Remote Work: *Fad or Future*

Executive Summary

Since the onset of the coronavirus pandemic, the share of American and British workers working remotely has dramatically increased. Employees and business owners have rapidly adapted to the significant shift towards online work, dramatically revolutionizing the labor landscape.

However, not all positions can be moved online. Determining how many workers can work without an on-premise location is essential for understanding this important labor trend. The first aspect of this report determined the percentage of jobs that are remote-ready in 2022, 2024, and 2027 in the three American cities of Seattle (41.5%, 41.7%, 41.9%), Omaha (41.0% , 41.2%, 41.5%), and Scranton (33.8%, 33.9%, 33.9%) and the British cities of Liverpool (28.0%, 27.7%, 27.2%) and Barry (46.6%, 46.8%, 47.0%). It did so by projecting the percentage of jobs in 10 different industries into future years using a linear regression and calculating the total proportion of jobs that would be remote-ready. The findings show a robust percentage of workers in each city that are capable of working from home now and in the coming years.

Other prerequisites for an increased remote workforce include the employer's willingness to allow employees to work from home, and the desire of employees to work remotely. The second part of this report details a model that determines whether a worker in a remote-ready position will actually work from home. The model takes multiple factors, including changes in productivity, time saved, childcare costs, and more, and runs a Monte Carlo simulation 1,000,000 times to determine the percent chance a worker is allowed to and chooses to work from home. An example worker with two childcare-aged children, an eight hour workday, a $30/hour wage, and a 30 minute commute time had a 99.7% chance of working from home. Conversely, a remote-ready worker with no children, a ten hour workday, a $50/hour wage, and a one hour commute time had a 73.8% chance of working from home.

The third part of this report multiplies the percentage of remote-ready workers in part one by the percentage of remote-workers that would actually work from home in part two for each of the five cities to estimate the percentage of workers who will actually work remote in Seattle (30.7%, 30.9%, 31.1%), Omaha (30.6% , 30.8%, 31.0%), Scranton (25.6%, 25.7%, 25.7%), Liverpool (21.2%, 20.9%, 20.6%), and Barry (35.1%, 35.2%, 35.3%). The impact of this shift to remote work was measured with an impact factor that was calculated based on the change in carbon emissions in a city and the inflow and outflow of residents into the city. Carbon emissions were quantified by a carbon tax and the population fluctuation was quantified by the property tax of a residence. The impact factors in 2027 for Seattle, Liverpool, Omaha, Scranton, and Barry were 0.1%, 0.5%, 0.02%, 0.03%, and 0.2% respectively. A higher impact factor signified a greater impact, so Liverpool had the greatest impact and Omaha had the least.

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Introduction

Due to the global Covid-19 pandemic, many jobs in the United States and around the world were forced to rapidly transition to remote work. This transition could have long-lasting effects on not only the individual laborers switching to remote work, but also the environment and the industries in which laborers are working.

In the first problem, we were tasked with estimating the percentage of workers with remote-ready jobs. We were then asked to use this estimate to predict the number of remote-ready jobs in 2024 and 2027 in Seattle, WA, Omaha NE, Scranton, PE, Liverpool, and Barry.

In the second problem, we were tasked with estimating the probability that a remote-ready worker would have both the permission and desire to work from home.

In the third and final problem, we were tasked with combining the two previous models to predict the percentage of workers who would work remotely for a given city. We were again asked to make predictions into 2024 and 2027; using these predictions, we were tasked with ranking the five earlier cities in terms of how greatly the transition to remote work would impact them.

Q1: Ready or Not

1.1 Defining the Problem

In this problem, we were tasked with estimating the percentage of workers with remote-ready jobs. This includes both the workers who are currently working online and those who are able to work online but have not yet transitioned from in-person work. We were then asked to use this estimate to predict the number of remote-ready jobs in 2024 and 2027 in Seattle, WA, Omaha NE, Scranton, PE, Liverpool, and Barry.

1.2 Assumptions

1. There will not be any technological advancements that significantly change the ability of an industry to be remote.

Justification: While technological changes can revolutionize the workforce in terms of remote-readiness, breakthrough technologies may take years to develop and the rollout is unpredictable.

2. The trends for future job growth and decline are city specific.

Justification: The changes in local job markets are not identical and must be considered separately because of legal, financial, and environmental differences.

3. The trends for future job growth and decline are the same as past trends.

In the short term, there are fluctuations within industries that dramatically change the number of jobs, such as the decline in the mining industry around 2010[9]. These variations are impossible to predict, so our model assumes that job growth and decline will follow the same long term trend shown in past data and that a large crash or boom in various industries will not occur.

4. The trends for job growth and decline for various industries are linear.
Justification: Linear extrapolation produces a long term trend and does not overfit the rapid increases and decreases in employment for various industries. While some of the linear regressions used in the model have low r-squared values, this is due to the inherent difficulty of predicting future economic outcomes.
5. Industries are made up of sub-industries.
Each industry, such as "education and health services" is made up of constituent sub-industries such as education, training and library; healthcare support; and healthcare practitioners and technical[1].
6. The percentage of remote readiness for an industry will be an unweighted average of the percentage of remote readiness of each sub-industry.
Justification: The makeup of sub-industries are representative of the industry as a whole. While the data given does give a list of sub-industries, due to time constraints, it was not feasible to determine the relative size of each sub-industry within their broader industries.

1.3 Variables

Symbol	Definition	Unit
P_i	Percentage of jobs in an industry that are remote-ready	%
p_s	Percentage of jobs in a sub-industry that are remote-ready	%
n_i	Number of sub-industries for a given industry	Number of sub-industries
$w_{i,t}$	Number of employees in an industry for a given year t	Number of employees
$r_{i,t}$	Number of remote-ready employees in an industry for a given year t	Number of employees
W_t	Total number of employees in all industries for a given year t	Number of employees
R_t	Total number of remote-ready employees in all industries for a given year t	Number of employees
$P_{f,t}$	Final percentage of workers that are remote-ready for a given year t	%

Table 1.3.1: Variable symbols, definitions, and units used in the model

1.4 The Model

We examined the occupational data for each American city and performed linear extrapolations on the monthly number of employees in each industry for the metro area from 2000-2021. Liverpool and Barry employee count was extrapolated using 2005-2021 data because of data constraints. We used these linear extrapolations to predict the number of employees, $w_{i,t}$, in each industry for a given year. The full list of linear regression coefficients by industry and city are shown in Table 1.5.1. Graphical representations of the linear regression for two example industries are shown below in Figures 1.5.1 and 1.5.2.

Industry	**Sub-industries (% remote-ready)**[1]	**Industry P_i (%)**
Mining, logging, construction	Construction and extraction (0) Farming, fishing, and forestry (1) Building and grounds cleaning and maintenance (0) Architecture and engineering (61)	(0+1+0+61)/4=**15.75**
Manufacturing	Production (1)	(1)/1=**1**
Trade, transportation, and utilities	Transportation and material moving(3) Building and grounds cleaning and maintenance (0) Installation, maintenance and repair (1)	(3+0+1)/3=**1.33**
Information	Computer and mathematical (100) Life, physical and social science (54)	(100+54)/2=**77**
Financial activities	Business and financial operations(88) Sales and related (28)	(88+28)/2=**58**
Professional and business services	Management (87)	(87)/1=**87**
Education and health services	Education, training and library (98) Healthcare support (2) Healthcare practitioners and technical (5)	(98+2+5)/3=**35**
Leisure and hospitality	Personal care and service (26) Community and social service (37) Food preparation and service related (0)	(26+37+0)/3=**21**
Other services	Arts, design, entertainment, sports and media (76) Protective service (6)	(76+6)/2=**41**
Government	Office and administrative (65) Legal (97)	(65+97)/2=**81**

Table 1.4.1: Industries, sub-industries, and percentage of remote readiness for each sub-industry

After this, the percentage P_i of workers in that industry that are remote-ready was calculated. Because exact data for each industry was not available, P_i was calculated by taking an unweighted average of the relevant sub-industry percentages p_s found in occupational category data[1]. The sub-industries for each industry are detailed in table 1.4.1 and the formula is shown below:

$$P_i = \frac{\sum_{s=1}^{n_i} p_s}{n_i}$$

Once we calculated the percentage of workers who are remote-ready P_i in each industry, which is shown in the rightmost column of table 1.4.1, it was multiplied by the predicted number of workers in an industry $w_{i,t}$ for the year to calculate the number of workers in an industry $r_{i,t}$ who have remote-ready jobs.

$$r_{i,t} = P_i \times w_{i,t}$$

The total number of remote-ready workers across all industries R_t was calculated by adding together each $r_{i,t}$.

$$R_t = \sum_{i=1}^{n} r_{i,t}$$

Then, the number of workers with remote-ready jobs across all industries R_t was divided by the number of total workers W_t to calculate the overall percentage of workers in a city who were remote-ready for a specific city in a given year $P_{f,t}$.

$$P_{f,t} = \frac{R_t}{W_t}$$

1.5 Results

Each linear regression for the number of employees by industry and city are shown in Table 1.5.1. Graphical representations of the linear regression for two example industries are shown in Figures 1.5.1 and 1.5.2.

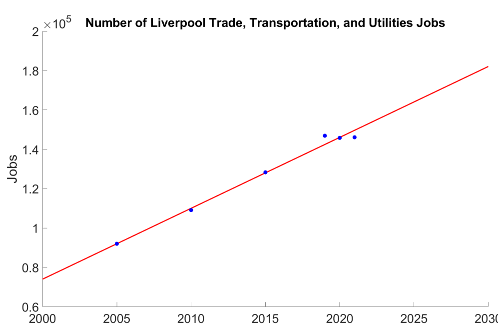

Figure 1.5.1: Trade, transportation, and utilities jobs projections for Liverpool

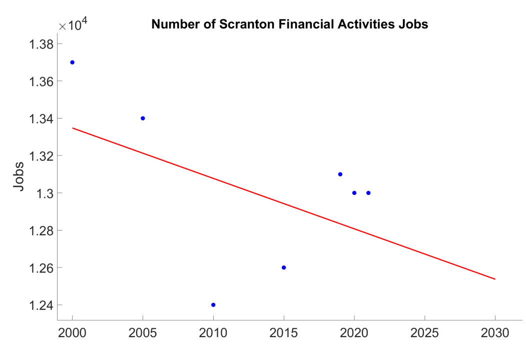

Figure 1.5.2: Financial activities job projections for Scranton

Industry		Seattle	Liverpool	Omaha	Scranton	Barry
Mining, Logging, and Construction	m ($\times 10^3$)	1.18	0.71	0.37	-0.02	0.005
	b ($\times 10^6$)	-2.26	-1.28	-0.72	0.05	-0.006
	r^2	0.36	0.49	0.60	0.11	0.004
Manufacturing	m ($\times 10^3$)	-1.68	1.91	-0.06	-0.74	-3.47
	b ($\times 10^6$)	3.56	-3.75	0.14	1.52	0.01
	r^2	0.39	0.72	0.11	0.74	0.0007
Trade, Transport, and Utilities	m ($\times 10^3$)	3.02	3.60	-0.56	0.36	-0.005
	b ($\times 10^6$)	-5.73	-7.13	1.22	-0.67	0.01
	r^2	0.43	0.99	0.70	0.92	0.01
Information	m ($\times 10^3$)	3.04	0.76	-0.24	-0.23	-0.002
	b ($\times 10^6$)	-6.02	-1.45	0.49	0.46	0.05
	r^2	0.86	0.87	0.92	0.99	0.27
Financial Activities	m ($\times 10^3$)	-0.38	0.08	0.47	-0.03	0.004
	b ($\times 10^6$)	0.87	-0.14	-0.90	0.07	-0.07
	r^2	0.23	0.08	0.95	0.25	0.28
Professional and Business Services	m ($\times 10^3$)	4.19	0.15	0.65	0.02	0.007
	b ($\times 10^6$)	-8.17	-0.26	-1.24	-0.39	-0.14
	r^2	0.81	0.08	0.84	0.46	0.28
Education and Health Services	m ($\times 10^3$)	3.69	-0.33	1.17	0.03	0.0066
	b ($\times 10^6$)	-7.20	0.68	-2.29	-0.52	-0.12
	r^2	0.67	0.67	0.96	0.56	0.31
Leisure and Hospitality	m ($\times 10^3$)	0.80	0.12	0.34	-0.003	0
	b ($\times 10^6$)	-1.44	-0.18	-0.64	0.07	0.01
	r^2	0.06	0.04	0.49	0.007	0
Other Services	m ($\times 10^3$)	0.55	0.18	0.16	-0.01	0.0004
	b ($\times 10^6$)	-1.03	-0.29	-0.31	0.22	-0.004
	r^2	0.34	0.10	0.78	0.75	0.001
Government	m ($\times 10^3$)	0.21	-0.25	0.46	-0.02	0.007
	b ($\times 10^6$)	-0.18	0.53	-0.86	0.39	-0.12
	r^2	0.005	0.34	0.78	0.78	0.31

Table 1.5.1: The slope m, y-intercept b, and r-squared value for each industry's linear regression by city

Using our model, the following table shows the predicted percentage of remote-ready jobs in each city for 2022, 2024, and 2027.

Year	Seattle	Liverpool	Omaha	Scranton	Barry
2022	41.5%	28.0%	41.0%	33.8%	46.6%
2024	41.7%	27.7%	41.2%	33.9%	46.8%
2027	41.9%	27.2 %	41.5%	33.9%	47.0%

Table 1.5.2: Final percentage of workers who are remote-ready per year for each city

1.6 Model Revision

Initially, we only assigned one sub-industry for each industry. We decided to include each of the related sub-industries because we wanted to have a more comprehensive and accurate model of the remote-readiness of the different cities.

1.7 Discussion

Our model predicted that the overall remote readiness of the five cities, with the notable exception of Liverpool, would increase. This makes sense, as the increasing prevalence of technology will continue to enable more workers to work remotely. Liverpool's decrease in remote-readiness could be attributed to its shift in the job market toward manufacturing as well as trade, transportation, and utilities which do not contribute greatly to the overall remote-readiness of a city.

Strengths:

- The model is very cost effective and can be easily scaled up to include more industries and sub-industries for a higher resolution model.
- Produces results similar to prior studies[2].

Weaknesses:

- Failed to account for the relative sizes of each sub-industry within their broader industries. If we had more time, we would have liked to do more research concerning the segmentation of certain industries to more accurately predict the future market landscape for remote readiness.
- Failed to account for potential major technological advancements that will impact job markets. Technology is developing at an unprecedented pace, and it is highly possible that technologies such as self-driving cars and remotely automated drones could dramatically increase the remote readiness of entire industries.

1.8 Sensitivity Analysis

The industry that contributes the most number of remote-ready jobs in Seattle in 2027 is professional and business services (275,160 out of 844,590 or 32.6% of all remote-ready jobs in Seattle according to our linear regression).
If we increase the predicted number of jobs in the professional and business services industry in Seattle by 10%, the overall percentage of remote-ready jobs in Seattle will increase from 41.9% in 2027 to 43.4%.

1.9 Technical Computing

Finding the line of best fit manually would be very time consuming and inaccurate, so using a computer to fit the lines was justified.

We used the built-in matlab “fit” function to create our linear extrapolations for the employee count for each industry over time. Years and the number of jobs for a given industry in a city were inputted to be fitted with a “poly1” or linear model. A variable was used to store the goodness-of-fit statistics, including r-squared, for each regression.

This was repeated in our program for each industry and city. The industries were then multiplied by the remote-readiness per industry. These totals were added up and the total percentage of remote-ready employees was calculated as a percentage of the total employees in the city.

To test the code, we set the percentage of remote-ready jobs in every industry to 0 and the code correctly predicted that there would be no remote-ready jobs.

Q2: Remote Control

2.1 Defining the Problem

In this problem, we were tasked with estimating the probability that a remote-ready worker would have both the permission and desire to work from home.

2.2 Assumptions

1. Hybrid workers are considered as working from home.

Justification: Hybrid workers (those who spend some time both in-person and at home) by definition choose to work from home. Trying to factor in whether or not a hybrid worker would work in-person on a given day would introduce too many confounding variables, so we considered hybrid workers as solely working from home.

2. The value of a worker's time during a commute is equal to the hourly rate that they are paid while working.

Justification: Workers decide to give up their time for money while at work, so we assume that workers value their time spent commuting equivalently to time that could be spent working.

3. The decision to work from home is based on the economic benefit to the worker and employer.
Justification: One of the major goals for the job market is to make money for both employees and employers in the form of mutually beneficial agreements. Working from home will be allowed and desired when the benefit to the worker and employer is greater than the cost to the worker and employer.
4. Workers are able to work on-site.
Justification: We assume that workers are able to work in-person if they want to and that companies have on-premises work opportunities, as workers would otherwise not be able to make a choice regarding their work status.
5. Workers who work from home do not need childcare for children not yet in school.
Justification: We assume that workers can supervise children while working from home and do not need to pay childcare costs.

2.3 Variables

Symbol	Definition	Unit	Value
T_w	Workday time length	Hours	
W	Wage of worker	\$/hour	
K	Number of under school-aged kids	People	
C_d	Cost of childcare for one under school-aged kid per hour	\$/(hour ×person)	16.20[3]
T_c	Commute time length	Hours	
B_c	Worker's economic benefit of working from home because of no commute	\$	
B_d	Worker's economic benefit of working from home because of no childcare expenses	\$	
B_w	Worker's economic benefit of working from home	\$	
B_e	Employer's economic benefit from letting an employee work from home	\$	
B_f	Total economic benefit from employee working from home	\$	
ΔP	Change in productivity from working at home	%	
μ	Mean of distribution of ΔP	%	0.22[4]
σ	Standard deviation of distribution of ΔP	%	0.50
F	Probability that the worker will work remotely if remote-ready	%	

Table 2.3.1: Variable symbols, definitions, units, and values used in the model

Note that the value for σ was assumed to be 0.5 in the model. This value can change depending on the work environment, but we chose this because it gives a chance for ΔP to be negative and thus create a more generalized model.

2.4 The Model

The chance that a worker will be able to work from home can be calculated by evaluating the economic benefits and costs of working from home for the worker B_w and the worker's employer B_e. If the net benefit to the worker and employer B_f is greater than 0, then the arrangement is economically beneficial.

First the worker's net benefits B_w after costs must be calculated. Workers who work from home do not need to commute, which saves commute time T_c. If this time is valued at the same rate W as normal work time, the economic benefit due to the eliminated commute is as follows:

$$B_c = T_c \times W$$

Workers also benefit from not needing to pay for childcare expenses B_d for children too young for school, which saves the following:

$$B_d = T_w \times K \times C_d$$

The combined total benefit B_w for the worker is shown below:

$$B_w = B_c + B_d$$

The worker's benefit B_w must also be combined with the employer's benefit from a work-from-home employee B_e to determine whether the employee will actually work from home. Employers will prioritize their employees' productivity, and working from home increases productivity ΔP by 22% on average[4]. However, it is clear that not everyone will have equal productivity benefits from remote work. Because of this, we created a normal distribution with a mean μ of 0.22 and a standard deviation σ of 0.5. This standard deviation was chosen because it provides a decent chance for ΔP to be negative, which accounts for the possibility of less efficient work online. ΔP is then randomly generated using a Monte Carlo simulation. For each trial, the benefit to the employer B_e due to productivity is as follows:

$$B_e = \Delta P \times W \times T_w$$

It is possible that productivity will decrease because of working from home. Even then, it is still possible for the employee to work remotely even though the employer does not benefit. This is because the employee may greatly value the ability to work remotely and would consider leaving for a different company if not given the opportunity to work from home, negatively impacting the business's total productivity more than simply allowing the employee to work remotely. Adding the total economic benefit to the worker and employer for the trial produces B_f:

$$B_f = B_w + B_e$$

Performing a series of 1,000,000 trials for a given worker determines the percentage of cases F in which the arrangement will produce a total benefit B_f greater than 0 and the employee will work from home.

As this model was designed in preparation for problem 3, it works much better for large populations than single instance problems because it provides a probability that a worker will work from home F. Thus, we simply used a random real number generator between 0 and 1 to determine whether a given individual would choose to work from home or not. If the number is greater than the chance to work in-person, they will work from home.

2.5 Results

We will apply the model to two imaginary workers: Mamma Mia and Basic Bill. Their information is shown below:

	Mamma Mia	**Basic Bill**
Childcare-aged kids	2	0
Work length per day	8 hours	10 hours
Wage	$30 / hour	$50 / hour
Commute time	0.5 hours	1 hour

Table 2.5.1: Imaginary workers' demographic information

Our simulation returned the following data after 1,000,000 trials for each worker.

	Mamma Mia	**Basic Bill**
Work from Home (F)	99.7%	73.8%
Work in-person	0.3%	26.2%

Table 2.5.2: Imaginary workers' remote work preferences

Random number generated for Mamma Mia: 0.009 > 0.003 → WILL work from home
Random number generated for Basic Bill: 0.883 > 0.262→ WILL work from home

2.6 Model Revision

Initially, we considered discussing the impact of education on one's choice to work from home as there is a large discrepancy between the number of workers working from home for each education level. However, this was taken out of the model as the education level would most readily affect the remote-readiness of a worker's job, not the worker's choice to work from home. In other words, education has a large impact on one's profession, which in turn has a large impact on one's probability of working from home. Since the imaginary worker in the problem is already working from home, we therefore decided that their education level would not have a major impact on their decision to work from home, as that is already factored into their ability to work remotely due to their job.

We also attempted to include the impact of a worker's gender on their desire to work from home. However, the data we were able to find regarding gender and working from home was not conducive to its inclusion in our model, so we unfortunately had to disregard gender.

We considered that the employers may force a worker to work in-person if productivity is lower at home which should give employers more power. Howev, forcing workers to work in-person may cause them to get another job or become unhappy, thus lowering their productivity, which gives workers a bargaining chip. Since these factors vary from person to person, we decided to weigh the worker and employer benefits equally.

2.7 Discussion

Our model considered an individual's work hours, wage rate, number of children, and commute time in order to determine the probability of their decision regarding whether or not to work from home. We also factored in the variation in productivity of remote workers and considered the preferences of employers regarding their employees' work statuses. Overall, the model indicates a strong preference toward working from home. This is consistent with real-life data, which indicates that the vast majority of people—85%—prefer working from home in some capacity[5].

Strengths:

- The formula used to calculate if a worker would choose to work from home is very modular and additional (quantifiable) factors can be easily added if they need to be taken into account.
- The model can be tailored easily to a specific circumstance if needed.

Weaknesses:

- People are not economically rational, so the decision to work from home is not completely based on the economic benefits/costs of working from home.
- Our model did not account for the gasoline savings from working from home. This would differ based on whether an employee drove, carpooled, took public transportation, walked, etc.

- Our model did not account for the impact of demographic differences such as gender. While some studies have indicated a higher preference for remote work for females, we were not able to find data that could be effectively incorporated into our model.
- Our model did not account for coworker pressure to either work from home or stay in the office. While this is a factor in deciding whether to work from home or not, there is not sufficient data to standardize it as a measure in our model.
- Our model did not account for the impact of health-related factors on the decision to work from home. The coronavirus and other diseases could affect an employee's decision to work from home.
- Productivity data was taken from an online survey. As a result, our data suffers from non-response bias, as individuals without access to or effective knowledge of the internet would suffer most in productivity due to the transition to remote work and would be unable to answer the survey.

2.8 Sensitivity Analysis

The standard deviation σ had the greatest impact on the model. Running the model with different standard deviations with Basic Bill's information gives the following results.

Standard Deviation	Percentage of times out of 1,000,000 Basic Bill works at home
0.1 (-80%)	99.9%
0.25(-50%)	90.0%
0.5 (+0%)	73.9%
0.75 (+50%)	66.5%
0.9 (+80%)	63.8%

Table 2.8.1: Different percentage work from home for different standard deviations

Although we see a variation in the chance that Bill chooses and is able to work from home, in all instances, the chance is above 50%.

2.9 Technical Computing

A Monte Carlo simulation requires randomness that humans do not have. The "randn" function, which takes the dimensions of an array, outputs random numbers that are normally distributed. We entered the number of trials and the number one as parameters to the "randn" function to create an array of random numbers equal in length to the number of trials. Benefit was computed with basic arithmetic after setting the variables to the correct amounts, and the sum function was used to find the number of successes (benefit greater than 0), which is equal to the number of times a person would decide to work from home.

Q3: Just a Little Home-work

3.1 Defining the Problem

In this problem, we were tasked with combining the two models above to predict the percentage of workers who would work remotely for a given city. We were again asked to make predictions for 2024 and 2027; using these predictions, we were tasked with ranking the earlier cities (Seattle, WA, Omaha, NE, Scranton, PA, Liverpool, Barry) in terms of how greatly the transition to remote work would impact them.

3.2 Assumptions

1.The average commute distance will not change within the next five years, and remote workers will have no commute.
Justification: Distances for in-person workers will not change, as workers will choose to live a similar distance from their workplace if they are moving into the workplace. Remote workers will not have to commute from home.
2.The current trend of suburbanization will continue.
Justification: Current trends of suburbanization already reflect a major shift into remote work. It is impossible to predict a sudden, unprecedented change in behavioral patterns, such as a mass migration from suburbs into cities.
3.The impact of remote workers moving out of a city will be equal to the loss of property tax.
Justification: While there are losses to the city such as fees, the majority of the loss will come from property tax, as that is the only tax paid directly to the city.
4.The environmental impact of remote workers will be equal to the carbon emissions from driving.
Justification: The majority of additional carbon emissions that come with office work as opposed to remote work are derived from commuting.
5.The carbon tax will be the same in the United States and the United Kingdom
Justification: The United States does not have a carbon tax in any state. The cost of carbon emissions will be the same regardless of location, so the price will be assumed to be the carbon tax in the United Kingdom in both countries.

3.3 Variables

Symbol	Definition	Unit
K_c	Average number of children under age 5 per worker for a given city	People
T_c	Average length of a working day for a given city	Hours
W_c	Average hourly rate for a worker for a given city	$/hour
C_c	Average commute time for a given city	Hours
$P_{c,t}$	Percentage of workers that are remote-ready for a given city c and year t	%

$F_{k,t,w,c}$	Probability that the worker will work remotely if remote-ready based on the model from problem two	%
$H_{c,t}$	The percentage of workers that work from home for a given city c and year t	%
$W_{c,t}$	Total number of jobs in all industries for a given city c and year t	Number of employees
X_c	Change in carbon tax per person	$
X_p	Change in property tax per person for a city	$
G	GDP of a city	$
I	Impact of work from home on a city	Ratio ($/$)
M	Percent of people who WFH who will move	%

Table 3.3.1: Variable symbols, definitions, and units used in the model

Variable	Seattle	Liverpool	Omaha	Scranton	Barry
K_c (people)	0.065[25]	0.074[27]	0.104[25]	0.102[25]	0.077[27]
T_c (hours)	6.92[6]	7.24[7]	6.94[6]	6.84[6]	7.24[7]
W_c ($/hour)	39.92[6]	20.31[8]	27.82[6]	23.14[6]	20.31[8]
C_c (hours)	0.527[1]	0.483[1]	0.352[1]	0.395[1]	0.423[1]

Table 3.3.2: Variable values

3.4 The Model

For each city, the percentage of workers that are remote-ready $P_{c,t}$ for a given year, calculated in question one, was multiplied by the percentage of remote-ready workers who would actually work from home $F_{k,t,w,c}$ using the model from question two and the variable values in table 3.3.2. The resulting percentage of workers who would work from home is calculated as follows:

$$H_{c,t} = P_{c,t} \times F_{k,t,w,c}$$

The Monte Carlo simulation for $F_{k,t,w,c}$ was not re-run for each city or time period because the Monte Carlo simulation itself only affects the change in productivity distribution and does not take time or city-specific data. However, $F_{k,t,w,c}$ did change for each city based on the model for problem two.

We measured the impact I of working from home on a city by subtracting the change in property taxes from the change in carbon emissions, then dividing by the GDP of that city. The change in carbon emissions was found by multiplying the carbon tax per metric ton by the tons of CO_2 emitted per mile by the average commute distance per person per day by the number of workdays in a year. This yields the carbon tax a person saved per year by working remotely to be \$353.60. The following is the full calculation for X_c.

$$\$108.15/ton^{[10]} \times 0.000411 ton/mile^{[11]} \times 15.3 miles/person^{[12]} \times 260 days/year^{[13]} = \$353.60$$

We then subtract the property tax lost by people moving out of the city because they work from home. This is simply the property tax per year for a given city times the number of people who move out of a city because of working remotely. M is estimated to be 21%[25].

Thus, the impact of working from home on a city is given by:

$$I = \frac{\left| X_c \times H_{c,t} \times W_{c,t} - X_p \times M \times H_{c,t} \times W_{c,t} \right|}{G}$$

where $H_{c,t}$ and $W_{c,t}$ multiply to give the total number of people working remotely in a given city in a given year.

	Seattle	Liverpool	Omaha	Scranton	Barry
Carbon tax	\$353.6 / person	\$353.6 / person	\$353.6 / person	\$353.6 / person	\$353.6 / person
Tax change	\$4,611[15] / person	4758.54[16] / person	\$2,164[17] / person	\$2,322[18] / person	\$2,369.11[19] / person
GDP(billion)	\$378.15[20]	\$19.910[21]	\$69.122[22]	\$27.40[23]	\$1.698

Table 3.4.1: Carbon tax, property tax, and GDP per city

3.5 Results

Combining problems one and two yielded the following percentages of workers who will work from home:

	Seattle	Liverpool	Omaha	Scranton	Barry
% of workers from a remote-ready industry who are able and willing to work from home	74.1%	75.5%	74.6%	75.8%	75.2%
% of jobs that are remote-ready in 2022 (from problem 1)	41.5%	28.0%	41.0%	33.8%	46.6%

% of workers who will work from home in 2022	**30.7%**	**21.2%**	**30.6%**	**25.6%**	**35.1%**
% of jobs that are remote-ready in 2024 (from problem 1)	41.7%	27.7%	41.2%	33.9%	46.8%
% of workers who will work from home in 2024	**30.9%**	**20.9%**	**30.8%**	**25.7%**	**35.2%**
% of jobs that are remote-ready in 2027 (from problem 1)	41.9%	27.2%	41.5%	33.9%	47.0%
% of workers who will work from home in 2027	**31.1%**	**20.6%**	**31.0%**	**25.7%**	**35.3%**

Table 3.5.1: Percentage of workers in various cities who will work from home in a given year

Below is the relative impact of workers working remotely in 2027 on the cities.

	Seattle	Liverpool	Omaha	Scranton	Barry
Total number of jobs in 2027	2,013,800	770,700	515,700	248,800	60,400
Total number of people WFH in 2027	625,486	158,533	159,764	63,966	21,333
Impact in 2027	**0.1%**	**0.5%**	**0.02%**	**0.03%**	**0.2%**

Table 3.5.2: Impact of remote work on various cities

In descending order of relative impact: Liverpool, Barry, Seattle, Scranton, Omaha.

3.6 Model Revision

We initially also considered changes in shopping habits amongst online workers by modeling the changes in city sales per person and considering the money lost through ecommerce. In the end, we could not come up with a way to correlate working from home to increases in ecommerce.

3.7 Discussion

Our model consisted of the percentage of remote-ready jobs and the probability that a worker would choose to work remotely for each city. These two factors combined to predict the percentage of total workers who would be working online in 2022, 2024, and 2027. In addition to this prediction, our model also created an impact factor value to estimate the relative impact the change in remote workforce will have on a city. The impact factor considered carbon emissions and population fluctuations, which were quantified with carbon tax and property tax values.

Strengths:

- The method of calculating the impact factor can easily be modified to include any monetarily quantifiable value.
- Money is an unbiased method of measuring impact that does not rely on weighted coefficients.
- The model normalizes total money change to the GDP of a city, so the impact is a relative factor that accounts for a city's size.

Weaknesses:

- Failed to account for local economic changes (restructuring within companies, large growth in E-commerce).
- Failed to account for differences in commute lengths among cities
- Failed to account for alternative methods of travel such as busing, biking, walking, or taking the subway.

3.8 Sensitivity Analysis

We test the sensitivity of the model by varying the impact of carbon emissions. Assuming the world has moved to an all-electric vehicle era, in which all cars have insignificant carbon emissions, the new ranking of relative impact is: Liverpool, Seattle, Scranton, Omaha, Barry. The volatility of Barry (from 2nd to 5th) suggests that GDP played a large role in determining relative impact, as its GDP was so low that a change in the numerator created a large change in the impact factor.

3.9 Technical Computing

We used the same code from questions one and two and simply used different inputs and multiplied the results. Problem3.m produces cityprop, which represents the proportion of workers whose jobs are remote-ready and will choose to work online. Problem1.m produces prop2024 and prop2027, which represent the proportion of jobs that will be remote ready in those years. By multiplying these arrays element-wise, we obtained the proportion of total workers who will work remotely.

Conclusion

We provided an estimate for the projected percentage of remote-ready jobs in cities across the US and the UK in 2022, 2024, and 2027. Our model uses a linear regression model to predict the number of workers in each of 10 different industries. The percentage of jobs in each industry that were remote-ready was calculated using an average of the percentage of remote-ready jobs in sub-industries. This percentage was then multiplied by the workforce for each industry, ultimately leading to the final percent of remote-ready jobs.

Next, we estimated the probability that an employer would allow the option of working from home and the probability that a user would choose to work from home. This model relied on the monetary gains and losses of workers and employers. If the monetary gain exceeded the monetary loss, employers would allow work from home and workers would choose to work remotely. The factors incorporated into monetary gain or loss included productivity, commute time, childcare, and work time. Inputting the values for specific workers would give an accurate prediction as to whether the worker would choose to work from home or not.

Finally, we developed a method to predict the proportion of the workforce in a city who will work from home in 2024 and 2027. This was done by combining the results of the previous two models to first figure out the proportion of jobs that were remote-ready, and then the proportion of workers in those jobs who would actually choose to work from home. In addition to this, we created an impact factor to measure the impact of the change in the workforce due to remote work. The impact factor included the changes in carbon emissions and residency, which were quantified by a carbon tax and income tax revenue.

Remote work has been slowly creeping into the workforce for years, and its growth has been accentuated by the COVID-19 pandemic. As the pandemic slowly winds down, however, remote work seems as though it is here to stay. Accounting for the potential impacts that remote work will have on cities is crucial, as based on our data, it is only a matter of time before it becomes even more commonplace. With an understanding of how quickly remote work will become incorporated into the workspace, both employers and cities can ensure a smooth transition into remote work.

References (Independent of Page Count Limit)

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

[2] Dingel, Jonathan I, and Brent Neiman. "How Many Jobs Can Be Done at Home? - National Bureau of ..." *NBER*, National Bureau of Economic Research, Apr. 2020, https://www.nber.org/system/files/working_papers/w26948/w26948.pdf.

[3] Staff, Care.com Editorial. "This Is How Much Child Care Costs in 2021." *Care.com Resources*, Care.com, Inc., 8 Aug. 2021, https://www.care.com/c/how-much-does-child-care-cost/.

[4] Bloom, Nicholas, et al. "Does Working from Home Work? Evidence from a Chinese Experiment." *Oxford University Press*, Oxford University, Feb. 2015, https://academic.oup.com/qje/article-abstract/130/1/165/2337855?redirectedFrom=fulltext&login=false.

[5] Slack, Slack Team. "Moving beyond Remote: Workplace Transformation in the Wake of Covid-19." *Slack*, 7 Oct. 2020, https://slack.com/blog/collaboration/workplace-transformation-in-the-wake-of-covid-19.

[6] BLS. "Table D-6. Average Hours and Earnings of All Employees on ..." *Bureau of Labor Statistics*, July 2019, https://www.bls.gov/web/laus/tabled6.pdf.

[7] Leaker, Debra. "Average Actual Weekly Hours of Work for Full-Time Workers (Seasonally Adjusted)." *Average Actual Weekly Hours of Work for Full-Time Workers (Seasonally Adjusted) - Office for National Statistics*, Office for National Statistics, 15 Feb. 2022, https://www.ons.gov.uk/employmentandlabourmarket/peopleinwork/earningsandworkinghours/timeseries/ybuy/lms.

[8] Clark, D. "UK: Average Hourly Wage 2019." *Statista*, 15 Nov. 2021, https://www.statista.com/statistics/280687/full-time-hourly-wage-uk/.

[9] PWC Staff. (2010). *Mine 2010 - back to the boom*. PricewaterhouseCoopers - PWC. Retrieved February 26, 2022, from https://www.pwc.co.uk/assets/pdf/mine-back-to-the-boom.pdf

[10] "Carbon Pricing in the United Kingdom." *OECD.org*, https://www.oecd.org/tax/tax-policy/carbon-pricing-united-kingdom.pdf.

[11] *EPA*, Environmental Protection Agency, https://www.epa.gov/greenvehicles/greenhouse-gas-emissions-typical-passenger-vehicle.

[12] *NRC: ML100621425 - Nuclear Regulatory Commission*. https://www.nrc.gov/docs/ML1006/ML100621425.pdf.

[13] Symmetry Software. "How Many Working Days Are in a Year?" *Symmetry Software*, 23 Apr. 2020, https://www.symmetry.com/payroll-tax-insights/how-many-working-days-are-in-a-year#:~:text=How%20many%20days%20%2D%20not%20including,averaging%20260%20days%20per%20year.

[14] Ioannou, Lori. "Vast Migration of over 14 Million Americans Coming Due to Rise in

Remote Work, Study Shows." *CNBC*, CNBC, 29 Oct. 2020, https://www.cnbc.com/2020/10/28/vast-migration-of-over-14-million-americans-coming-due-to-remote-work.html.

[15] "Washington Property Tax Calculator." *SmartAsset*, https://smartasset.com/taxes/washington-property-tax-calculator#:~:text=The%20county%27s%20largest%20cities%20are,property%20tax%20payment%20at%20%244%2C611

[16] Liverpool City Council. "How Much?" *Liverpool City Council*, https://liverpool.gov.uk/council-tax/how-much/.

[17] "The 2021 Tax Resource." *Nebraska Property Taxes By County - 2022*, http://www.tax-rates.org/nebraska/property-tax.

[18] "Pennsylvania Property Tax Calculator." *SmartAsset*, https://smartasset.com/taxes/pennsylvania-property-tax-calculator#4wpSOZxNm4.

[19] Powell, Leah. "This Is How Council Tax in the Vale Compares with the Rest of Wales." *Barry And District News*, Barry And District News, 1 June 2021, https://www.barryanddistrictnews.co.uk/news/19342643.council-tax-vale-glamorgan-compare-wales/#:~:text=The%20Vale%20of%20Glamorgan%20is,per%20cent%20of%20annual%20pay.

[20] Published by Statista Research Department, and Jan 25. "Seattle Metro Area - GDP 2020." *Statista*, 25 Jan. 2022, https://www.statista.com/statistics/183863/gdp-of-the-seattle-metro-area/.

[21] Liverpool City Council. "Economy." *Liverpool City Council*, https://liverpool.gov.uk/council/key-statistics-and-data/headline-indicators/economy/.

[22] "Total Gross Domestic Product for Omaha-Council Bluffs, Ne-Ia (MSA)." *FRED*, 8 Dec. 2021, https://fred.stlouisfed.org/series/NGMP36540.

[23] "Total Gross Domestic Product for Scranton--Wilkes-Barre--Hazleton, PA (MSA)." *FRED*, 8 Dec. 2021, https://fred.stlouisfed.org/series/NGMP42540.

[24] *U.S. Census Bureau Quickfacts: United States* https://www.census.gov/quickfacts/fact/table/US/PST045221.

[25] Published by Statista Research Department, and Feb 10. "U.S.: Number of Full-Time Workers 1990-2018." *Statista*, 10 Feb. 2022, https://www.statista.com/statistics/192356/number-of-full-time-employees-in-the-usa-since-1990/#:~:text=The%20number%20of%20full%2Dtime,127.16%20million%20employees%20in%202021

[27] "Quality and Methods." *Quality and Methods - Office for National Statistics*, 27 Mar. 2011, https://www.ons.gov.uk/census/2011census/2011censusdata/2011censususerguide/qualityandmethods

Code Appendix (Independent of Page Count Limit)

Problem 1

```
% percentage of jobs in each industry that are remote ready
% see table 1.4.1
rr = [0.1575;0.01;0.0133;0.77;0.58;0.87;0.35;0.21;0.41;0.81];

% years that matches with the data in d1 for each country
usyears = [2000;2005;2010;2015;2019;2020;2021];
ukyears = [2005;2010;2015;2019;2020;2021];

% initialize arrays to hold p1 (slope), p2 (y-intercept), and r
% (r-squared) for each of the job growth/decline linear regressions
% for each of the 10 industries in each of the 5 cities
seattlep1 = zeros(10,1);
seattlep2 = zeros(10,1);
seattler = zeros(10,1);

omahap1 = zeros(10,1);
omahap2 = zeros(10,1);
omahar = zeros(10,1);

scrantonp1 = zeros(10,1);
scrantonp2 = zeros(10,1);
scrantonr = zeros(10,1);

liverpoolp1 = zeros(10,1);
liverpoolp2 = zeros(10,1);
liverpoolr = zeros(10,1);

barryp1 = zeros(10,1);
barryp2 = zeros(10,1);
barryr = zeros(10,1);

% for each industry, use linear regression to fit the data and store
% the results in the arrays above
for job = 1:10

    % seattlejobs was manually imported from D1 City Employment Data
    [seattlefit,seattlegof] =
fit(usyears,seattlejobs(job,:)','poly1');
    % p1 is the slope of the regression
    seattlep1(job)= seattlefit.p1;
    % p2 is the y intercept of the regression
```

```
    seattlep2(job)= seattlefit.p2;
    % seattegof stores rsquared and other goodness-of-fit statistics
    seattler(job)= seattlegof.rsquare;

    % The same procedure is carried out for the rest of the cities
    [omahafit,omahagof] = fit(usyears,omahajobs(job,:)','poly1');
    omahap1(job)= omahafit.p1;
    omahap2(job)= omahafit.p2;
    omahar(job)= omahagof.rsquare;

    [scrantonfit,scrantongof] =
fit(usyears,scrantonjobs(job,:)','poly1');
    scrantonp1(job)= scrantonfit.p1;
    scrantonp2(job)= scrantonfit.p2;
    scrantonr(job)= scrantongof.rsquare;

    [liverpoolfit,liverpoolgof] =
fit(ukyears,liverpooljobs(job,:)','poly1');
    liverpoolp1(job)= liverpoolfit.p1;
    liverpoolp2(job)= liverpoolfit.p2;
    liverpoolr(job)= liverpoolgof.rsquare;

    [barryfit,barrygof] = fit(ukyears,barryjobs(job,:)','poly1');
    barryp1(job)= barryfit.p1;
    barryp2(job)= barryfit.p2;
    barryr(job)= barrygof.rsquare;
end

% initialize arrays to hold the predicted number of jobs
% 10 industries for each of the 5 cities for each time period
jobs2022 = zeros(10,5);
jobs2024 = zeros(10,5);
jobs2027 = zeros(10,5);

% for each industry, store the predicted number of jobs in the
vectors
% above
for job = 1:10
    % multiplying the slope by the year and adding the y intercept
for
    % each of the job linear regressions
    jobs2022(job,1) = seattlep1(job)*2022 + seattlep2(job);
    jobs2024(job,1) = seattlep1(job)*2024 + seattlep2(job);
    jobs2027(job,1) = seattlep1(job)*2027 + seattlep2(job);
```

```
    jobs2022(job,2) = liverpoolp1(job)*2022 + liverpoolp2(job);
    jobs2024(job,2) = liverpoolp1(job)*2024 + liverpoolp2(job);
    jobs2027(job,2) = liverpoolp1(job)*2027 + liverpoolp2(job);

    jobs2022(job,3) = omahap1(job)*2022 + omahap2(job);
    jobs2024(job,3) = omahap1(job)*2024 + omahap2(job);
    jobs2027(job,3) = omahap1(job)*2027 + omahap2(job);

    jobs2022(job,4) = scrantonp1(job)*2022 + scrantonp2(job);
    jobs2024(job,4) = scrantonp1(job)*2024 + scrantonp2(job);
    jobs2027(job,4) = scrantonp1(job)*2027 + scrantonp2(job);

    jobs2022(job,5) = barryp1(job)*2022 + barryp2(job);
    jobs2024(job,5) = barryp1(job)*2024 + barryp2(job);
    jobs2027(job,5) = barryp1(job)*2027 + barryp2(job);
end

% multiply the number of industry jobs by the percentage of jobs in
% that industry that are remote-ready to get the total number of jobs
% that are remote-ready
rr2022 = jobs2022.*rr;
rr2024 = jobs2024.*rr;
rr2027 = jobs2027.*rr;

% sum the total number of jobs in a city
total2022 = sum(jobs2022);
total2024 = sum(jobs2024);
total2027 = sum(jobs2027);

% sum the total number of remote-ready jobs in a city
totalrr2022 = sum(rr2022);
totalrr2024 = sum(rr2024);
totalrr2027 = sum(rr2027);

% find the proportion of remote-ready jobs in a city
prop2022 = totalrr2022./total2022; prop2024
= totalrr2024./total2024; prop2027 =
totalrr2027./total2027;
```

Problem 2

```
% hours of work per day
worktime = 10;
% price of daycare per hour
daycare = 16.20;
% number of kids below school age
kids = 0;
% wage in dollars per hour
wage = 50;
% hours of commute time per day
commute = 1;

% standard deviation of change in productivity
sig = 0.5;
% mean of change in productivity (positive 22% boost in productivity)
mu = 0.22;
% number of trials
n = 1000000;
% x contains n random points from the normal curve
x = (randn(n,1)*sig) + mu;

% worker benefit from working at home (no daycare or commute costs)
worker = wage*commute + daycare*kids*worktime;
% employer benefit (change in productivity of the worker)
employer = x*wage*worktime;
% total benefit to the worker and employer
benefit = worker + employer;

% cases that the total benefit is greater than 0
flags = benefit>=0;

% cases when work from home was chosen
home = sum(flags);
% cases when in-person was chosen
inperson = n-home;
disp(home);
disp(inperson);
```

Problem 3

```
% average hours of work per day for each of the cities
% the order of the cities is as follows:
% Seattle -> Liverpool -> Omaha -> Scranton -> Barry
worktime = [6.92 7.24 6.94 6.84 7.24];
% price of daycare per hour
daycare = 16.20;
% average number of kids below school age per worker for each city
kids = [0.065 0.074 0.104 0.102 0.077];
% average wage
wage = [39.92 20.31 27.82 23.14 20.31];
% average hours of commute time per day for each city
commute = [0.527 0.483 0.352 0.395 0.423];

% initialize array to hold the proportion of people in the city that
% will work from home if the job is remote-ready (problem 2)
cityprop = zeros(5,1);

% standard deviation of change in productivity
sig = 0.5;
% mean of change in productivity
mu = 0.22;
% number of trials
n = 1000000;
% n random points from the normal curve
x = (randn(n,1)*sig) + mu;

%for each city, calculate the proportion in problem 2 for the average
%citizen of that city
for city=1:5
    % worker benefit from working at home (see problem2_15333.m)
    worker = wage(city)*commute(city) +
daycare*kids(city)*worktime(city);
    % manager benefit from allowing an employee to work from home
    employer = x*wage(city)*worktime(city);
    % total benefit
    benefit = worker + employer;

    % cases that the total benefit is greater than 0
    flags = benefit>=0;
    % number of time work from home was chosen
    home = sum(flags);
    %proportion of times work from home was chosen
```

```
    cityprop(city) = home/n;
end

% In order to calculate the total percentage of workers in a city
that will
% actually work remotely, cityprop needs to be multiplied by
% the remote-ready percentage calculated in problem one.
disp(cityprop)
```