Unemployment Before–Amidst COVID-19: Shifts in the Predictive Factors of the Number of Weeks Spent Looking for Work

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ABSTRACT

Further exacerbated by the lack of studies on unemployment duration, the Philippines' economic situation has been one of the worsts in years due to the COVID-19 pandemic. The issue moved the research to determine the predictiveness of the various characteristics (e.g., demographic) of the unemployed, in the Philippines, to the number of weeks they spent looking for work. Furthermore, it also drove the paper to explore the shifts in these features as the pandemic started. To do that, the study fitted the 2019 and 2020 Labor Force Surveys of the Philippines Statistics Authority into a Random Forest Regression Model. The results revealed that the predictive factors of unemployment duration in 2019 were age, currently attending school, and relationship to the household head. By 2020, age was now the only factor that was significant to the model prediction.

Keywords: Forest Unemployment, Duration Looking for Work, Random Regression

INTRODUCTION

More people are becoming jobless—the reason: COVID-19. With the spread of the virus, many were affected. Besides its health implications, the pandemic has caused the Philippine economy to spiral into a downfall: businesses closed, employees became jobless, and wages dropped (Asian Development Bank, 2020; Vasig & Sablan, 2020). The lockdown has caused many to transition into, if not unemployment, underemployment (Lim, 2020). Additionally, only a handful of research tackled the predictive factors of unemployment duration. Due to the growing issue coupled with the lack of studies, there has not been a more crucial time to address the problem.

The Philippine unemployment rate has been one of the worsts in recent years. Based on the survey conducted by the Philippine Statistics Authority (PSA) (2020d), the country experienced one of the highest unemployment numbers in recent years in April 2020. Approximately 7.3 million Filipinos became unemployed (PSA, 2020). It is higher by nearly 5 million compared with the same quarter of 2019—more than three times higher. Meanwhile, in the next quarter (July 2020), PSA reported an unemployment rate of 10% (2020). Around 4.6 million Filipinos (15 years old and above) were unemployed, 4.6 percentage points higher than in the same month of 2019 (PSA, 2020).

The economic situation is still far from recovering. Although the unemployment rate drastically fell from 17.6% in (April 2020) to 9.96% (PSA, 2020a, 2020d)—a decrease of approximately 2.5 million unemployed Filipinos (PSA, 2020a, 2020b)—the Philippines continued to be, on the average, at least a percentage point higher (reaching up to more than three percentage points) in the succeeding years when compared with that in 2019. Additionally, we should note that along with this decrease, there was a substantial depreciation in the value of the Philippine peso versus the US dollar (Domingo, 2022). The Philippine peso worsened to 55:1 US dollar (Domingo, 2022). It is one of the worst it has recently been, making the Philippines the worst performer among all the ASEAN countries (Domingo, 2022).

Further, the lack of research on unemployment duration, especially in developing countries (Ahmed, 2015), further exacerbates the issue. In general, most of these studies focused on the post-effect of recent recessions on the length of unemployment (Elsby et al., 2011; Nikolaos, 2015; Valletta, 2013; Valletta & Kuang, 2012). Meanwhile, studies covering the predictive factors are dated, with the latest spanning back to the late 2000s (Arntz& Wilke, 2009; Kupets, 2006; Shumway, 1993). In the Philippines, on the other hand, this scarcity is more evident. Only one tackled it directly (Mapa& De Jesus, 2016), with some limited by their analysis scope, covering only a particular city (Deluna & Berdos, 2015).

Despite its national scope, the study only looked at a handful of samples. It focused on the unemployed (15 years old and above) during the 2019 and 2020 Labor Force Survey (LFS). For the demographic characteristics, the research specifically considered these variables: relationship to the household head, sex, age, marital status, currently attending school, job search method, highest grade completed, and graduate of technical/vocational course. The research used un weighted data for the analysis. Using survey weights has its advantages and drawbacks (Bollen et al., 2016); nonetheless, with the lacking consensus, the need for them and their implementation in regression models is still unclear (Faiella, 2010). Moreover, due to lacking data access to more recent Public Use Files (PUFs) of PSA, the research limits itself to the 2019 and 2020 PUFs.

Due to the pandemic, many transitioned into unemployment or underemployment (Lim, 2020). This issue highlights the need for analytical insights to produce effective recovery initiatives. This research would hopefully encourage Philippine workers and organizations to act on the outcomes and for the government to create more informed unemployment benefit policies that would ultimately improve employment, reduce unemployment, and shorten unemployment duration, stimulating economic activity. Besides businesses and the labor force, this research also sought to provide interest to future researchers to look into unemployment duration in the Philippines.

Why is unemployment duration so long? Past studies have long established that the chances of getting a job diminish the longer one stays unemployed (Cockx & Dejemeppe, 2005; Kroft et al., n.d.; Niedergesäss, 2012; Steiner, 2001). They have explored why this is the case. Meanwhile, Fernández-Blanco and Preugschat’s study (2018) looked into how employers rank individuals by unemployment duration contributes to the phenomenon. Another discovered its effects’ extent various times during an unemployment spell (Kospentaris, 2017). What is shocking is that despite the abundance of research on the duration dependence of unemployment, literature on the predictive factors of unemployment duration is still scarce, especially in developing countries (Ahmed, 2015).

According to Deluna and Berdos (2015),job creation was not able to keep up due to the growing labor force population in Davao City and many workers from private sectors and graduates of private institutions switched jobs. The increasing demand and struggling supply for work left many looking for jobs, averaging five months. Furthermore, the study revealed that being a household head and age contributed to the length of time for employment search.

Similarly, due to the increasing unemployment rate in Germany, Arntz and Wilke (2009) set out to put the influence of regional and institutional factors on unemployment duration into the picture. They did this by looking into how they contributed to cutting down the length of unemployment and the results showed that despite the varying influence of the regional factors between states, there is a consensus that changes in the tailored local employment policies; and administrative restructuring did not significantly reduce unemployment duration.

Additionally, the varying effects highlight the importance of a more general model to assess the influence of these factors. Due to the 2011 recession, the economic letter by Valletta and Kuang (2012) set out to answer the question, why is unemployment duration so long? The answer: weak labor demand; however, it is not surprising that the reluctance to hire has weakened the labor force, given the surrounding anecdotal stigma of the economy.

Who is the Philippine Labor Force? It includes individuals 15 years old and above who are either employed or unemployed (PSA, 2012). About 47.3 million Filipinos make up the group, consisting of approximately million (91.2%) employed individuals and 4.2 million unemployed (8.8%), based on the recent February 2021 Labor Force Survey (PSA, 2021). Besides their characteristics providing an insight into unemployment duration, they also play an essential role in production (PSA, 2012). They are an indispensable resource to the country's economy that provides stability to its growth (PSA, 2012).

Despite their crucial role, the Philippine labor force participation rate (LFPR) was just at its lowest point in April 2020, reaching the worst record of 55.7% (PSA, 2020). Although it has improved to 58.7% in the next quarter (PSA, 2020), it is still far from recovering; it is still four percentage points lower than last year (PSA, 2019, 2020). Following that, other factors worsened in October, such as unemployment and employment rates, which were lower than last year (PSA, 2019, 2020).

What makes the problem worse is that precarious employment persists in the Philippines because Filipinos are bound to unemployment after their contracts end. In response, the government needs to plan clear agenda. The following administrations must achieve an all-encompassing growth of the different sectors (Japan Issues, 2017).

The high unemployment rate is stifling the country's economy. It is stagnating household consumption at 7.1% (Mapa, 2021). Much of it is due to the effects of COVID-19 (Mapa, 2021; Camba & Camba Jr, 2020; Lim, 2020). It has affected various facets of the economy, highlighting the need for better recovery initiatives (Camba & Camba Jr, 2020; Lim, 2020).

The pandemic has affected many major commodities in the Philippines. Many predictions estimated its effects (Wren-Lewis 2020; FRED Blog, 2020; Baldwin & Tomiura 2020 cited by Camba & Camba Jr, 2020); however, it was recent when further studies uncovered these links, such as how COVID-19 significantly influenced the Philippines stock exchange index and the monetary exchange rate, but not retail pump price of diesel (Camba & Camba Jr, 2020).

The Philippine economy did not cope well. In East Asia and the Pacific, the Philippines performed worst in COVID prevention and economic recovery (Lim, 2020). The second quarter of 2020 faced the highest unemployment rates and steepest fall in Gross Domestic Product (GDP) (Lim, 2020), and due to the lockdown, most (90%) of the labor force was affected (Lim, 2020). Besides, the legislatures were lacking. There were only two major social amelioration programs: Bayanihan Act one and two (Lim, 2020). There was a deep need for a bill to protect consumers and businesses from further financial crises (Lim, 2020).

The research aims to contribute analytical insights to the Philippine labor force and organizations using the PSA's Labor Force Survey data (2019 and 2020). Its goal is to use it to determine what changed in the factors that significantly influenced the number of weeks spent looking for work before (2019) and amidst the pandemic (2020). It determined the predictiveness of the characteristics of the unemployed to the unemployment duration for both periods. The research intends to construct a predictive model, determine the importance of the different features in predicting the unemployment duration, and which were significant for the predictions.

The study particularly sought to answer these questions:

1. What is the level of unemployment duration in the Philippines per quarter before and amidst the pandemic?
2. What was the importance of each factor in predicting the Philippine unemployment duration before and during the pandemic?

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3. What factors were the most and least important in predicting the Philippine unemployment duration before and during the pandemic?
4. What were the significant factors in predicting the Philippine unemployment duration before and amidst the pandemic?
5. Which significant features were the same and different before and amidst the pandemic?

METHODOLOGY

The researchers examined LFS data in the Philippines. It included all identified barangays, except those classified as least accessible or LABs (PSA, n.d.-b; Varona, 2019). Excluding a total of 910 barangays, the criterion for classifying LABs may be any of these: takes more than eight hours to walk, transportation visits one week at most, or a trip costs more than PhP1,000 (Varona, 2019). Given its objectives, the study only focused on unemployed Filipinos (15 years old and above) during the four quarters of 2019 (pre-pandemic) and 2020 (pandemic).

The study prepared the data (LFS 2019 & 2020) and the necessary libraries into R Studio 1.4.1106. It mainly used caret and rf Permute packages. It used those two to create, optimize, and evaluate the models. Specifically, the researchers used the rf Permute to—not only to build the model—but also to perform a nonparametric form of hypothesis testing. The package uses permutation testing to estimate them. Meanwhile, the study used genetic algorithm to optimize the model using a fitness function adopted from Viadinugroho (2021).

The researchers extracted the needed variables with the Census and Survey Processing System (CS Pro 7.6.0) to make PUF usable for modelling. The observations were filtered to the unemployed, and were exported as a comma-separated values (CSV) file. Then the data were concatenated and removed missing values.

To better understand the data, the researchers evaluated the descriptive statistics such as means and standard deviation (SD) of the unemployment duration using R 4.2.1.

The researchers compared the models' performances using Root Mean Squared Error and used a genetic algorithm that searched for the best discrete hyper parameters (number of trees, repetitions, and variables sampled) to optimize both models.

For the model interpretation, the study again plotted the feature importance; however, this time, it also highlighted which ones significantly affected the response variable. Additionally, it listed the specific values of importance.

RESULTS AND DISCUSSION

The effect of the pandemic shows itself clearly near the end of October 2020. The unemployment duration spiked and, more so, became widespread all over the Philippines as shown in Table 1 by the relatively high mean and standard deviation in October 2020.

Table 1. Level of the Unemployment Duration before and amidst the Pandemic

Quarter	Mean	SD
2019		
January	4.92	7.74
April	4.63	5.1

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July	4.18	5.08
October	5.46	9.38
2020		
January	4.62	8.06
April	5.53	6.23
July	4.58	6.47
October	7.04	1

Note. Values were rounded off to the 2nd decimal place. Frequencies and proportions were tabulated from *Philippines Labor Force Survey 2019 & 2020* [Data Files], by Philippine Statistics Authority. Copyright n.d. by the Philippine Statistics Authority.

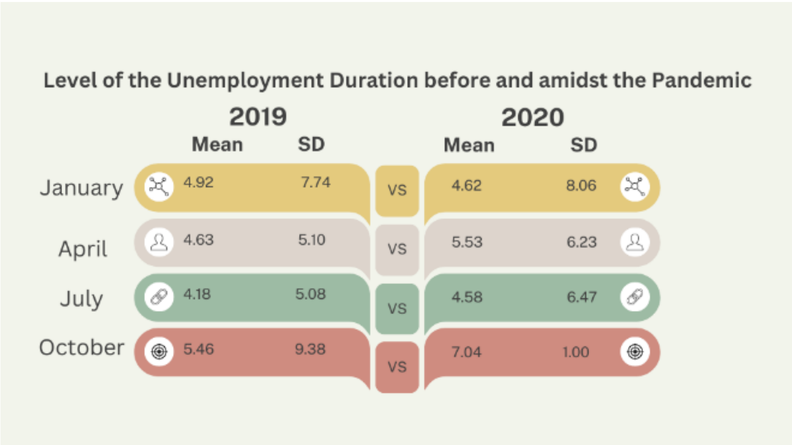

Figure 1. Level of the Unemployment Duration before and amidst the Pandemic

This may also infer that occurrences, such as the lockdowns, may have delayed the job search of the unemployed. This can be observed in the difference in spikes of those who became unemployed in April 2020, which only translated to a noticeable increase in unemployment duration in October 2020.

Table 2. shows the importance of the features in determining unemployment duration before the pandemic. It shows that age %IncMSE = 27.05) was the most important feature for the model in determining unemployment duration, while sex (%Inc MSE = 0.17) as the least. It also shows that age (%IncMSE = 27.05), currently attending school (%IncMSE = 14.34), and relationship with the household head (%IncMSE = 4.32) the ones that were significant for the model.

Table 2. Feature Importance and Significance of Prepandemic Model.

Factors	Importance	p value
Age**	27.05	0.00990099
Currently Attending School**	14.34	0.00990099
Relationship to the Household Head*	4.32	0.04950495
Highest Grade Completed	4.31	0.18811881
Job Search Method	3.96	0.11881188
Marital Status	1.07	0.47524752
Graduate of technical/vocational course	0.44	0.62376238
Sex	0.017	0.57425743

Note. * $p < .05$.. ** $p < .01$. The importance values were rounded off to the 2nd decimal place.

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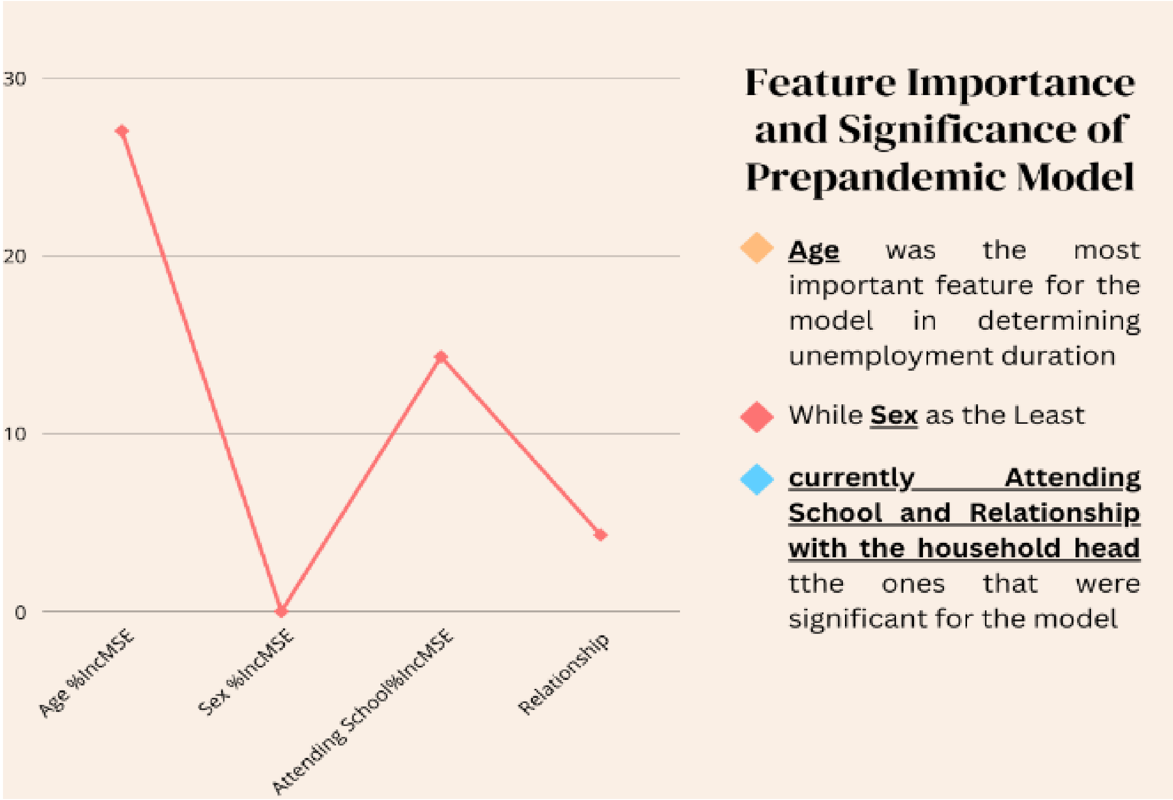

Figure 2. Feature Importance and Significance of Prepandemic Model.

The results affirm the long known effects of the three employment: different age groups react to unemployment differently (Rowley & Feather, 1987), like how young graduates face immense difficulties in finding jobs that suite their degree (Bureau international du travail, 2020); how having a degree undoubtedly helped with people's finding a job (Bureau international du travail, 2020); and how the burden of having a job fall into a particular role in the family, especially male household heads (Paul Flaim & Christopher Gellner, 1972).

Table 3 shows the importance in determining unemployment duration during the pandemic. It reveals that age (%IncMSE = 134.85) was the most important; meanwhile, graduate of teachnical/vocational course (%IncMSE = 0.52) as the least. Lastly, it shows that age (%IncMSE = 134.85) was the only factor that was significantly important in predicting unemployment duration.

Table 3. Feature Importance and Significance of Pandemic Model.

Factors	Importance	p value
Age**	134.85	0.00990099
Highest Grade Completed	10.09	0.23762376
Job Search Method	9.55	0.14851485
Currently Attending School	5.73	0.18811881
Relationship to the Household Head	4.80	0.18811881
Sex	1.81	0.44554455
Marital Status	0.95	0.56435644
Graduate of technical/vocational course	0.52	0.44554455

Note. * $p < .05$.. ** $p < .01$. The importance values were rounded off to the 2nd decimal place

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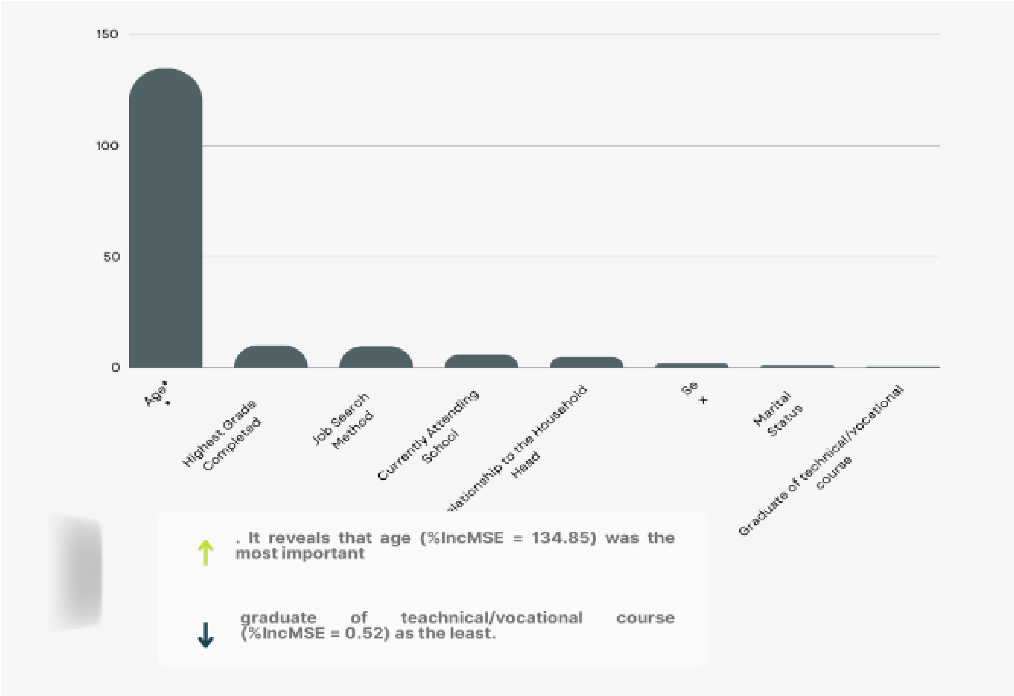

Figure 3. Feature Importance and Significance of Pandemic Model.

Furthermore, the results revealed that age is the predictive factor that persisted through. Meanwhile, currently attending school and relationship to the household head became insignificant when it came to unemployment duration. It reveals the unpredictability brought about by the pandemic. This is observed in the less significant factors in the pandemic model. What is shocking is how age continued to be and, more so, became relatively more important than the others compared with the prepandemic model. Since the others became insignificant, the researchers also expected the same for age. Its resulting this way may suggest that there may have been a change as to how age affects unemployment duration when the pandemic struck, which further studies may explore.

CONCLUSION AND RECOMMENDATION

To summarize, this study explored what changes happened to the predictive factors of unemployment duration before and after the pandemic hit (2019 and 2020). The study used the LFS data of PSA. It constructed, optimized, and compared the two random forest regression models to identify these predictive factors and shifts between them.

The research discovered that the predictive factors before the pandemic were age, schooling status, and relationship to the household head. Meanwhile, during the pandemic, it shifted to only age. The results highlights how the pandemic catalyzed an ever increasing uncertainty.

The new question now becomes about tailoring national and local policies to better address the increased length in unemployment duration, as seen in October 2020. Moreover, despite the age being significant between the two, further research should explore if there is any change in how age affected unemployment duration before and after pandemic in the Philippines. Finally, future research should explore the use of other models and with more recent data.

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