Virtually Functional: The Impact of Remote Work

1 Executive Summary

Remote work has long been hailed as the future. The COVID-19 pandemic ushered in a new era of work, where how and where people work changed drastically. Despite the advantages posed by virtual workspaces, many employers are calling employees back to in-person workspaces, presenting a question of the impact of virtual work on various cities in terms of environmental, political, and economic factors. We aimed to analyze previous employment data to predict the proportions of remote ready jobs in five cities, process various factors to determine the likelihood of individuals to remain in remote work if given the opportunity to choose between remote and in-person, and combine conclusions drawn from the previous two models to understand the overall impact that remote work can have.

We sought to predict the number and proportion of jobs that will be remote-ready by 2024 and 2027 with consideration of job growth and change of workers in a given sector. A neural network using the keras python library was used to synthesize data from the Bureau of Labor Statistics from 2011-2020. It was found that between 35-45% were remote-ready.

Next, we used a game theory approach to predict the stable situation for both the employer and employee based on the needs and desires of each. Creating models for both the employee and employer that output utils, a measure of satisfaction in economics, we placed these outputs in a three-by-one grid to determine the most stable condition based on various conditions that took into account area factors such as COVID-19 cases, household concerns, and the dullness of the job. The model predicted that in most situations where COVID-19 cases are extremely high, that both employer and employee desired to stay in a virtual work environment. However, if COVID-19 cases were low or non-existent, then employers with non-menial tasks tended to trend to staying virtual. Meanwhile, employers with menial tasks tended to trend to staying non virtual. For employees, when COVID was no longer a large factor, their relations with their families and co-workers was usually the determining factor.

Finally, we synthesized the models from Parts I and II to investigate the impacts of virtual work on the cities for which we previously modeled. Considering environmental, political, and economic impacts, it was found that hybrid work models were disfavored. Virtual models were found to have a higher utility, especially in tasks where the worker performing them is of a higher education level.

Contents

2 Part I: Ready or Not

2.1 Problem Restatement

This section of our paper seeks to create a model for the number of remote-ready jobs that will be available in given years, and we apply our model to predict the percentage of remote-ready jobs available by the end of 2024 and the end of 2027.

2.2 Variables and Assumptions

2.2.1 Variables and Definitions

Symbol	Definition
t	time, measured in years
p	percentage of jobs that are remote-ready

2.2.2 Assumptions and Justifications

1. *The proportion of jobs that can be remote in a given sector does not vary by locality.* The specific job makeup within a given sector is largely consistent and independent of locality.

2. *The percentage of jobs that can be done at home will remain unchanged over time.* While new technologies may affect the jobs that can be done virtually, this percentage will not vary greatly in a 10 year period.

2.3 Model Development

In this model, we sought to study the deeper patterns behind changes of employment in our country by using a neural network to generate more reliable and accurate predictions for future job growth in select industries, which were used to calculate the percentage of jobs that will be available virtually.

2.3.1 Data Pre-processing

Before running any form of modeling or statistical analysis, we obtained and cleaned our data in order to provide better results in our solution proposals. The US Bureau of Labor Statistics (USBLS) provides a wide range of data regarding worker's behaviors ranging back to the year, 1990. Using a RESTful API, we pulled data from the USBLS and used it for the Neural Network. Data was ordered and formatted with a Python library, known as NumPy. The data was obtained and placed in NumPy arrays, which is an object known as an ndarray.

2.3.2 Neural Network

In our modeling methods, we created a neural network using the Keras python library, the code of which is shown in Appendix A. In this model, we used two hidden layers of 16 neurons that use ReLU activation functions. We passed in the values gained from our data mining in Section 2.3.2 to the input layers.

2.4 Results

Through the neural network model, we determined the numbers of jobs in the years of 2024 and 2027 and the percentage of remote-ready jobs. The number of jobs in each year was calculated by summing the projected number of jobs in each sector. The number of remote-ready jobs in each sector was determined by multiplying the projected number of jobs in each sector and the percentage of jobs that were remote-ready in each sector [2]. Then, we summed the products to get the total number of remote-ready jobs for each city, then divided by the total projected number of jobs to get our percentage. The results of these calculation are as follows:

In Seattle, in the year 2024, our simulation predicted that 40.368% of the predicted 1,760,000 jobs would be virtual, and 40.447% of the predicted 1,800,000 jobs will be virtual in 2027.

In Omaha, in the year 2024, our simulation predicted that 45.980% of the predicted 893,000 jobs would be virtual, and 45.778% of the predicted 923,000 jobs will be virtual in 2027.

In Scranton, in the year 2024, our simulation predicted that 38.216% of the predicted 306,000 jobs would be virtual, and 38.139% of the predicted 313,600 jobs will be virtual in 2027.

The English data was not very commonly found, so a simple linear regression was used to analyze this data. If time had permitted, more information would have been obtained through different methods to also run neural training on these data sets.

2.5 Sensitivity Analysis

This model is not very sensitive due to the fact that it has two layers of hidden layer of 16 nodes each in order to better predict patterns. And since it is using large amounts of past data, the simulation is very deeply rooted.

2.6 Strengths and Weaknesses

A strength of this model is that it incorporates data from a relatively long period of time in the predictions for each sector. In addition, the correlation coefficients were high, indicating strong correlations and a high degree of predictability.

Weaknesses of this model include its reliance on extrapolation from existing data and its failure to account for variance in some of its input metrics. Additionally, employment in some sectors in some localities followed an unclear trend, making future trends difficult to predict. Unfortunately, the data we received for the UK cities was not sufficient to effectively train and run a neural network. If we had more time, we would have determined the best way to mine data from the labor statistics of the UK and applied our neural network model to those values as well.

3 Part II: Remote Control

3.1 Problem Restatement

This problem asks or a model to determine if a given worker in a remote-ready job is able, and chooses, to work remotely, considering their personal and their employer's abilities and desires.

3.2 Variables and Assumptions

3.2.1 Variables and Definitions

Symbol	Definition
E_e	Number of utils an employer gets from going to a certain work environment e
V	The utils gained by the employee from going virtual
H	The utils gained by the employee from going hybrid
NV	The utils gained by the employee from going non-virtual
D	Number of house mates
R	Number of rooms in housing unit
κ	Level of concern about COVID-19, measured on a scale from 1 to 10
S_i	Dummy variable that corresponds to how much a certain category matters

3.2.2 Assumptions and Justifications

1. *There are many but finite factors that go into the satisfaction of an employee towards their employers and work environment.* This means that the attitude of an employee towards their work environment can be modeled as an input and an output in utils.

2. *There are many but finite factors that go into the employer opinion on work environments.* This means that the opinion towards work environments of the employers can be modeled as an input of factors and an output of utils from going to a certain work environment.

3. *Workers will not change jobs.* This is an assumption made to simplify the model. Given more time, we would account for unemployment rates and account for the possibility of an employee switching jobs to one that better matches their preferences.

4. *The amount of utils lost due to increased power cost due to being virtual is around 10-25% incrase in power consumption therefore the increase power cost is around 6-20$ per month* since 6-20 dollars per month is relatively small compared to all other cost considerations. Therefore increased energy consumption due to being virtual is insignificant.

3.3 Model Development

In this question, we look at how willing an employee is to go back to work or stay virtual or go hybrid compared to the employer's decision. Each of these values can be modeled by quantified variables

The decision for an employee and employer to go virtual can be modeled by a 1x3, 2 dimensional game.

	Employer decision/wish		
Employee wish	V, E_V	H, E_H	NV, E_{NV}

Notice how the diagonals of this decision matrix correspond to optimal conditions where the employee wish and employer decisions match and therefore both will be happy. While the Nash Equilibrium is applicable to tell us what the employer should do to balance employee happiness and productivity, it must be noted that the employer does not always need to do this so we must also consider the employee's decision to either stay or leave the job based on current job availability and current satisfaction. Remember that this game is not a true game as the employer has ultimate control over what the employee has to do, this game is used because it can predict how a employee will react seeing the decision of the employer. Now that we have established what we need to find for this game, we need to find the values shown in the 1x3 game above.

3.3.1 The Employee Part of the Game

There are several factors that go into employee satisfaction:

- Childcare and family
- Cost of Living, including commuting costs
- Interactions with co-workers
- COVID-19 concerns

All of these factors can be quantified and converted into a function that outputs utils. First, we can take a look at childcare and family, which is often considered one of the largest factors that determine whether or not an individual decides to work remotely. While teleworking, an employee would have greater capacity to also serve in caretaking and homemaking roles. However, this may provide no benefit to both the employer and employee as staying virtual may mean distractions like dependents, housemates, and pets that create an environment that may become unworkable. On the other hand, if the employee does not have any dependents or housemates, they do not need to be considered this function. Therefore, the utils gained or loss for working virtually due to family concerns is 0.

According to the US Department of Housing, the mental health of an individual starts to decline when stuck in a housing situation where there is greater than 0.75 people per room ([5]). As the number of people per room increases, so does the loss of utils due to loss of productivity and degradation of mental health. This relation is logistic which reaches a maximum at around 4 people per room on average. With this in mind, one of the inputs that we need to acknowledge is the number of room and number of housemates (children, spouse, parents, and in-laws). In a function, the number of utils lost due to overcrowding in a household is represented by:

$$F_{UL} = \begin{cases} 0 & \frac{D}{R} < 0.75 \\ -\frac{1}{1+100e^{-2.5\left(\frac{D}{R}-0.75\right)}} \cdot S_F & \frac{D}{R} \geq 0.75 \end{cases}$$

S_F is the importance of family to the worker on a scale of 0-100. Now, consider at the utils and happiness gained from being around family. Depending on how this individual views the importance of family, they will gain an amount of utils. We can call this scalar factor S_E, representing on a scale of 1-5 how connected the employee is to their family.

At this point, we have the utils for the employee for staying virtual (V) as $F_{UL} + S_E$. Now we need to find the other 3 factors. Next, we can look at the costs of living and cost of commuting due to work. While some companies reimburse employees on the amount of money spent on gas that was used to commute to and from work, not all jobs do so. Some may also opt for a partial reimbursing of funds or no reimbursing. As a result, it is necessary to consider the amount of utils gained from money saved from being virtual. Therefore, we can call r_j the proportion of commuting costs that are reimbursed by the company. The amount of utils gained by the money that you save from being virtual can be modeled by the equation

$$C_U = r_j \cdot \frac{d}{25} \cdot P_g \cdot S_c$$

where d is the distance from work in miles and 25 is representative of the average miles per gallon of gas of a car. P_g is the price of gas for the locality and S_c is the importance commuting costs to the individual employee.

Some people just don't like their coworkers, while some people work very well with coworkers. The distinction depends on their personality and preferences. This can be expressed on a scale, S_γ of domain -20 to 20 as a general hatred or love for their fellow coworkers. This yields:

$$\gamma_U = -S_\gamma$$

Furthermore, we have to look at the losses that result from working from home. As mentioned in the assumptions section increases of power costs are usually insignificant to the income of the individual (around a $10-15 increase in power bill per month).

An individual's concerns about COVID-19 also impact the utils they lose from having to go into alternate types of work if they would prefer to remain virtual. At the extreme, an individual who is extremely concerned about COVID-19 may refuse to work in-person, and instead leave employment. The function of utils gained by an employee staying virtual who would like to remain virtual is given as follows, where κ represents the individual's concern about COVID-19, where $0 \leq \kappa \leq 10$

$$K_U = \begin{cases} \infty & \kappa = 10 \\ \frac{\kappa^2}{3} & 0 \leq \kappa < 10 \end{cases}$$

Putting it all together, we get:

$$V = F_{UL} + S_E + C_U + \gamma_U + K_U$$

Now, we need to find the utility caused for the employee by going hybrid. Hybrid working is where an employee gets to work partially in virtual and partially in non-virtual spaces. As a result, the utils gained by an employee on hybrid work environments should be all of the variables in V multiplied by the proportion of days they are in virtual over total days working, with the exception of the coworkers portion, p_w. As in hybrid, the amount of coworkers that are seen in the office are less than that of a non-virtual environment. As a result, it will also have a proportion, p_C for the proportion of coworkers that the employee shares a hybrid shift with over the amount of coworkers the employee shares a shift with in a non-virtual shift. In this case:

$$H = p_w \left(F_{UL} + S_E + C_U + \gamma_U + K_U \cdot p_C \right)$$

Our model now accounts for V and H, but we must also account for NV. The distaste for virtual environments will result in a positive reaction with the same magnitude towards non-virtual environments. This means that:

$$NV = -V = -\left(F_{UL} + S_E + C_U + \gamma_U + K_U \right)$$

One final note is that the COVID concern part of this model will approach 0 as years after COVID hit increases as the pandemic eventually goes away. After COVID has passed, in order to use this model, reduce all COVID constants to 0.

3.3.2 The Employer Part of the Game

There are two factors that the employers must consider when thinking about going virtual, non-virtual, or hybrid:

- Losses due to COVID infection
- Losses or gain of productivity

Losses due to COVID-19 infection is a major concern for productivity loss. Of course, as mentioned in the previous sub-sub-section, the COVID concern will eventually be reduced to 0. For virtual, working, the the reduction of COVID passivity rate among employees is very substantial going from 24% to 0.2%. [1] If someone was to contract COVID-19, on average, they will have symptoms for around 10-14 days meaning that they would not be able to work for 10-14 days. This means that for any given time, an employer (in high COVID-19 transmission environments) could have 24% of their work force out due to COVID at a given time. Meanwhile, the number of employees that would be unable to work due to COVID in virtual settings would be 0.2%. We can represent this proportionality as $p_{\kappa e}$ where e represents the work environments.

$$p_{\kappa V} = 0.002$$

$$p_{\kappa NV} = 0.24$$

$$p_{\kappa H} = \frac{0.24 \cdot w_{NV} + 0.0002 \cdot w_V}{w_V + w_{NV}}$$

where w_e is the amount of days in each environment (for hybrid only). As time goes on, the amount of infections also would go down. Both of these values will be scaled by a scaling factor, S_I, which is a a scale from 0-100 and is found by this equation:

$$S_I = \frac{N_C}{M_C} \cdot 100$$

Where N_C is daily new COVID-19 cases per 7 day rolling average and M_C was the highest amount of cases per 7 day rolling average historically. Combined together this would reduce the amount of utils that employers get from that work environment.

$$E_{\kappa eL} = S_I \cdot p_{\kappa e}$$

An additional factor that employers should consider when deciding whether to allow employees to work from home is the potential for a gain or loss in productivity. In general, workers gain productivity at home when performing creative tasks and lose productivity when performing dull tasks compared to in the office [3]. The utils gained by the employer can then be represented as follows, with δ representing the dullness of the work ($0 \leq \delta \leq 10$) where 0 is completely creative work and 10 is completely dull work.

$$D_U = 30 - 4\delta$$

In total, E_e would be expressed as:

$$E_e = E_{\kappa eL} + D_U \cdot \frac{w_V}{w_V + w_{NV}}$$

3.3.3 Quitting Jobs

Due to the nature of this model, there is a high possibility that the employer and the employee disagree on what work environment the employee should be working in. As a result, there will be a group of people that leave their jobs as a result of not being able to work in the environment that they wanted. This can be modeled with the dissatisfaction of the system that was chosen vs a threshold, x. If the magnitude of dissatisfaction with the decision is greater than the threshold, then the employee will leave the workplace.

3.3.4 Specific Case

Dan Green works for a company and lives with his non-working spouse and their two children in Seattle Washington. He lives in a 3 room apartment in Seattle and has 40 mile commute to work. In Seattle, the price of gas is \$4.090 per gallon. His company reimburses him for 20% of his commute cost and currently, COVID is at its peek and Dan Green fears for his family's safety and scores an 8/10 for concern about COVID. His job is not very dull with a rating of 4. His employment place is considering a hybrid plan with 4 virtual days and 1 non virtual day with 10% of the original coworkers for that shift in attendance. After calculations we get this table:

Employer decision/wish

Employee wish	8.97, 13.8	8.18, 2.53	−8.97, −12.8

This shows that at the height of the COVID pandemic, Dan Green and his employer would both like for the employee to work virtually. In this case, the Nash Equilibrium will be for Dan Green to work virtually.

At this point, we can suppose that the pandemic has passed and there are no more cases of COVID. This sets the COVID values in our models to 0, and we can get this table:

Employer decision/wish

Employee wish	−10.37, 14	−8.30, 11.2	10.37, −14

In this case, the NE is to stay virtual, however, Dan Green dislikes the thought of staying virtual. Instead, he would prefer to go back work in an in-person workplace. In this case, we have a disagreement between the employee and employer. If Dan Green's job threshold was $x = 10$, then he would quit this job in order to find a new, non-virtual job. This varies based on the supply of the job market.

In an opposite case, Dr. Enderson is an extreme germophobe as he has cancer and is immunocompromised which means that his V_{util} value will be ∞ and $-\infty$ for both H and NV. This means that Dr. Enderson, as long as there is a COVID concern, will refuse to work in-person or in a hybrid environment.

3.4 Results

This model demonstrates how willing an employee is to accept a work environment and at the same time explain which work environment a employer is likely to choose based on conditions of the surrounding community. An unexpected outcome was that both employers and employees disagreed with hybrid working as it didn't really provide any advantages and really only presented disadvantages.

3.5 Sensitivity Analysis

After some sensitivity testing, the conclusion was drawn that the family portion was not very sensitive. This is fairly reflective of how Americans felt during the pandemic. Meanwhile, the COVID-19 factor for both employees and employers were very sensitive. This was found by plugging varying numbers for our models to find the amount of change and total weight for each section.

3.6 Strengths and Weaknesses

One weakness of this model is that instead of using a 1x3 game, we could have used a 2x3 game. This way, we could have incorporated the employee's decision to leave or keep the job into the game based on market availability instead of using a threshold. However, we ran out of time to implement a 2x3 game.

However, a strength of this model is that it considers a wide variety of factors in predicting utility for employees and employers. While there are more factors that play into the decision to work remotely than we can possibly consider, we consider enough of them that considering any more can cause for flase positives or negatives and many errors to pop up.

4 Part III: Just a Little Home-work

4.1 Problem Restatement

Through synthesis of our models from Parts I and II, we are tasked with discussing the impacts of working remotely on our given cities. This requires consideration of environmental impacts, political impacts, and economic impacts.

4.2 Variables and Assumptions

4.2.1 Variables and Definitions

Symbol	Definition
E	education level, described below
t	years since 2022

4.2.2 Assumptions and Justifications

1. *Commute times are independent of occupation and sector.* Inadequate data is available on the city-level to allow for sector to be considered when determining commute.

2. *Use of public transportation is independent of occupation and sector.*

4.3 Model Development

Workers who work in-person are likely to support businesses near where they work, whereas economic activity from those who work from home would more likely concentrated in residential areas.

Environmentally, there is a slight positive impact from work from home. Workers may be more likely to travel outside of work if they work from home. If people are working partially from home, they may be more willing to live further away from the city, leading to an increase in travel for leisure and longer commutes on their in-person days ([4]).

4.3.1 Modification of Inputs to the Part 2 Model

The creativity of the tasks being performed by a worker can be estimated by the education level of the worker. Educated workers are more likely to be performing creative tasks, whereas less educated workers in remote-ready jobs are more likely to be performing "dull" tasks. Thus, δ can be estimated by the education level of a worker. We assigned each education level a value in the following way:

Value (E)	**Description**
1	Less than high school diploma/NQF level 1 or less
2	High school/NQF level 2-3
3	Some college/NQF level 4-5
4	Bachelor's degree/NQF level 6
5	Post-graduate degree/NQF level 7-8

In the case of the Liverpool data, levels 3-5 were merged. All of the data was placed as level 4. For Barry, levels 3 and 4 were merged. The proportion in that category was split over levels 3 and 4 for purposes of the simulation.

Then, we assumed δ $N(2(E-1), 1.5)$, but we set any values less than 0 or greater than 10 to 0 and 10 respectively.

4.3.2 Predicting the Proportion of Remote-Ready Jobs Done Virtually

We ran a simulation (see Appendix) to predict the proportion of jobs that would be optimally done virtually, based on Model 2. This made use of random employees and random jobs generated from normally distributed variables (except for family members, which were distraction).

We used Python code for this, which allowed us to efficiently run thousands of simulations.

4.4 Results

Our results showed that virtual work produced a higher utility. Interestingly, hybrid was strongly disfavored. Therefore, despite claims to the contrary, we conclude that hybrid is not ”the future of work.”

This strongly indicates a trend toward virtual work. The impacts of this on localities will be large. Urban planners should consider a decrease in commutes and a potential increase in sprawl.

Proportion of Virtual-Ready Jobs That Will Be Virtual At x Years After 2022

Year	Seattle	Omaha	Pennsylvania	Liverpool	Barry
0	0.810455	0.849355	0.894105	0.91046	0.90085
2	0.81265	0.84779	0.89368	0.910175	0.90016
5	0.812445	0.84931	0.893905	0.91028	0.8987

4.5 Sensitivity Analysis

Because the model use random number generators, the values that are spit out may become volatile. However, it will get normalized with large amounts of reruns.

4.6 Strengths and Weaknesses

The strength of using this model is that it incorporates a random sample which allows for a truly random number of jobs being virtual vs non virtual. It also address COVID concerns as we don’t know how long this pandemic will last, it is important to consider the fact that the pandemic will last through 2024 and 2027. On the flip side, there is limited data available to predict the future of the pandemic. Thus, a weakness of our model is that the influence of COVID may not be accurately predicted due to a lack of data.

An additional strength of this model is that it uses thousands of simulations, so the Law of Large Numbers indicates that our experimentally generated proportions are likely close to the true values.

5 Conclusion

5.1 Further Studies

Due to the wide-ranging impacts of the COVID-19 pandemic, much remains unknown about workers’ preferences. In addition, the pandemic remains unpredictable, and a new variant necessitating increased precautions could emerge at any point.

Additionally, further studies are needed to determine attitudes toward remote work and the factors that influence those attitudes.

References

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[5] US Department of Housing and Urban Development. *Measuring Overcrowding in Housing*. Sept. 2007. URL: https://www.huduser.gov/publications/pdf/measuring_overcrowding_in_hsg.pdf.

A Neural Network for Analyzing Data (General Template Insert Data and Run)

```
import requests
import json
import numpy as np
import csv
import tensorflow #Machine learning things
from keras.models import Sequential
from keras.layers import Dense
import matplotlib.pyplot as plt
# In[7]:
#USBLS pull request to get data from API
headers = {'Content-type': 'application/json'}
data = json.dumps({"seriesid": ['SMU53426441000000001'],"startyear":"1990",
    "endyear":"1999"})
p = requests.post('https://api.bls.gov/publicAPI/v2/timeseries/data/', data=data,
    headers=headers)
```

```
json_data1 = json.loads(p.text)
headers = {'Content-type': 'application/json'}
data = json.dumps({"seriesid": ['SMU53426441000000001'],"startyear":"2000",
    "endyear":"2009"})
p = requests.post('https://api.bls.gov/publicAPI/v2/timeseries/data/', data=data,
    headers=headers)
json_data2 = json.loads(p.text)
headers = {'Content-type': 'application/json'}
data = json.dumps({"seriesid": ['SMU53426441000000001'],"startyear":"2010",
    "endyear":"2019"})
p = requests.post('https://api.bls.gov/publicAPI/v2/timeseries/data/', data=data,
    headers=headers)
json_data3 = json.loads(p.text)
headers = {'Content-type': 'application/json'}
data = json.dumps({"seriesid": ['SMU53426441000000001'],"startyear":"2020",
    "endyear":"2021"})
p = requests.post('https://api.bls.gov/publicAPI/v2/timeseries/data/', data=data,
    headers=headers)
json_data4 = json.loads(p.text)
# In[8]:
#Creating Array of all values
#Because there is a limit to the amount of pull requests that we could do, we use a
    range of years
for m in range(119, -1, -1):
    array.append(float(json_data1["Results"]["series"][0]["data"][m]["value"]))
for m in range(119, -1, -1):
    array.append(float(json_data2["Results"]["series"][0]["data"][m]["value"]))
for m in range(119, -1, -1):
    array.append(float(json_data3["Results"]["series"][0]["data"][m]["value"]))
for m in range(10, -1, -1):
    array.append(float(json_data4["Results"]["series"][0]["data"][m]["value"]))
npArr = np.array(array)
npArr
# In[9]:
npArr
# In[16]:
#creates a neural network with two hidden layers each with 16 nodes
model = Sequential()
model.add(Dense(16, input_dim=1, activation='relu'))
model.add(Dense(16, input_dim=1, activation='relu'))
model.add(Dense(1))
model.compile(loss='mean_squared_error', optimizer='adam')
model.fit(X, npArr, epochs=200, batch_size=2, verbose=2)
trainPredict = model.predict(X)
# In[19]:
model.predict(np.array([419]))
# In[15]:
```

```
x = []
for z in range(371):
    x.append(z)
X = np.array(x)
```

B Python Monte Carlo Simulation for Number of Virtual Workers, Hybrid Workers, and Non-Virtual Workers

```
import numpy as np
avgCommute = 16 #in miles
eduBuckets = [1,2,3,4,5]
eduDist=[.072, .191, .295, .269, .173]

class Employee:
  def __init__(self, locale):
    self.edu = np.random.choice(eduBuckets, None, True, eduDist)
    self.job = Job(self.edu)

    # sets baseline level of concern about covid-19
    tempCV = np.random.normal(5, 2)
    if tempCV < 0:
      self.covid = 0
    elif tempCV > 10:
      self.covid = 10
    else:
      self.covid = tempCV

    # sets the amount they care about their coworkers
    tempCo = np.random.normal(0, 7)
    if tempCo < -20:
      self.coworkers = -20
    elif tempCo > 20:
      self.coworkers = 20
    else:
      self.coworkers = tempCo

    # sets their number of family members
    tempFam = np.random.normal(2.5, .75)
    if tempFam < 1:
      self.family = 1
    else:
      self.family = round(tempFam)

    # sets their connection with their family
```

```
    self.famConn = np.random.normal(5, 1.3)

    # sets the number of rooms in their house
    self.rooms = self.family + round(np.random.normal(1.5, 1))

    # calculates their commute distance by city
    self.commute = np.random.normal(avgCommute, 0.2*avgCommute)

    # generates a random proportion for days in the week spent in hybrid and
       proportion of co-workers in the building
    self.p_w = np.random.randint(1, 5) / 5
    self.p_c = np.random.random()

  def info(self): #debugging function
    print("covid: " + str(self.covid))
    print("coworkers: " + str(self.coworkers))
    print("fam size: " + str(self.family))
    print("rooms: " + str(self.rooms))
    print("commute: " + str(self.commute))
    print("edu: " + str(self.edu))
    print("job dullness: " + str(self.job.dullness))
    if self.utilV:
      print("virtual utility: " + str(self.utilV))
      print("nv utility: " + str(self.utilNV))

  def utils(self):
    # calculates overcrowding
    homeRatio = self.family / self.rooms if self.rooms != 0 else 0
    if homeRatio < 0.75:
      famLoss = 0
    elif homeRatio >= 0.75:
      famLoss = np.reciprocal((1+100*np.exp(-2.5*(homeRatio - 0.75))))

    if self.covid == 10: #calculates utility based on covid concerns
      covidUtil = 9999999
    else:
      covidUtil = self.covid**2 / 3

    self.utilV = self.famConn - famLoss - self.coworkers + covidUtil
    self.utilNV = -self.utilV
    self.H = self.p_w * (self.famConn - famLoss - self.coworkers + covidUtil *
       self.p_c)



class Job:
  def __init__(self, edu):
```

```
    # predicts dullness based on education level of employee
    temp_dullness = np.random.normal(2*(edu-1), 1.5)
    if temp_dullness < 0:
      self.dullness = 0
    elif temp_dullness > 10:
      self.dullness = 10
    else:
      self.dullness = temp_dullness



joe = Employee(0)
joe.utils()
joe.info()

class Employer():
  def __init__(self, locale, job):
    self.w_NV = np.random.randint(1, 5)
    self.w_V = 5 - self.w_NV

    covid_cases = [365, 0, 54, 27847, 1059]
    self.S_I = covid_cases[locale] / 18782 * 100

    self.p_V = 0.002
    self.p_NV = 0.24
    self.p_H = (self.p_V * self.w_V + self.p_NV * self.w_NV) / 5
    self.ps = np.array([self.p_V, self.p_NV, self.p_H])

    self.Es_kL = self.ps * self.S_I

    self.D_U = 30 - 4 * job.dullness

    self.Es = self.D_U * np.array([1, 0, self.w_V / 5])

employer = Employer(0, joe.job)
employer.Es

arr_opts = np.zeros(3)

#Monte Carlo part for running all of this many times with lots of random generated
    employees and employers
for i in range(100000):
  employee = Employee(0)
  employee.utils()
  employer = Employer(0, employee.job)

  nash_eq = np.argmax(employer.Es)
```

```
  arr_opts[nash_eq] += 1

print(arr_opts)
```