PREVIEW PAPER: AVERAGE

The team provided a response to all three questions, but their approach to the first two questions were more complete. They explicitly state their models, but it is not clear how some of their calculations were completed.

The team's summary does not include a good overall summary of their results. Within the narrative, the models were explicitly stated which was good. They note the general trend of the data which hints at their choices for their models, but it is not clear why their models are appropriate for the phenomena examined. For example, the team used quadratics in their responses to the second and third questions. The results provide a reasonable fit to the data, but they did not explain how these functions address the general trends discussed.

With respect to their final results, the team's predictions for some locations were odd. For example, Barry was predicted to see a sharp decline in remote workers, and the growth in remote workers in some sectors was unexpectedly large. There was little discussion of these results and insights were provided into the results. On the plus side, the team did note that the pandemic resulted in a sharp change in the data, and they incorporated a limit on their results resulting in a nice link between questions one and two. Also, their assumptions were clearly stated.

**from among the screened sample of papers examined during pre-triage work.*

Suits to Pajamas: The Evolution of the Workplace

Executive Summary:

As the world continues to overcome the socioeconomic setbacks of the pandemic, there have been significant, new trends in employment and working circumstances. The necessity of remote work has evolved into a relevant alternative to the traditional office life. However, there continues to be immense strife regarding the necessity of maintaining an online workplace as companies worry over the lack of face-to-face interaction. Our team aims to discover past and present trends regarding remote-work employment in the United States and United Kingdom to interpret the long-term economic impact on several cities.

We first utilized several data sets to best estimate the percentage of workers whose jobs are currently remote-ready, applying our results to several major United States and United Kingdom cities to determine a relevant trend in the rate of change of said remote-ready jobs.

From there, we used the Vernier Graphical Analysis application to model several linear regression graphs regarding both long and short-term remote-work employment rates to better determine the percentage of workers with both the ability and company permission to assume a remote-work position.

Finally, we synthesized our models from the previous parts to best determine the percentage of workers who will go online in a given city, using the same United States and United Kingdom models as relevant examples.

Table of Contents

2 Part 1: Are They Ready?!

2.1 Restatement of the Problem

In this problem, we are tasked with developing a model to determine across several different cities within the U.S. and U.K. the percentage of workers whose jobs are currently remote-ready. With this model, we are also tasked with predicting the number of remote-ready jobs in 2024 and 2027.

2.2 Assumptions

1. The number of people that can work remotely in each occupational category is rounded to the nearest whole number.
2. All data (for example: 100% of the Computer and mathematical category can be done at home) is considered accurate.
3. Computers and mathematics fall under the occupational category of Information.
4. Education, training and library, Life, physical and social science, Healthcare practitioners and technical, and Healthcare support all fall under the category of Education and health services.
5. Legal falls under the category of Government.
6. Business and financial operations, Management, Office and administrative, and Architecture and engineering all fall under the category of Professional and business services.
7. Arts, design, entertainment, sports and media, Community and social service, Protective service, and Building and grounds cleaning and maintenance all fall under the category of Other services.
8. Sales and related all fall under the category of Financial activities.

9. Personal care and service and Food preparation and service-related all fall under the category of Leisure and hospitality.
10. Transportation and material moving falls under the category of Trade, transportation, and utilities.
11. Production falls under the category of Manufacturing.

2.3 Data

To analyze the behavior of the number of available remote-ready jobs,we used a linear regression model to find the predicted total number of jobs in 2024 and 2027 and multiplied them by the percentages found in “” based on the occupation category. The below table, sorted by occupational category, is data on the number of remote-ready jobs in Seattle, WA and serves as an example for the data calculations we conducted on each city. To get the 2024 and 2027 predicted total, we added each value in the respective columns. Once we created a linear regression model, we then used it to predict the number of remote-ready jobs in 2024 and 2027.

Seattle	**2024**	**2027**
Mining, logging, construction	819	8388
Manufacturing	1576	1526
Trade, transportation, and utilities	11,362	11,634
Information	140,108	149,234
Financial activities	26,233	25,911
Professional and business services	228,507	237,957
Education and health services	109,683	114,087
Leisure and hospitality	695	22,464
Other services	33,592	35,872
Government	247,692	248,317

The below table shows the total number of predicted remote-ready jobs in each city in 2024 and 2027.

City	2024 Predicted	2027 Predicted	2024 Remote-Ready	2027 Remote-Ready
Seattle, WA	1,900,699	2,060,554	800,267	855,390
Omaha, NE	831,185	915,716	551,627	554,492
Scranton, PA	205,052	198,001	84,368	84,230
Barry, Whales	59,842	60,258	75,072	28,355
Liverpool, England	749,881	770,628	193,178	195,783

2.4 Development and Application of the Model

Our data primarily consisted of the table of “Average monthly number of employees by industry for the entire metro area” and the table of “percent of work that can be done at home per occupation category” provided by the given spreadsheet. We used the two tables to calculate the number of remote-ready jobs in each occupation category with the following equation:

$$\frac{(x^*y)}{100},$$ where…

x = average monthly number of employees by industry for the entire metro area of particular city

y = percent of work that can be done at home per occupation category

We used the data we extracted from the year 2021 to calculate the percentage of workers who are remote ready in the current year. Then, we used the data from the years 2000-2021 to create a linear regression to predict the percentage of workers who will be remote ready in the years 2024 and 2027.

2.5 Limitations of the Model

The model poses limitations when it comes to drastic economic changes. Since the model predicts general trends, it will not be able to accurately account for significant recessions due to the pandemic. Our team also did not take certain demographic statistics into account. This includes age, education level, as well as personal and familial situations. Additionally, we did not effectively incorporate the percentage of work that can be completed at home per occupational category.

3 Part II: It's Up to Them Now

3.1 Restatement of the problem

This problem tasks us with creating a model estimating the proportion of workers who are both readily willing and permitted by their employer to work from home.

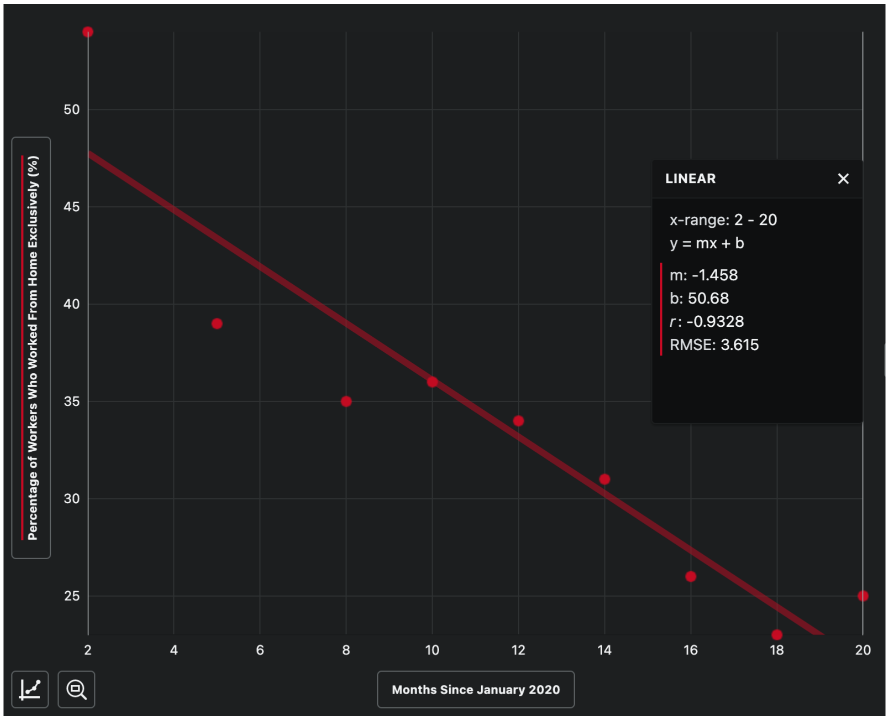
3.2 Assumptions

Given that the US and the UK both are well-developed countries, as well as having similar major industries and workers' conditions, we assume the rate of change of remote work from home would apply similarly to both countries.

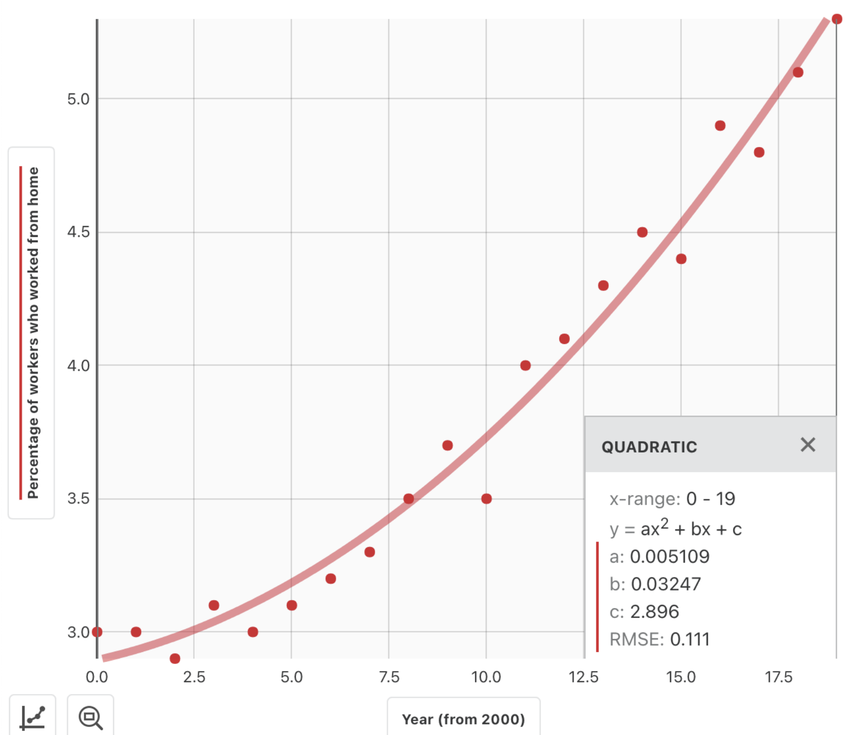
3.3 Model Development

In order to solve this problem, we produced two separate functions that contribute to the same model: a long-term and short-term function. The short-term function resides within the long-term function, but the data within the short-term function are outliers in the long term. The unexpected increase of at-home work due to the covid-19 pandemic doesn't allow a combined function to accurately represent the trend. When making predictions, we model based on the long-term regression function due to the short-term one trending downward representing the fact that it will reconvene with the trend of the historic data.

Short Term Linear Regression

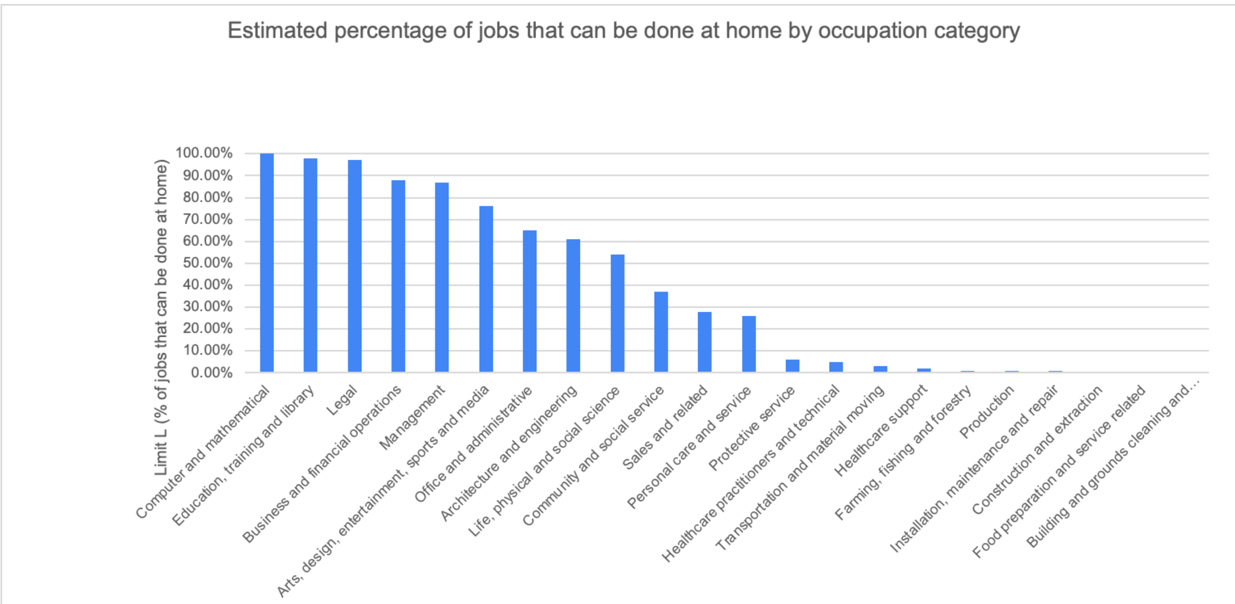


Long Term Quadratic Regression



Applying Limits to the Graph

The graph above applies to the workforce's estimated percentage of people who can work at home but fails to factor in specific jobs' capacities to allow employees to work at home. Since no limit is set for the graphs the transition from in the office to working at home jobs would continue to increase past the job's capacity to have workers in the home. To determine a specific job's limit keeping their workers at home, the following modification to the graph is provided.



This graph will apply until the function reaches the limit L for each job. The limit L represents the maximum estimated percentage of workers that can do work at home per occupation. For each particular job, a unique limit L is set. When assessing a jobs percentage of workers that work from home the function will approach the limit L and will plateau. The function's limit cannot be surpassed due to restraints in the job's respective workplaces. Factors such as the human-on-human interactions (medical), the geographical requirements (construction, grounds cleaning, etc) or technological requirements (factory jobs) individuals are restrained by their abilities to work from home.

3.4 Results

These regressions provide us with two equations, but the primary function in terms of modeling the future is the long-term regression with the equation.

Long Term:

$$P = 0.005109y^2 + 0.03247y + 2.896$$

Where *P* represents the percentage of eligible workers and *y* represents the year from 2000. An RMSE of 0.111 means that our quadratic model is a good predictor of the future long-term remote-work employment percentage for the coming years.

With our limit L modification to the graph, we will be able to analyze how a specific job's *P* will plateau once its percentage of workers at home reaches its maximum capacity.

3.5 Strengths and Weaknesses

The primary shortcoming of this data is that it doesn’t fully contextualize the demographics we are modeling. Although the populations are very similar, this overgeneralization doesn’t fully represent the subtle differences in the growth of at-home work. In addition, this function doesn’t accommodate part-time at-home workers, only those who work full time. The strengths of this function are the fact that the constraints are fairly simple and produce very concise predictions off of the model.

4 Part III: Will It Happen?

4.1 Restatement of Problem

This part tasks us with synthesizing the models from both Part I and II in order to most effectively predict the proportion of people who will opt for remote work in 2024 and 2027.

4.2 Modeling the Data

To combine the models in order to produce a number to predict how many people in a given city are working remotely from home, we must modify the previous models. The given equation will produce a value W_R that will be equal to the number of people in a given city working from home.

$$W_R = N_w(0.005109y^2 + 0.03247y + 2.896)/100$$

N_w represents the number of workers eligible for remote work, and y represents the year after 2000. The given quadratic equation produces a predicted percentage of workers who fill up the available remote-work positions within a specific city, combing both the predicted values of available remote-work positions in Part I and the decimal form of the Part II model used to predict workers eligible for remote-work status. Doing so produces a value equivalent to that of the number of online spots filled by the percentage of workers able to work remotely.

4.3 Results

From the model above, we are able to predict the number of available remote-work positions acquired by the percentage of people eligible for remote-work conditions.

City	Predicted Number of Remote Workers in 2024	Predicted Number of Remote Workers in 2027
Seattle, WA	52,962	64,129
Omaha, NE	36,507	41,571
Scranton, PA	5,583	6,314
Barry, Whales	4,968	2,125
Liverpool, England	12,784	14,678

4.4 Limitations

Although our mathematical model produces an estimate of the amount of workers that could work remotely in a specific city, it fails to address the potential impact of the pandemic or account for major, unpredictable economic events that may occur in the future. Also, similar to the linear regression model for Section 2.3, our team did not account for certain demographics such as age, education level and commute. Additionally, major changes in technology that will shift the necessity of certain workers could drastically affect the worker populations for certain jobs.

5 Conclusion

5.1 Future Studies

Our first model is built on the foundations of linear regression–inferring trends from several different data sets, using an approximate fit to best predict future points. As a result, there remains some degree of variability between the actual future values and the predicted ones. Additionally, linear regression requires a simplification of the problem down to a minimal amount of factors; thereby excluding possible variability as a result of age, minority, etc. Our second model, although accurate for a general upward trend, failed to account for the possibility of growth leveling out. Our third model falls into much of the same problem as the first. It represents a very simplistic abstraction of the data as a whole, especially in terms of different job industries and ethnicities.

5.2 Summary

We first utilized several data sets to best estimate the percentage of workers whose jobs are currently remote-ready, applying our results to several major United States and United Kingdom cities to determine a relevant trend in the rate of change of said remote-ready jobs. We ended up finding a general downward trend in remote-work jobs.

From there, we used the Vernier Graphical Analysis application to model several linear regression graphs regarding both long and short-term remote-work employment rates to better determine the percentage of workers with both the ability and company permission to assume a remote-work position. Long-term remote-work employment percentages had steadily risen about 2% from 2000 to 2017 before surging to almost 54% in 2020. By the end of 2021, however, the figure had fallen to 25%.

Finally, we synthesized our models from the previous parts to best determine the percentage of workers who will go online in a given city, using the same U.S. and U.K. models as relevant examples. We found that online employment will eventually flatten out, resulting in a stable in-person and online hybrid. Although precedent will be given to in-person employment, online will continue to provide a pertinent alternative to industries that don't require an actively coordinating staff on-site.

6 Works Cited

Remote Work: Fad or Future, MathWorks Math Modeling Challenge 2022, https://m3challenge.siam.org/node/559.