Remote Work: *Fad or Future*

Executive Summary

As the world encounters highly disruptive events such as the emergence of unpredictable, infectious diseases, it becomes increasingly important for societies to adapt. In particular, the global economy has undergone a series of significant transformations as a result of the recent pandemic, one of which is a drastic increase in remote working. Although teleworking has proven to be an effective solution for health risks in many industries, it is far from universal. Thus, as society progresses and leaves COVID-19 in the past, the future of the workforce is uncertain. Will the current system of teleworking persist with the expectation of future crises, or will it fade along with the pandemic that fostered it? In this paper, our team aims to create a model that can anticipate the percentage of workers whose job is "remote-ready" in a given city from 2024 to 2027, as well as the likelihood of an employee choosing to work from home based on their willingness and ability.

In order to estimate the percentage of workers who are remote-ready in five given cities, historical data was gathered for the number of workers per industry in each city, as well as the estimated percentage of workers whose jobs could be done from home. Linear regression models for each industry in each city were constructed using historical trends and used to estimate the number of workers per industry in 2024 and 2027. Using these values, we calculated percentages corresponding to the weight of each industry in the overall workforce, allowing us to apply a weighted average model to find the total percentage of remote-ready jobs in all five cities for both years.

To construct a predictive model for the choices of people with the opportunity to work remotely, we first considered the elasticity of an employee's age, commute time, education, and whether the individual has children. Then using the collected data, we moved on to determining the elasticity of each category with respect to people's choice of working remotely. Additionally, accommodating the calculations, formulated equations, and data points, we developed a Java simulation that built simulations of 20 random individuals and then assessed the predicted probability of certain individuals—with defined characteristics—working remotely. After analyzing the data, we discovered that the 20 simulations produced a mean of $\mu = 26.816$ and a median of 18.545. The functions were found to have a positive skew, which means that the majority of the data is characterized to the left of the mean, but there are more extreme values to the right. However, because the variations between education levels are discrete step differences rather than continuous differences, this skew is acceptable. Finally, the simulation underlines and confirms the characteristics revealed in employees' preference for remote work.

Finally, we synthesized our models from parts one and two to create a model that estimates the final percentage of workers in a given city who will work remotely. In order to analyze the magnitude of impact on each city, we determined the percentage of individuals, with remote-ready jobs, that were permitted and willing to work remotely. Following these calculations, we arrived at the conclusion that Barry, Wales, is the city most affected by the transition to telework, while Liverpool, England, is the least affected. Seattle, Washington comes in second, Scranton, Pennsylvania comes in third, and at last, Ohama, Nebraska comes in fourth.

Contents

1 Part I: *Ready or Not*

1.1 Restatement of the Question

In Part I, we are tasked with creating a model that estimates the percentage of workers whose jobs are "remote-ready" (meaning they already are or can be working remotely) at a certain time in the following cities:

1. Seattle, Washington
2. Omaha, Nebraska
3. Scranton, Pennsylvania
4. Liverpool, England
5. Barry, Wales

1.2 Assumptions

1. *No major technological changes will occur over the next three years.* Given current rates of innovation, it is safe to assume that no large advancements in technology regarding remote work will transpire in the near future. Thus, the given percentage of jobs per occupational category that are remote-ready will remain constant throughout our model.

2. *There will be no significant changes in labor or industrial legislation, especially regarding the ability of workers to work from home.* Given the unpredictable nature of policy changes and their effects, we are unable to account for such factors in our model.

3. *The percentage of jobs per occupation that can be done at home will be roughly similar in the US and UK.* There are no outstanding discrepancies in industrial or technological capability between the two countries; hence, the given percentage of remote-ready jobs per occupation will be kept the same for both.

4. *Industries will retain similar properties in urban and rural areas.* Similar industries, as listed by the data provided, will likely maintain similar characteristics regardless of location.

1.3 Modeling

1.3.1 Identifying Factors

The main factors that we considered in our model were the number of people working in each industry, the total number of people in the workforce for a given city, and the percentage of jobs that can be done remotely in each industry.

The number of people working in a given industry in a particular city and the number of people in the overall workforce for the aforementioned city were used in tandem to derive a percentage that we referred to as the "composition distribution" for that industry. The composition distribution of different industries across the workforce population refers to the relative percentage of people in the given workforce of a city that works in a particular industry. This would serve as a weight in measuring how much a particular industry affects the overall diversity of job types.

The percentage of jobs that can be done remotely in each industry was listed in the provided data sheet [1]. This parameter serves as an identification of how many of the jobs in each of the industry categories can be performed remotely with the current level of automation and technological advancement.

1.3.2 Setting Up Data

Given that our model needed to produce a percentage, we decided to design it to contain functions that all work with percentages. In the remote work data provided [1], we categorized each occupation into the types of industries provided in the city employment data. Therefore, each "industry" contains a subset of included occupations that are considered as a whole and not distinguished within the model. The estimated percentage of jobs that could be done remotely were averaged into such subsets of industries. For example, education, training, and library; healthcare practitioners and technical; and healthcare support were condensed into a value that pertained to education and health services.

To achieve our model, we created linear regressions of each of the ten given industries (consisting of subsets of similar occupations that fall within the industry, as mentioned previously) to project growth in the near future. This would later be applied to each of the five given cities, each composed of these industries.

The percentage of jobs that can be done remotely in each industry was then multiplied by the composition distribution to attain the percentage of people in the given industry that will be able to work at home, weighted with the industry's effect on the workforce. This value was calculated for each industry and summed together to achieve our "Percent Remote" function ($P_R(t_s)$; [See 1.3.3 and 1.3.4]).

1.3.3 Regressions

In order to calculate our final percentage of workers whose jobs are remote-ready, we decided to create regressions using the remote work data provided [1] in order to predict how many workers each job category will have in the years 2024 and 2027. For the cities in the U.S., we designated the x values to be the number of years after 2000 (i.e. 2000 was the x-value 0 and 2005 was the x-value 5) and for the cities in the U.K., we designated the x values to be the number of years after 2005. This change is due to a slight discrepancy in the data sets for each country; the data from the US starts in the year 2000 and the data for the UK starts in the year 2005. As previously mentioned, the output of the regression function is the number of workers within a certain job category.

x (years after 2000)	y (number of workers in Mining, logging, construction in Seattle, Washington)
0	101,700
5	104,700
10	83,600
15	107,100
19	127,600
20	129,900
21	109,600

Table 1: Dataset used to create regression; number of workers in "mining, logging, construction" industrial category in Seattle Washington

Additionally, while deciding the type of regression to use (linear, quadratic, exponential, or others), we prioritized the activity of the function between the years 2024 - 2027, ignoring unreasonable changes that may arise several decades or centuries after the designated time period.

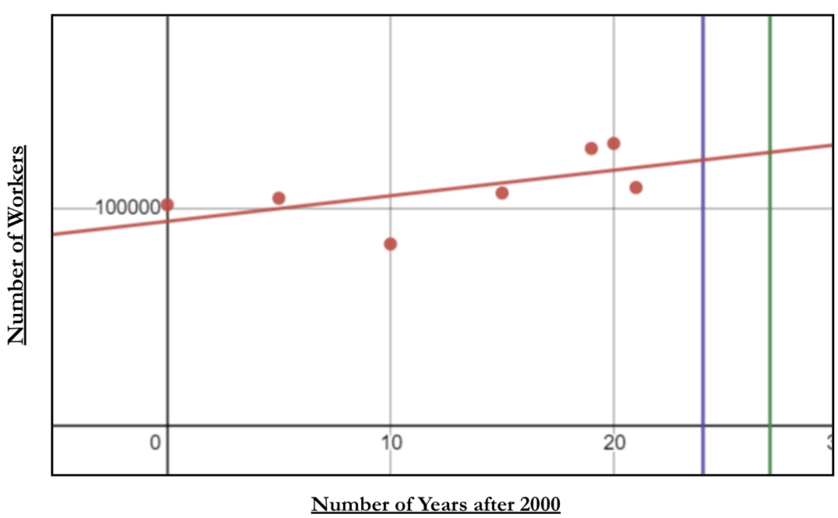


Figure 1: Linear regression made from the dataset in Table 1;
the purple line represents the year 2024 and the green line represents the year 2027

After creating regressions for each job category and city, and predicting the number of workers in each category in the years 2024 and 2027, we calculated how many workers each job category had in the form of percentages for each city and each year. This was achieved by dividing the number of workers in one category; predicted using the previous regressions, by the total number of workers; found by calculating the sum of every industry size for the appropriate time period. Overall, this provided us with the compositional data necessary to apply our model.

Our regression data can be found here: Team #15400 - M3 Challenge Regressions

1.3.4 The Model

We observed that the amount of remote-ready jobs were dependent on the makeup of industries in the workforce. By creating regressions for each industry in each city and factoring that into our model, we can more accurately calculate the percentages of "remote-ready" jobs. The model we developed covers the number of people in the industry compared to the workforce in each city($w(t_s)$), with t_s representing the time in years after the starting year [See 1.3.3]), as well as the estimated percentage of jobs that could be done remotely I_i. We categorized these occupations into ten industry categories. Thus, the model is shown below:

$$P_R(t_s) = \sum_{i=1}^{i=10} (I_i \cdot w(t_s))$$

I_i **value**	**Category Described**	**Percentages Remote**
I_1	Mining, Logging, and Construction	15.75%
I_2	Manufacturing	1.00%
I_3	Trade, Transportation, and Utilities	3.00%
I_4	Information	77.00%
I_5	Finance	58.00%
I_6	Professional and Business Services	52.67%
I_7	Education and Health Services	35.00%
I_8	Leisure and Hospitality	34.00%
I_9	Other Services	18.50%
I_{10}	Government	97.00%

Table 2: Description of I_i values

To find the percentage of people in each industry compared to the entire workforce of industries, we created and applied the function below to our final model:

$$w(t_s) = \frac{Number\ of\ people\ in\ industry}{Number\ of\ people\ in\ workforce}$$

Both “Number of people in the industry” and “Number of people in workforce” were constructed using the regressions developed. The “Number of people in the industry” was represented as the regression for that industry for either 2024 or 2027, and the “Number of people in workforce” was represented as the sum of all the industry predictions for each given city and date. The $w(t_s)$ function thus models the proportion of all workers that work in a certain industry, which can then be utilized in the complete model.

1.4 Results

The regressions produced from the provided historical data were used to calculate the percentage of the total workforce that each industry made up in 2024 and 2027. Using this compositional data, we calculated the weighted average of the percentage of “remote-ready” jobs in each industry. This process was repeated for each of the five given cities, yielding the results detailed in the table below.

	Percentage of jobs in workforce that are “remote-ready” in **2024**	Percentage of jobs in workforce that are “remote-ready” in **2027**
Seattle, WA	39%	38%
Omaha, NE	39%	39%
Scranton, PA	33%	32%
Liverpool, England	25%	25%
Barry, Wales	41%	38%

Table 3: Results of weighted average function.

Our results seem to be reasonable when compared to reputable estimates regarding the percentage of jobs that can be done entirely at home. For example, a study by Dingle and Neiman of UChicago in 2020 found that 37% of jobs across the United States can be performed entirely at home; roughly equivalent to our model’s average estimate of “remote-ready” jobs in the United States over the next three years [5].

1.5 Analysis of Strengths & Weaknesses

Our weighted average model accurately ensures that the impact of each industry on the total workforce is properly accounted for. For example, growth in the size of an industry relative to the general workforce will cause its weight to increase, painting a more precise picture of the amount of “remote-ready” jobs in the city.

Furthermore, our use of separate linear regressions for each industry in the datasheet improves the accuracy of our compositional predictions by accounting for a wider range of potential changes. Within each industry, we sought the most accurate representation of our datasets by choosing regressions with higher coefficients of determination (R^2), or lines of best fit. The repeated use of this simple concept allows us to maintain precision without an overly complex model.

Our model has several flaws that can be further improved upon. First of all, because different datasets are not uniformly designed, we occasionally had to merge similar industries by averaging their estimated percent of "remote-ready" workers. This could have led to slight discrepancies in our data. Second of all, our model's accuracy decreases after approximately a decade of prediction, as our linear regressions are selected to be reasonable predictions for the next three years in particular.

2 Part II: *Remote Control*

2.1 Restatement of the Question

In Part II, we are tasked with creating a model that can predict whether an individual worker with a remote-ready job will be allowed and willing to work from home.

2.2 Assumptions

1. *If an employee works from home, he will be treated as an individual functioning on a full-time remote schedule.* Given the inaccuracy of determining hybrid workers' schedules, it's more efficient and reasonable to assume that all teleworking individuals are on a fully remote work schedule.

2. *Employees in the United States and the United Kingdom will make similar enough choices to be insignificant in the model.* Given the rough cultural similarities between the two countries, it would be reasonable to assume that the decisions people make in each region will be similar.

3. *Employers will continue to allow remote work if it has been previously beneficial to the company.* Due to the variety of unpredictable factors surrounding a company's decision to continue remote work policies, we are unable to account for such changes in our model. Specifically, although factors such as office rent prices and worker productivity can potentially affect a company's attitude toward remote work, it is extremely difficult to gather and incorporate such data into our model without information regarding the internal architecture of companies.

4. *In the given cities, the number of employees with a commute time of over three hours is zero.* It is unlikely that people will choose to commute three hours to work. Any outliers may skew the data and the number will be insignificant in this model. Thus, they will be neglected.

2.3 Modeling

2.3.1 Identifying Factors

The factors we implemented into this simulation consider employee age, commute time, whether or not they have children to care for, and education level. Each factor contributes its own probability to the final probability, as each will be presumed to be a consideration for any employee considering working from home. The trend of employee age indicates that generally, older employees prefer to use remote work in comparison to their younger counterparts, most likely due to physical limitations in tandem with higher positions in their occupations. Next, the trend of employee commute time to work displays that longer commute times incentives employees to sway towards remote learning more. For the effect of having children to care for, having children notably increased the probability of employees working from home. Finally, the education level of the employee played the biggest effect on probability, with higher education producing higher probabilities for going remote. Table 2 below shows the probabilities for each parameter in their given ranges:

Parameter	**Ranges** (probabilities refer to likelihood of working remote based on the corresponding single parameter)
Age	16-24 → Probability = 0.12 25-54 → Probability = 0.29 55-62 → Probability = 0.25
Commute Time	0 → Probability = 1.0 1-15 → Probability = 0.56 16-60 → Probability = 0.63 61-120 → Probability = 0.81 121-180 → Probability = 0.84
Children Care	No Children → Probability = 0.23 Children → Probability = 0.26
Education Level	Less than high school diploma → Probability = 0.03 High school → Probability = 0.09 Some college → Probability = 0.17 Bachelor's degree → Probability = 0.41 Post-graduate degree → Probability = 0.54

Table 4: Probability for each range of each parameter

2.3.2 Setting Up the Data

In order to calculate the sensitivities of each of our factors as they pertain to the overall model, we utilized the data provided [1] of the percentages of people ages 16 to 62 (the average age of retirement) who work remotely and the percentages of people who work remotely based on their level of education. We did the same based on whether the employee has children or not [7], and their commute time on a scale from zero to three hours [6]. These values were then plotted to find the slopes, which would be adjusted to attain our sensitivity parameters. The graphs of each factors compared to the data we found are depicted below:

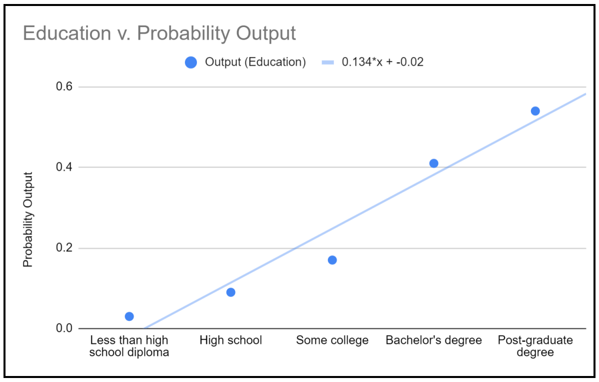


Figure 2.1: An employee's level of education vs. the probability of them working remotely

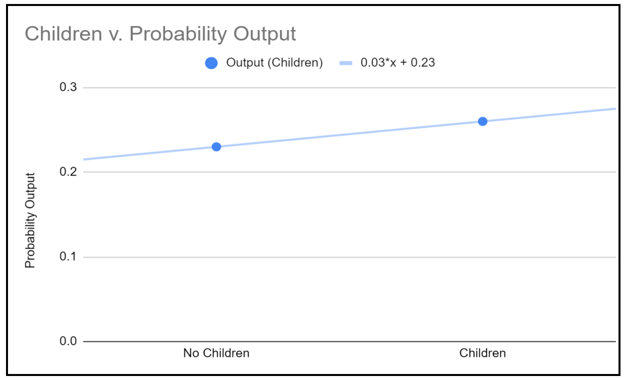


Figure 2.2: The probability of an employee working remotely vs. whether they have children or not

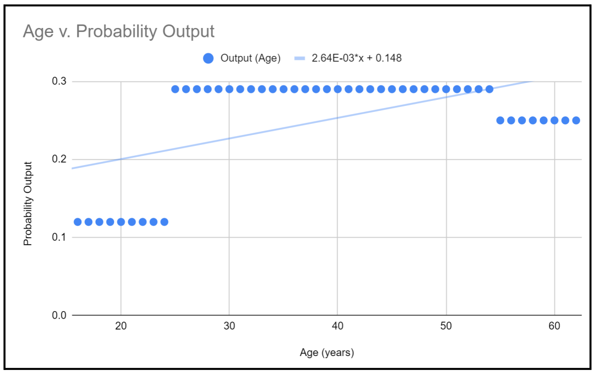


Figure 2.3: The age of an employee vs. the probability of the employee working remotely

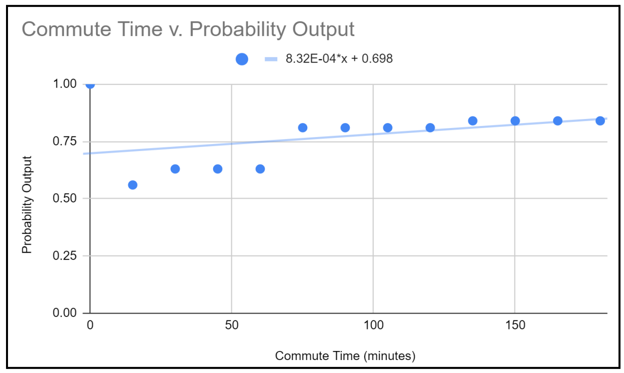


Figure 2.4: The commute time of an employee vs. the probability of them working remotely

In order to create a value greater than or equal to one to use as coefficients, we took the slopes of each linear graph and divided them by the category that yielded the smallest slope value (commute). This resulted in the final sensitivities that would be used in the model simulation to determine whether an employee will choose to work remotely or not, and the higher the sensitivity, the more weight each factor holds. The sensitivities of each factor are shown in the table below:

Category	**Slopes Adjusted (Sensitivities)**
Commute	1.00
Age	3.35
Children	38.07
Education	170.05

Table 5: Final sensitivities determined by the slopes of the graphs pertaining to each category (See Figures 2)

2.3.3 The Model

With the sensitivity models, we wrote a Java program that incorporates the "sensitivity" model that was developed (See 6.2). The Java program contains two constructors for possible calls, one "no-args" constructor and one that accepts the previously mentioned four categories (age, commute time, child care, and education level), and sets the four private field values initialized to those parameters. In the "getPercentRemote" method, the four fields are inspected for their range and matched to their corresponding probability values (as previously mentioned in Table 3).

Subsequently, the determined four probabilities were adjusted with coefficients (using the sensitivities in "Slopes Adjusted") to take a weighted average of the effect each category (also listed in Table 4) had. This finally returned a final probability of the person with the given parameters to decide to switch to remote work.

2.4 Results

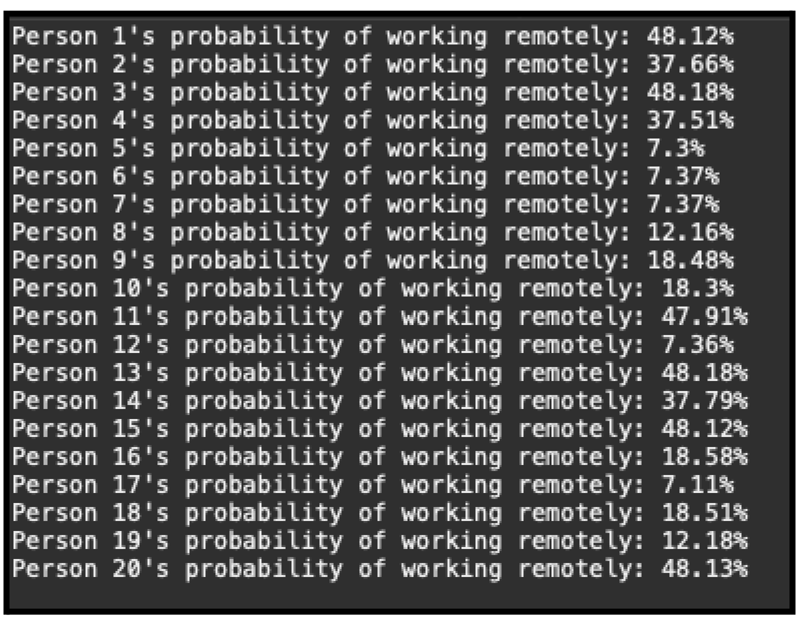
Using the Java program described in 2.3.3, 20 simulations were run using the "sensitivity" function developed. These produced the final percentages as listed below, as well as seen in Figure 3:

Person:	1	2	3	4	5	6	7	8	9	10
Probability	48.12%	37.66%	48.18%	37.51%	7.30%	7.37%	7.37%	12.16%	18.48%	18.30%

Table 6.1: 1st part of simulated values

Person:	11	12	13	14	15	16	17	18	19	20
Probability	47.91%	7.36%	48.18%	37.79%	48.12%	18.58%	7.11%	18.51%	12.18%	48.13%

Table 6.2: 2nd part of simulated values



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Person 1's probability of working remotely: 48.12%
Person 2's probability of working remotely: 37.66%
Person 3's probability of working remotely: 48.18%
Person 4's probability of working remotely: 37.51%
Person 5's probability of working remotely: 7.3%
Person 6's probability of working remotely: 7.37%
Person 7's probability of working remotely: 7.37%
Person 8's probability of working remotely: 12.16%
Person 9's probability of working remotely: 18.48%
Person 10's probability of working remotely: 18.3%
Person 11's probability of working remotely: 47.91%
Person 12's probability of working remotely: 7.36%
Person 13's probability of working remotely: 48.18%
Person 14's probability of working remotely: 37.79%
Person 15's probability of working remotely: 48.12%
Person 16's probability of working remotely: 18.58%
Person 17's probability of working remotely: 7.11%
Person 18's probability of working remotely: 18.51%
Person 19's probability of working remotely: 12.18%
Person 20's probability of working remotely: 48.13%
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Figure 3: Screenshot of the 20 simulations modeled using the "sensitivity" function

The results show a mean of $\mu = 26.816$ and a median of 18.545. This shows that the function's simulation shows a positive skew, meaning that the majority of the data shows in to the left of the mean, but there are more extreme values to the right. Additionally, the found standard deviation of 17.296275, a relatively large standard deviation for the range of 41.07, indicates that the derived data takes on a very spread out form, rather than being centralized to a few values. These values overall adequately reflect the distribution of the parameters used to model the function, and by extension the applicability to real-world probabilities of decisions to work remotely. The skew and large standard deviation match, as the differences between education levels (the most influential parameter by far, as reflected by the data) are discrete step differences rather than more continuous differences (as with age or commute time). Overall, the simulation highlights and supports the properties observed in the preferences of employees to choose remote working.

2.5 Analysis of Strengths & Weaknesses

Our model's most significant feature is that it is tested on a simulated person created with the help of our unique code. With this additional step, we were able to test our constructed model and conclude whether it produces accurate and desirable results. Another advantage of our approach is that rather than focusing on a single category, it takes into account all of the given variables as a whole and measures their elasticity, and considers the likelihood of people working remotely. As a result, the possibilities of overestimating or underestimating are reduced.

One of the limitations of our model is that it is composed of limited categorical information therefore, it won't provide efficient results for unaccounted components like the employer's decision. Even with excessive research, we were not able to find reliable data for employers' preferences, income, and geography in respect to workers who were allowed to and were willing to work remotely. Additionally, another weakness of our model is that it fails to incorporate time into the defined calculations. Moreover, the algebraic equations we employed for our calculations were based on best-fit lines, which meant that certain data points were overlooked.

3 Part III: *Just a Little Home-work*

3.1 Restatement of the Question

In Part III, we are tasked with synthesizing the models we created from Part I and Part II and applying them to a given city to estimate the percentage of workers who will work remotely. We then rank the cities provided in Part I (Seattle, Washington; Omaha, Nebraska; and Scranton, Pennsylvania in the United States, as well as Liverpool, England, and Barry, Wales in the United Kingdom) in terms of the magnitude of the impact that remote work has on each city.

3.2 Assumptions

1. *All previously made assumptions regarding Part I and Part II will apply to Part III.* As our model in Part III will be synthesized from the models we created in Part I and Part II, all assumptions made in Part I and Part II must apply to Part III.

2. *The distribution of ages for the population of a given city roughly reflects the same distribution of ages in the workforce.* Both younger children and retired members of a town will serve to balance out

both extremes of population distribution, so as long as the median age for a given city is within the working range of years, it can be assumed that the median age of the workforce is similar.

3. *The "magnitude of impact" that remote work will have on the city will be directly proportional to the change in the percentage of workers who will work remotely.* Due to the number of unpredictable factors, such as societal opinion regarding remote work, we will not be able to account for other factors and will mainly have to focus on the change in the percentage of workers who will work remotely.

3.3 Modeling

3.3.1 Identifying Factors

Our relevant factors will be carried on from Part I and Part II, as our model is synthesized from these earlier parts. Factors from Part I include the number of people working in each industry, the size of the workforce for a given city, and the percentage of remote-ready jobs in each industry. Factors from Part II include the age of an employee, the commute time for an employee, whether or not an employee has children, and their education level.

3.3.2 The Model

We concluded that the models from Part I and Part II could be synthesized into Part III by integrating the two models. This factors in the effects of both Part I and II: Part I calculates the percentage of the total workforce whose jobs are remote-ready while Part II calculates the percentage of the remote-ready workforce who actually work remotely. These two percentages can be integrated together into one overall percentage that calculates the percentage of workers who will work remotely. In doing so, we incorporate the two models into an ultimate, singular model.

3.3.3 Applying The Model

In order to determine the impact of remote learning on a given city, we must first use our model from Part II and determine the percentage of individual employees who work remote-ready jobs, and will choose to do remote work if allowed to do so by their employers. To calculate these percentages, we must first determine the parameters to be used for the model from Part II.

	Seattle, Washington	Omaha, Nebraska	Scranton, Pennsylvania	Liverpool, England	Barry, Wales
Age in years	37	36	42	38	38
Commute in minutes	32	21	24	29	25
Children	Yes	Yes	Yes	Yes	Yes
Average	3	3	3	3	2

Education Level					

Table 7: Table of parameters to be input into the model (code) from Part II, most of the data was obtained from the provided data sheet [1]

Initial probability of working remote for each city, derived from the model of Part II:
Seattle, Washington: 19.05%
Omaha, Nebraska: 19.02%
Scranton, Pennsylvania: 19.02%
Liverpool, England: 19.02%
Barry, Wales: 12.62%

3.4 Results

With the models produced from Part I (Table 3) and Part II (Table 5), we can now see each city's percentage of workers who worked remotely.

	2024	2027	Magnitude of Change in Percent of Remote Workers from 2024 to 2027
Seattle, Washington	7.43%	7.24%	0.19%
Omaha, Nebraska	7.42%	7.42%	0%
Scranton, Pennsylvania	6.28%	6.09%	0.19%
Liverpool, England	4.78%	4.78%	0
Barry, Wales	5.17%	4.8%	0.37%

Table 8: Magnitudes of impact of given cities

With such information, we can now rank them in accordance to the impact that remote working will have on each city, from most impacted to least impacted.

1. Barry, Wales
2. Seattle, Washington
3. Scranton, Pennsylvania
4. Omaha, Nebraska
5. Liverpool, England

Overall, the data seems to indicate that smaller cities seem to be more impacted by a shift to remote workers, which matches with the real work observation of smaller cities being impacted by a stronger shift in lifestyle due to occupation changes than a large city would, relatively.

3.5 Analysis of Strengths & Weaknesses

Our model for Part III benefits from the simplicity of the models we used in Part I and Part II. This allows our model for Part III to also be very simple and easy to understand, despite the large amount of information that went into our models. Other strengths from previous parts also apply to Part III, such as the usage of weighted averages and multiple linear regressions in Part I which helped increase accuracy - they also lead to increased accuracy in Part III.

However, this also means that any weaknesses from Part I and Part II carry over to our model for Part III. One such flaw would be that our model for Part II is strictly dependent on the data the model is sourced from. This limits the regions that our model would be applicable to and also does not take into account other potential effects on the impact of remote work - such as societal opinion regarding remote work. Another flaw is that our model for Part III only applies to the near future, since this factor was left out from Part II. A final flaw would be the model only accepting the parameters as integers, which forces the parameters to be rounded to the nearest integer. For education level, which has a significant effect on the probability outputted by the model in Part II, this rounding to the nearest integer.

4 Conclusion

4.1 Reflection

Our outlined model is, for the most part, based on prior trends in people's decisions to work remotely instead of in person; it focuses on the consequences of people working remotely in five cities in the United States and the United Kingdom. This, however, is dependent on the premise that an employer's decision to offer telework remains consistent over time, and that they will offer remote work for enough job openings. When seen in a societal context, this seems implausible. As a result, it would be reasonable to consider employer preferences in future studies, although this would necessitate a separate survey due to the absence of such content on the internet. Furthermore, all of our statistical data includes the effects of COVID-19; however, because this is a rare occurrence, if a similar study is conducted in the future and such circumstances are not anticipated, it should be a critical component to examine the opinions of employers and employees on teleworking while ignoring the effects of such circumstances.

5 References

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[7]. Matthew Dey, Harley Frazis, Mark A. Loewenstein, and Hugette Sun, "Ability to work from home: evidence from two surveys and implications for the labor market in the COVID-19 pandemic," Monthly Labor Review, U.S. Bureau of Labor Statistics, June 2020, https://doi.org/10.21916/mlr.2020.14.

6 Appendix

6.1 Part I: *Ready or Not*

<No Code Used>

6.2 Part II: *Remote Control*

Person.java (IMG 1)

```java
package main;

/*
 * Team #15400
 * 2022 M3 Challenge
 * Question 2 Code
 */

import java.text.DecimalFormat;

public class Person {
    private int age; //age between 16 to 62, with 62 representing the average age of retirement age in the US
    private int commuteTime; //average time to get to work, in increments of 15 minutes
    private boolean children; //true represents having children, false represents not having children
    private int education; //Ranges from 1-5, representing the 5 established levels of education defined, with 1 being the lowest and 5 being the highest
    private double probabilityRemote; //final probability of working remote

    public Person() {
        /* Sets each private field to a random variable within each range
         *
         */
        int randomVar1 = (int)(Math.random() * 47 + 16);
        age = randomVar1;

        int randomVar2 = 15 * (int)(Math.random() * 13);
        commuteTime = randomVar2;

        int randomVar3 = (int)(Math.random() + 1);
        if (randomVar3 == 0) {
            children = true;
        }
        else {
            children = false;
        }

        int randomVar4 = (int)(Math.random() * 5 + 1);
        education = randomVar4;
    }

    public Person(int a, int c, boolean ch, int e) {
        age = a;
        commuteTime = c;
        children = ch;
        education = e;
    }

    public String getPercentageRemote() {
        //initiate the output probabilities for each individual factor
        double outputAge, outputCommuteTime, outputChildren, outputEducation = 0;

        //assign probabilities to age
        if (isBetween(age, 16, 24)) {
              outputAge = 0.12;
        }
        else if (isBetween(age, 25, 54)) {
            outputAge = 0.29;
        }
        else {
            outputAge = 0.25;
        }

        //assign probabilities to commuteTime
        if (commuteTime == 0) {
            outputCommuteTime = 1; //Assuming commute time = 0 represents an individual already working from home
        }
        else if (isBetween(commuteTime, 0, 15)) {
            outputCommuteTime = 0.56;
        }
        else if (isBetween(commuteTime, 16, 30)) {
            outputCommuteTime = 0.63;
        }
        else if (isBetween(commuteTime, 31, 60)) {
            outputCommuteTime = 0.69;
        }
        else if (isBetween(commuteTime, 61, 120)) {
            outputCommuteTime = 0.81;
        }
        else {
            outputCommuteTime = 0.84;
        }

        //assign probabilities to children
        if (children == true) {
            outputChildren = 0.26;
        }
        else {
            outputChildren = 0.23;
        }

        //assign probabilities to education
        if (education == 1) {
            outputEducation = 0.03;
        }
```

Person.java (IMG 2)

```java
        else if (education == 2) {
            outputEducation = 0.09;
        }
        else if (education == 3) {
            outputEducation = 0.17;
        }
        else if (education == 4) {
            outputEducation = 0.41;
        }
        else {
            outputEducation = 0.54;
        }

        probabilityRemote = applySensitivity(outputAge, outputCommuteTime, outputChildren, outputEducation);

        DecimalFormat f = new DecimalFormat("##.##");

        return f.format(probabilityRemote * 100.0) + "%"; //return as percentage rounded to 2 decimal places (String)
    }

    /*
     * Private method that takes in four outputs (Age, Commute Time, Children, and Education, respectively in that order)
     */
    private static double applySensitivity(double op1, double op2, double op3, double op4) {
        double sensitivtyAdjustedProbability = 0;

        /*
         * sensitivity is calculated using the slopes of each parameter as a measure of each's "elasticity" with change in magnitude,
         * with each coefficient representing the "weight" of each parameter; the divisor is the total weight, which divided to achieve
         * a weighted average
         */
        sensitivtyAdjustedProbability = (3.35 * op1 + op2 + 38.07 * op3 + 170.05 * op4) / 212.47;
        return sensitivtyAdjustedProbability;
    }

    /*
     * Boolean method to determine if target is between a range of values, used in getPercentageRemote methods
     */
    public static boolean isBetween(int n, int lower, int upper) {
          return lower <= n && n <= upper;
    }
}
```

6.3 Part III: *Just a Little Home-work*

Main.java

```java
package main;

public class Main {
    public static void main(String[] args) {
        Person residentSeattle = new Person(37, 32, true, 3);
        System.out.print("Seattle's Resident probability of working remotely: ");
        System.out.println(residentSeattle.getPercentageRemote());

        Person residentOmaha = new Person(36, 21, true, 3);
        System.out.print("Omaha's Resident probability of working remotely: ");
        System.out.println(residentOmaha.getPercentageRemote());

        Person residentSranton = new Person(42, 24, true, 3);
        System.out.println("Scranton's Resident probability of working remotely: ");
        System.out.println(residentSranton.getPercentageRemote());

        Person residentLiverpool = new Person(38, 29, true, 3);
        System.out.print("Liverpool's Resident probability of working remotely: ");
        System.out.println(residentLiverpool.getPercentageRemote());

        Person residentBarry = new Person(38, 25, true, 2);
        System.out.print("Barry's Resident probability of working remotely: ");
        System.out.println(residentBarry.getPercentageRemote());
    }
}
```