffs In Start-ups According To Branches Of Activity

The consequences of the COVID-19 health crisis are multi-dimensional. They are at the same time sanitary, social and economic. On this last aspect, many researchers are analyzing the effects of the pandemic on employment and the well-being of populations. This work is based on the idea that unemployment affects economic and social well-being (Blustein, 2019) and the mental health of the individual (Wanberg, 2012). Brinca et al. (2020) assess COVID-19 labor demand and supply shocks using a Bayesian structural var and monthly data of hours worked and real wages. They find significant supply and demand shocks in most industries. However, they show that the magnitude of the shocks differs across sectors.

Such a result justifies that many works quickly move away from the idea that the COVID-19 constitutes an external shock that puts all countries and all societies on an equal footing, as it affects everyone.

Looking specifically at the labor market, the empirical literature on the link between the COVID-19 health crisis and unemployment focuses primarily on three transmission channels: amplification of the effect through the inequality channel (Couch et al. 2020; Thebault, Tran, and Williams, 2020; Antipova, 2021), differences in education levels (Blustein et al. 2020; Couch et al. 2020; Mueller et al. 2021), and geographic areas (Batty, 2020; Mueller et al. 2021; Antipova, 2021). Indeed, while it is true that all societies are vulnerable to the labor market consequences of COVID-19, it appears that the magnitude of the impact is related to many factors of inequality. Disparities in background, education, community, age, and geographic location interact with the COVID-19 (Dorn et al., 2020; Albanesi and Kim, 2021; Millett et al., 2020). The social strata most vulnerable before the pandemic are most at risk and therefore more affected by unemployment and degradation of well-being.
With respect to the inequality channel, in countries where minorities are victims of inequality, the COVID-19 has destructed the jobs according to these inequalities. The work of Couch et al. (2020) shows that the effects of COVID-19 on unemployment in the U.S. population are more pronounced for minorities. In contrast to whites, black and Latino minorities are the groups with the highest unemployment rates. Part of the reason for these job losses is that these groups have traditionally been marginalized in the labor market. In general, access to employment is more difficult for African Americans, Latinos, and other communities of color. As a result, they work in precarious jobs that expose them to unemployment whenever there is a negative shock to economic activity. In a crisis, communities of color are the first to be affected (Couch et al., 2020; Thebault, Tran, & Williams, 2020), but Whites emerge from unemployment first, amplifying the gap between White unemployment and Black or Latino unemployment (Couch et al., 2020). The White community is thus less affected by unemployment during COVID-19 because of the advantages they enjoy, particularly economically, which provide a sort of shield against negative shocks to the economy (Antipova, 2021).

With respect to education, another strand of research shows that the effects of COVID-19 on unemployment vary by level of education and type of job held prior to the health crisis (Blustein et al., 2020; Couch et al., 2020; Mueller et al., 2021). In this regard, a distinction must be made between skilled and unskilled labor. The first category of labor occupies jobs that have easily adapted to the COVID-19 context through the practice of remote work. This mode of work has allowed them to protect themselves from possible contamination by the virus, while continuing to carry out their activity. On the other hand, for the second category, the jobs are precarious and the work cannot be done remotely. Physical presence in the workplace is required, thus increasing the risk of contagion. As a result, people with no or low qualifications, who cannot work from home, are the most exposed to unemployment. Adams-Prassl et al (2020) find that in both the United States and the United Kingdom, job and income losses are related to workers' personal characteristics. Education and age play a key role in determining the concentration in activities that cannot be performed at home (Yasenov, 2020).

In this regard, Couch et al (2020), who use the decomposition method to determine the most important factors that characterize community employment, show that the particularly high unemployment rate of Latinos is explained by their very low level of education. This community is characterized by a lower level of education than blacks and therefore whites. Choosing to protect themselves from the virus caused them to lose their jobs. Goolsbe and Syverson's (2021) study shows that the fear of being infected contributed more to the destruction of jobs and therefore to the increase in unemployment, compared to the containment policies taken by the Government.

A final group of empirical works examines the impact of COVID-19 on the labor market based on geographic areas. Indeed, this work emphasizes that the vulnerability or resilience of the population to the pandemic may be related to area of residence. Antipova's study (2021) examines the effects of COVID-19 on employment and unemployment through different indicators of socioeconomic inequalities and vulnerabilities across urban areas. Using Bureau of Labor Statistics (BLS) data and benchmarking methodology, the study shows that COVID-19 did not particularly magnify differences in unemployment.
across minorities, industries, and education levels. These differences were already noticeable before the pandemic. Instead, unemployment rate differences were shown to be sensitive to inequalities between cities. The most disadvantaged cities before COVID-19 had the highest unemployment rates, while advantaged areas were able to contain unemployment. The very high unemployment rate in Tennessee state cities, especially Memphis, is explained by the structural characteristics of their economies. Indeed, cities in decline and heavily dependent on tourism, hospitality and other leisure services have suffered from unemployment. In these cities, the job losses associated with COVID-19 affect both highly skilled workers and those in precarious jobs. Even sectors such as public administration, health care, and education, which are likely to maintain jobs in favored areas, have not been spared in these cities.

While Batty's (2020) study found that the vulnerability of some urban areas amplified the impact of the pandemic compared to other less disadvantaged cities, Antipova (2021) points out that this reality is the same in rural areas. This view is confirmed by work conducted by Mueller et al. (2021) in rural areas. In particular, this study concludes that the COVID-19 has had a significant negative impact on unemployment in rural areas in the Northwestern United States of America. The magnitude of unemployment is primarily explained by the high vulnerabilities of the populations in these areas. Also, as in the case of studies conducted in vulnerable urban areas, factors such as skill level, social group, age, and gender were not significant in explaining differences in rural unemployment. All categories were affected by the rise in unemployment.

To the best of our knowledge, only one study incorporates workers’ industry as a factor that can explain differences in the labor market impact of COVID-19. Indeed, Montenovo et al. (2022) analyze the factors that explain the unequal distribution of job losses during the COVID-19 crisis. They use the technique of decomposing the population into the different factors that may promote job loss and CPS data. The results of this research indicate that the type of industry in which one is employed played a strong role in explaining differences in unemployment. Indeed, populations employed in industries considered critical were more resilient to unemployment. On the other hand, government policies of closing down non-essential activities have contributed to the unemployment of people working in these industries. Indeed, the very high unemployment rate affecting Latin Americans at the beginning of the crisis can be explained by the strong presence of this community in nonessential activities, mainly services such as wholesale and retail trade, construction, hotels and leisure (Couch et al., 2020). At the same time, the White community's resilience to rising unemployment is provided in part by jobs in government, education, and healthcare.

Unlike Montenovo et al (2022) who focus on core and non-core industries according to the nomenclature of public authorities, we focus our analysis on layoffs in Start-ups in the United States of America (USA) according to the branches of activity. This methodological approach allows us to have a microeconomic overview of the effects of the health crisis in a category of companies that are at the forefront of innovation, that provide jobs in normal times and that are currently booming in the world.
iii. The Impact Of Covid-19 On Start-ups In The Us: A Differential Effect According To The Branch Of Activity

Geographical distribution of start-up layoffs in the US

To analyze the effect of COVID-19 on layoffs in US startups, we work on a sample of 297 startups from the "Layoffs.fyi Tracker" database covering the period from 3/31/2020 to 3/9/2021. For this purpose, the following industries were included in the study, depending on data availability: Media, Infrastructure, Data, Consumer, Food, Transportation, Retail, Recruiting, Finance, Education, Security, Travel, Healthcare, Real Estate, Marketing, Construction, HR, Product, Logistics, Support and Other. The number of startups that had made layoffs of 15% or less of their workforce was 102, of which 57 were in California, 26 in New York, 7 in Massachusetts, etc. In addition, 141 startups had layoffs between 15 and 50% of their workforce, of which 69 were in California, 29 in New York, 14 in Massachusetts, 9 in Washington, etc. Finally, 44 startups had layoffs between 50 and 100% of their workforce, of which 22 were in California, 8 in New York, 6 in Washington, etc. The purpose of this section is not to analyze the spatial distribution of layoffs as in the literature (Batty, 2020; Antipova, 2021). We wish to enrich the existing literature with an original approach that incorporates membership in a specific branch of activity. Thus, we calculate the probability of a worker becoming unemployed according to his or her branch of activity.

The objective is to predict the layoff variable (LAIDOFF) defined in \{laidoff_1, laidoff_2, ..., laidoff_K\} with two modalities for the variable LAIDOFF \{1;0\} using a binary logistic regression. We note LAIDOFF (branch), the value taken by LAIDOFF in a given branch of activity. Let \{X_1, X_2, ..., X_J\} be the J descriptors. The vector of values for a given branch of activity is then written:

\[
\begin{pmatrix}
X_1(\text{branch}), X_2(\text{branch}), ..., X_J(\text{branch})
\end{pmatrix}
\]

Thus, the probability for LAIDOFF to come from a given branch of activity is noted:

\[
P[\text{LAIDOFF}(\text{branch}) = 1 = p(\text{branch})]
\]

Therefore, the estimated logistic model is the following:

\[
\ln\left[\frac{p(\text{branch})}{1 - p(\text{branch})}\right] = a_0 + a_1X_1(\text{branch}) + a_2X_2(\text{branch}) + ... + a_JX_J(\text{branch})
\]

With \(a_0, a_1, a_2, ..., a_J\) the parameters to be estimated. The table below gives the results of four estimations. If we denote \(L\) layoffs, in model 1, modality 1 corresponds to \(L\leq15\%\) and 0 the rest. In model 2, modality 1 corresponds to \(15\%<L\leq50\%\) and 0 the rest. In model 3, modality 1 corresponds to \(50\%<L\leq75\%\) and 0 the rest. Finally, in model 4, modality 1 corresponds to \(75\%<L\leq100\%\) and 0 the rest.

Table 1: Estimation results
<table>
<thead>
<tr>
<th>Laid Off</th>
<th>Odds Ratio</th>
<th>15% L Odds Ratio</th>
<th>50% Odds Ratio</th>
<th>Odds Ratio</th>
<th>50% Odds Ratio</th>
</tr>
</thead>
<tbody>
<tr>
<td>Media</td>
<td>0.45**</td>
<td>0.208***</td>
<td>0.5*</td>
<td>(3.46)</td>
<td>(5.24)</td>
</tr>
<tr>
<td>Infrastructure</td>
<td>0.1***</td>
<td>0.15***</td>
<td>0.5</td>
<td>(9.247)</td>
<td>(16.8)</td>
</tr>
<tr>
<td>Data</td>
<td>0.337*</td>
<td>0.5</td>
<td>0.006</td>
<td>(2.608)</td>
<td>(0.153)</td>
</tr>
<tr>
<td>Consumer</td>
<td>0.692</td>
<td>1.031</td>
<td>0.214</td>
<td>(0.65)</td>
<td>(2.7)</td>
</tr>
<tr>
<td>Food</td>
<td>0.257</td>
<td>0.313</td>
<td>0.261</td>
<td>(2.148)</td>
<td>(0.241)</td>
</tr>
<tr>
<td>Transportation</td>
<td>0.415***</td>
<td>0.295*</td>
<td>0.261</td>
<td>(2.835)</td>
<td>(0.184)</td>
</tr>
<tr>
<td>Retail</td>
<td>0.128</td>
<td>0.3</td>
<td>0.15***</td>
<td>(1.252)</td>
<td>(15.1)</td>
</tr>
<tr>
<td>Recruiting</td>
<td>0.204</td>
<td>0.375</td>
<td>0.428</td>
<td>(1.579)</td>
<td>(0.259)</td>
</tr>
<tr>
<td>Finance</td>
<td>0.236</td>
<td>0.35*</td>
<td>0.48*</td>
<td>(1.603)</td>
<td>(0.212)</td>
</tr>
<tr>
<td>Education</td>
<td>0.45</td>
<td>0.54***</td>
<td>0.1*</td>
<td>(5.141)</td>
<td>(8.259)</td>
</tr>
<tr>
<td>Security</td>
<td></td>
<td>0.75</td>
<td>0.15**</td>
<td></td>
<td>(0.986)</td>
</tr>
<tr>
<td>Travel</td>
<td>0.281</td>
<td>0.9</td>
<td>0.642**</td>
<td>(0.328)</td>
<td>(0.644)</td>
</tr>
<tr>
<td>Healthcare</td>
<td>0.321*</td>
<td>0.375</td>
<td>0.2727</td>
<td>(2.588)</td>
<td>(0.281)</td>
</tr>
<tr>
<td>Real Estate</td>
<td>1</td>
<td>0.541</td>
<td>0.1428</td>
<td>(0.781)</td>
<td>(0.349)</td>
</tr>
<tr>
<td>Marketing</td>
<td>0.421***</td>
<td>0.309**</td>
<td>0.1</td>
<td>(2.781)</td>
<td>(0.185)</td>
</tr>
<tr>
<td>Construction</td>
<td>0.135***</td>
<td>0.125*</td>
<td>0.1</td>
<td>(1.728)</td>
<td>(0.156)</td>
</tr>
<tr>
<td>HR</td>
<td>0.169</td>
<td>0.1</td>
<td>0.1</td>
<td>(1.474)</td>
<td>(0.829)</td>
</tr>
<tr>
<td>Product</td>
<td>0.45</td>
<td>0.125*</td>
<td>0.1</td>
<td>(5.141)</td>
<td>(0.156)</td>
</tr>
<tr>
<td>Logistics</td>
<td>0.45*</td>
<td>0.375</td>
<td>0.1</td>
<td>(4.038)</td>
<td>(0.32)</td>
</tr>
<tr>
<td>Support</td>
<td>0.45</td>
<td>0.125*</td>
<td>0.1</td>
<td>(5.141)</td>
<td>(0.156)</td>
</tr>
<tr>
<td>Other</td>
<td>0.135</td>
<td>0.437</td>
<td>0.1***</td>
<td>(1.16)</td>
<td>(0.321)</td>
</tr>
<tr>
<td>Cst</td>
<td>0.222***</td>
<td>0.2666***</td>
<td>0.033</td>
<td>(0.122)</td>
<td>(0.006)</td>
</tr>
</tbody>
</table>

Source: authors
Regarding model 1, the probability of layoffs that are less than or equal to 15% of the start-up's workforce is 45% if it belongs to the "Media" branch, 10% if it is the "Infrastructure" branch, 33.7% if it is the "Data" branch, 41.5% if it is the "Transportation" branch, 32.1% if it is the "Healthcare" branch, 42.1% if it is the "Marketing" branch, 13.5% if it is the "Construction" branch and 45% if it is the "Logistics" branch.

As for model 2, the probability of making layoffs whose number is strictly greater than 15% of the start-up's workforce, but less than or equal to 50% of the workforce is 20.8% if it belongs to the "Media" branch, 29.5% if it belongs to the "Transportation" branch, 35% if it belongs to the "Finance" branch, 30.9% if it belongs to the "Marketing" branch, 12.5% if it belongs to the "Construction" branch, 12.5% if it belongs to the "Product" branch and 12.5% if it belongs to the "Support" branch.

For model 3, the probability of layoffs that are strictly greater than 50% of the start-up's workforce, but less than or equal to 75% of the workforce is 11.5% for the "Consumer" branch, 10.8% for the "Recruiting" branch, 54% for the "Education" branch, 10.1% for the "Travel" branch and 36% for the "Real Estate" branch.

Finally, for model 4, the probability of making layoffs whose number is strictly greater than 75% of the start-up's workforce, but less than or equal to 100% of the workforce is 50% for the "Media" branch, 15% for the "Infrastructure" branch, 15% for the "Retail" branch, 48% for the "Finance" branch, 10% for the "Education" branch, 15% for the "Security" branch, 64.2% for the "Travel" branch, 10% for the "Product" branch, 10% for the "Support" branch, and 10% for the other branches.

Overall, the results show that the "Media" industry is significant in all three models where it was tested, with a 50% probability of being in the highest layoffs. In the two models in which it was tested, the "Infrastructure" industry remains significant. The same is true for the "Construction" branch. The other branches most affected are: "Transportation", "Product", "Support" and "Education" with two significant models out of three, and "Finance", "Travel" and "Marketing" with two significant models out of four. Apart from "HR" and "Food" which are not significant in all the models tested, all the other branches are significant in at least one of the models tested. Thus, we can see that the COVID-19 health shock did not impact all the branches of activity in the same way and to the same extent in the US.

These results suggest that, in addition to the factors identified in previous work, the branch of activity in which an individual is employed determines his or her level of exposure to layoff. Thus, our results are in line with those of Brinca et al. (2020). The insignificance of the Food industry may be explained by the resilience of this industry during the health crisis. In general, the food industry maintained its activities and therefore its jobs. It has even undergone changes, notably with home delivery services. This is not the case, for example, in the "Construction", "Education", "Transportation" and "Travel" sectors, which were strongly affected by the total or partial containment measures, leading to waves of layoffs.

Therefore, the implementation of policies to support activity should take into account these disparities by targeting the most affected sectors. It is also important to analyze the factors that make certain
industries more vulnerable than others, in order to provide better support and understanding of their difficulties.

Iv. Conclusion

The COVID-19 health crisis has had damaging effects on the economy in general and on employment in particular. Initial research examining the effects of this health shock on the labor market concludes that job losses are significant and unevenly distributed across social strata. The magnitude of unemployment rates is mostly related to the inequalities already discernible before COVID-19 with respect to, among other things, social origin, level of education, geographical location and type of industry.

The originality of this study lies in its approach and results. In terms of approach, the analysis provides an overview of the impact of COVID-19 on layoffs in American start-ups according to the branch of activity. On the results, populations employed in the Media are more likely to be unemployed as a result of the health shock. The probability of a Media start-up laying off more than 75% of its workforce during COVID-19 is 50%. Layoffs are also common for start-ups in the Infrastructure, Construction, Transportation, Product, Support and Education industries. On the other hand, layoffs seem to be negligible for start-ups in the "HR" and "Food" industries. These results are consistent with the existing literature regarding the uneven distribution of the negative effects of COVID-19 on employment.

Declarations

CONFLICT OF INTEREST STATEMENT:

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- Author contribution: Dr. Joseph Stévy Mba-Ollo worked on the literature review, the introduction and the overall proofreading of the paper. Prof. Giscard Assoumou-Ella took care of the modeling, estimations, interpretations, translation into English and the overall proofreading of the paper. Finally, Dr. Augustin Impawe did the overall proofreading of the paper.

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