Fad or Failure - Executive Summary

When the coronavirus pandemic hit the world drastically in early March of 2020, many people were left with only one plausible option for keeping their occupations: remote work. However, with the pandemic easing with the distribution of vaccines and safer health measures, there is still a high percentage of people who remain working from home, although their job allows for them to work in-person [2].

We first created a model that evaluated the proportion of remote-ready workers for any city, given its workforce distribution across the ten industries defined in the D1 dataset [1]. Our model takes into account occupation specific remote-ready information provided in the D3 Occupational Category dataset [1] to more accurately calculate the true number of remote-ready workers in any of the five given cities: Seattle, Omaha, Scranton, Liverpool, and Barry. We made transformations to the data provided by the m3 data spreadsheets [1] and the BLS datasets [5] to make the dataset easier to work with and quantify. Through summation and simple algebra, our model found that Seattle had a consistent remote-ready job percentage in the 28% range all three years; Omaha's remote-ready job percentages fluctuated in the early 30% range; Scranton's percentages stayed consistent in the 30% range, Liverpool in the 18% range, and Barry in the 30% range.

We created a model to predict the probability that a remote-ready individual will work remotely using a set of heuristic weights. By analyzing data on 10 categorical variables, each representing a circumstance which might influence the probability that a remote-ready individual will work remotely, we calculated a set of heuristic weights for each defined category of each categorical variable. Ultimately, we were able to incorporate the national average probability of 46.3% and an adjusted sigmoid function to program a Python algorithm that could calculate a probability for an individual based on information about that individual for our 10 categorical variables. For example, our model predicts that a remote-ready individual that falls into the following categories: some college or associate's degree, 55 years and older, has children, works part time, is female, is married, lives in a Metropolitan area with a population range of 500,000–1,000,000, is Non-Hispanic White, works in a sales or related occupation, and is in the financial activities industry, will have approximately a 64.27% probability of working remotely.

Lastly, we incorporated our results and models from the first two parts to create a final mathematical model to predict the total number of people who *would* work from home in 2022, 2024, and 2027. Upon finding the total number of remote-ready workers in each city in 2027 to be 429,479 (Seattle), 96,147 (Omaha), 31,022 (Scranton), 44,900 (Liverpool), and 6,318 (Barry), we used these values to determine the magnitude of impact that remote work would have on each of the cities. We defined impact in terms of dollars, because the value of a location is largely dependent on the strength of its economy, and USD is a unit that all of our variables could be reduced to. We broke our model into three sections–Environmental Impact, Money Saved on Gas, and Money Saved by Commute Time–and ranked each of the five cities based on how much money they would save in total. Our model found that Seattle had the greatest magnitude of positive impact, by saving a total amount of $\$5.5 \times 10^9$.

Global Assumptions

1) *The US national proportion of occupations that can be done at home will be the same among each city, even those in the UK.* We are assuming that if 98% of educators in the US are able to work from home, then 98% of educators are able to work from home in the UK.
2) *The current statistical trends regarding the spread of the coronavirus will persist until 2027.* With the implementation of numerous vaccines and safer health measures, we do not anticipate another extreme quarantine period that will skyrocket the necessity for remote-ready occupations.
3) *Growth rate in each job sector will remain constant for the next 5 years*.
4) *Only those between the age of 15 and 64 are considered working people* [7].
5) *For uniformity, all UK data has already been converted to USD, miles, and gallons*.

Global Definitions

1) **Remote working:** the act of contributing paid labor without commuting to a central workplace, or in general being far from an employer. This will most commonly be in the form of working from home.
2) **Remote-ready:** The problem defines remote-ready as jobs "where employees already are or could be working remotely."

1 Part I: Ready or Not

1.1 Restatement of the Problem

In this part, we were asked to create a mathematical model that can estimate the percentage of workers whose jobs are remote-ready [1.2] in five major cities: Seattle, WA; Omaha, NE; Scranton, PA; Liverpool, England; Barry, Wales.

1.2 Assumptions

1) *The distribution of occupations that can be done at home will be roughly similar among each city.* We are assuming that someone in Omaha with a computer has the same capability to work from home as someone in Liverpool.
2) *The percentage of remote-ready jobs in 2024 and 2027 will increase, not due to the pressures of companies having to offer new remote-ready jobs because of a pandemic quarantine, but because of the increasing convenience workers see in working from home as opposed to in-person*. As we see a decline in coronavirus cases currently [4], we are assuming that our generation will not see another extreme quarantine period that we saw in early 2020. Thus, we will not see an influx of remote-ready jobs at one time because of an emergency event, such as that.
3) *Our data sorting methods properly sorted each occupation subsector into our greater occupational categories*. For example, when looking at the Employment by Occupation for the "Arts, Entertainment, and Recreation: NAICS 71" subsector, one of the allotted occupations was "Gaming Supervisors." Instead of putting that in the "Arts, design, entertainment, sports and media" occupation category, we put it in the "Management" occupation category.
4) *The distribution of government occupations across industries is the same as that of the private sector*. For example, if manufacturing accounts for 10% of all jobs in the private sector in Seattle, it will account for the 10% of all jobs in the government in Seattle as well.

1.3 Variables

Name	Symbol		Name	Symbol
Remote-Ready Population	R		Indexed Industry	E_i
City	C		Industry Remote-Ready Factor	P
Year	t		Indexed Industry Remote-Ready Factor	P_i

Transformed Industry Workforce	E_T	Occupation Indexing	j
Initial Industry Workforce	E_0	Indexed Occupation Workforce	e_j
Government Industry Workforce	E_g	Indexed Occupation Remote-Ready Proportion	ρ_j
Total City Workforce	E_c	Number of Occupations in an Industry	N
Industry Indexing	i	BLS Industry Workforce Total	E

1.4 Model Development

1.4.1 The Process

To start our modeling process, we used the third tab on the spreadsheet [1] to extrapolate the 22 given occupation categories into the ten industries [5]: Manufacturing; Education and Health Services; Financial Activities; Information; Leisure and Hospitality; Natural Resources, Mining, and Construction; Professional and Business Services; Trade, Transportation, and Utilities; Government*; and Other Services. (*please see Assumption 3 in 1.2)

We looked into each of the subsectors of each industry listed above, and found the distribution of "Employment by Occupation" for each industry. For example, the following data tables are from the subsectors of "Leisure and Hospitality":

Arts, Entertainment, and Recreation: NAICS 71

Employment by Occupation

Data series	Employment, 2020
Actors	10,840
Amusement and recreation attendants	168,090
Fitness trainers and aerobics instructors	155,720
Gaming supervisors	8,210
Musicians and singers	18,700

(Source: Occupational Employment and Wage Statistics)

Accommodation and Food Services: NAICS 72

Employment by Occupation

Data series	Employment, 2020
Combined food preparation and serving workers, including fast food	2,928,760
Cooks, fast food	532,170
Cooks, restaurant	1,040,430
Hotel, motel, and resort desk clerks	206,170
Waiters and waitresses	1,791,080

(Source: Occupational Employment and Wage Statistics)

DATA SERIES	Employment, 2020	Employment/Total Occupations in Major Category	Assigned Occupational Category (out of 22)	% Remote-ready (out of 22 Ocupational Categories)	x% in D3 Corresponding Category
Accomodation and Food Services (NAICS 72)					
Combined food preparation and serving workers, including fast food	2928760	0.4269223649	Food preparation	0	0
Cooks, fast food	532170	0.07757387936	Food preparation	0	0
Cooks, restaurant	1040430	0.1516624224	Food preparation	0	0
Hotel, motel, and resort desk clerks	206170	0.0300531911	Sales and related	0.28	0.008414893508
Waiters and waitresses	1791080	0.261083909	Food preparation	0	0
Arts, Entertainment, and Recreation (NAICS 71)					
DATA SERIES	Employment, 2020	employment/total occupations in education category			
Actors	10840	0.001580135769	Arts, design, entertainment, sports and media	0.76	0.001200903185
Amusement and recreation attendants	168090	0.02450230825	Arts, design, entertainment, sports and media	0.76	0.01862175427
Fitness trainers and aerobics instructors	155720	0.02269914594	Arts, design, entertainment, sports and media	0.76	0.01725135091
Gaming supervisors	8210	0.001196763346	Management	0.87	0.001041184111
Musicians and singers	18700	0.002725879971	Arts, design, entertainment, sports and media	0.76	0.002071668778
				TOTAL:	0.04860175477
				As a %:	4.90%

For each subsector, we found their respective constituent occupations (the symbol of which is O) and counted the number of workers in each occupation (e_i). For example, the occupation, Actors, had an employment of 10,840 in 2020.

Then we had to assign each of the occupations to one of the 22 occupation categories, and multiply the total jobs in that occupation by the percentage of jobs that are remote-ready *in* said occupation(ρ_i). So, for ACTORS, we reasoned that they fell in the "Arts, design, entertainment, sports, and media" occupation category, which had a 0.76 estimate of jobs in that field that could be done at home. Thus, we multiplied 10,840(e_i) by 0.76(ρ_i) to find that ≅ 8238 people in the Acting occupation are remote-ready.

For each industry, we summed the number of remote-ready people in each of the occupations present in the industry and then divided by the total number of workers in that industry(E) to find the portion of remote-ready people in the industry. For example, we found that around 0.0486 of people working in the Leisure and Hospitality industry were remote-ready.

1.4.2 Summation Notation & Equations

Our goal is to create a model that takes a city, C, and a year, t, as arguments and returns the proportion of remote-ready workers in that city for that year, R:

$$R(C, t)$$

Our initial investigation yielded a fairly simple way of finding R for any given city:

eq(1)

$$R = \sum_{i=1}^{n} E_i P_i,$$

which outlines the sum of the remote-ready workers across all industries within a city where (i) indexes through the industries in that city, (E) is the size of the workforce in that current indexed industry, and (P) is the portion of remote-ready workers for that industry.

Upon further consideration, we decided the city industries were too broad to match confidently with the Remote Work Data provided in D3 [1]. We felt that doing so would rely on too many simplifications to accurately capture the true number of remote-ready workers in each city. We decided to deconstruct each industry into more specific sub-industries and match those to the information in D3 to get more accurate proportions for each industry. Unfortunately, the city datasets identified Government as a unique industry while the BLS dataset [5] did not. To address this discrepancy, we tried to incorporate the Government industry within the rest of the industries in the city datasets by allocating the Government workers according to the relative size of the remaining industries. One assumption we worked under during this transformation was that the proportion of government workers in each remaining industry was proportional to the relative size of that industry. In effect, all of the remaining nine industries have the same percent of government workers.

To transform our city datasets we adjusted the size of the nine other industries through this function:

eq(2)

$$E_T = E_0 + \left(\frac{E_0}{E_c} E_g\right),$$

where (E_T) represents the transformed industry size for a given city, (E_0) represents the initial size of the 2021 industry for a given city, (E_g) represents the government industry size for a given city, and (E_c) represents the size of the summation of the nine industries excluding government for a given city.

eq(3)

$$E_c = \sum_{i=1}^{9} E_{i0}$$

This transformation was performed on all 2021 city datasets. All remote-ready conclusions, as well as industry growth models, were created with this dataset in mind. We will take such to be a given from here on out.

With this, we felt confident moving forward with nine industries that could be easily deconstructable into more specific areas that would be easier to match to the remote-ready list provided on D3.

We returned to our initial model eq(1) feeling as though it had not outlived its usefulness. There was an opportunity to incorporate growth of certain industries over time with the factor E_i (the number of workers in a specific industry for a given city):

eq(4)

$$R = \sum_{i=1}^{9} E_i P_i,$$

where (E_i) is the transformed (E_T) for each industry in each city dataset. R is implicitly defined on location and time because $E_i(C,t)$.

With our entire motivation as transforming the city datasets to match the BLS data [5] for increased specificity in match industries to the D3 chart [1], we started to deconstruct each industry into its constituent occupations to get a more accurate estimate for (P_i). We matched every occupation within an industry to a row on the D3 remote-ready percentage table (ρ_j). We then multiplied the number of BLS recorded workers (e_j) within each occupation with this proportion to get the number of BLS recorded remote-ready workers said occupation ($e_j\rho_j$). Summing across the number of occupations within an industry (N) yields the total number of remote-ready workers for a given industry in the BLS dataset [5]. Dividing this number by the total number of BLS recorded workers (E_i) in that industry gives (P_i) as the "industry remote-ready factor".

eq(5)

$$P = \frac{\sum_{j=1}^{N} e_j \rho_j}{E^*}$$

*Note: This E refers to the BLS dataset total for an industry, not the city data.

Assuming no drastic change occurs in the BLS dataset, this "industry remote-ready factor" is independent of location and time and, as such, can be used across all city data sets and years.

Ultimately to find the Remote-Ready proportion for a city:

eq(6)

$$\frac{R}{E_c}$$

1.4.3 Results for 2020 Occupational Percentages (Table)

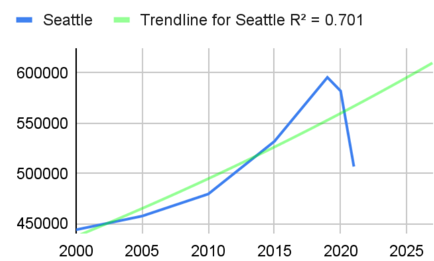
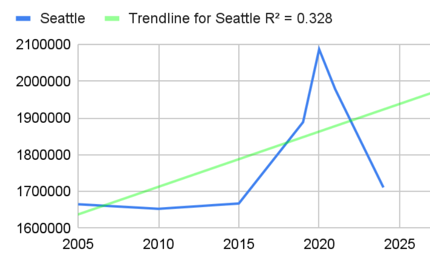
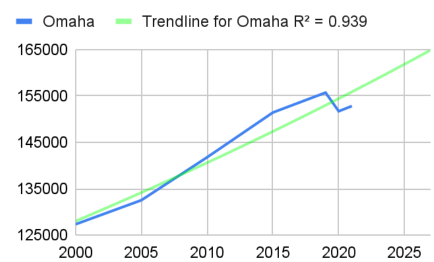
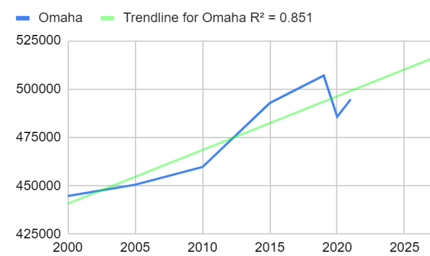
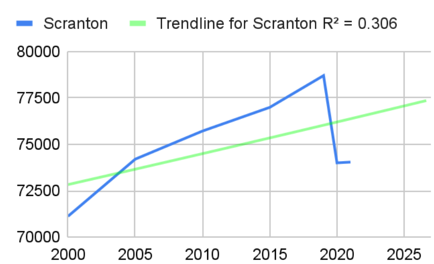
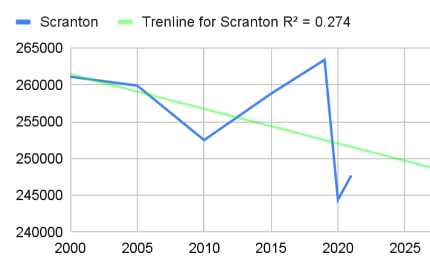
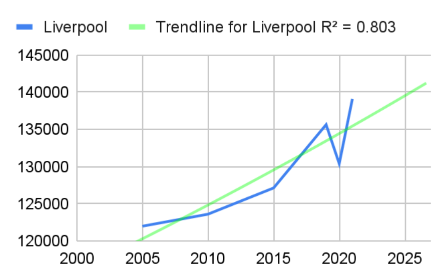
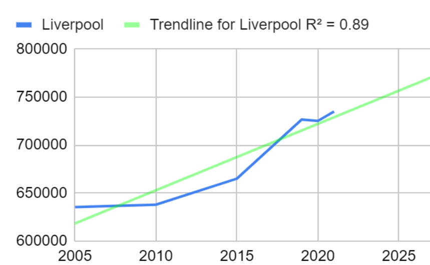
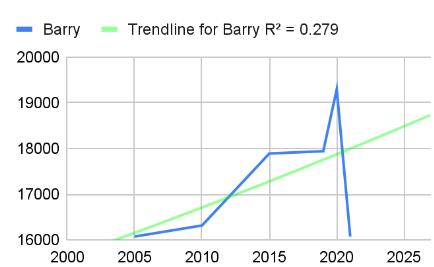
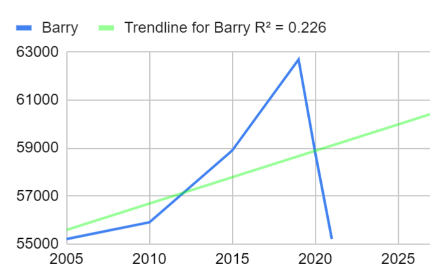
We applied the same logic explained in 1.4.1 to create the following data table, with all ten major occupational categories:

i	Occupation Category	Percentage of Workers that are Remote Ready	P_i
1	Manufacturing	2.3%	0.023
2	Education and Health Services	63.1%	0.631
3	Financial Activities	55.0%	0.550
4	Information	41.5%	0.415
5	Leisure and Hospitality	4.9%	0.049
6	Natural Resources, Mining, and Construction	8.9%	0.089
7	Professional and Business Services	39.7%	0.397
8	Trade, Transportation, and Utilities	18.2%	0.182
9	Other Services	14.0%	0.140

1.5 Results (apply 1.4.2 on 1.4.3)

After applying the equations from 1.4.3 and using the P_i values from 1.4.2, we can come to the following conclusions about each of the five cities, bound by the year our data was collected, in 2021:

City	Number of Remote-Ready Jobs in Given City	Number of Jobs in Given City

Seattle, WA $R_{Se}(x) = 8.11(10^{-6})e^{0.0124x}$ 2022: 628057 jobs 2024: 643828 jobs 2027: 668229 jobs		
Omaha, NE $R_O(x) = 9.45(10^{-4})e^{0.00936x}$ 2022: 156623 jobs 2024: 159582 jobs 2027: 164127 jobs		
Scranton, PA $R_{Sc}(x) = 7.92(10^{2})e^{0.00226x}$ 2022: 76442 jobs 2024: 76788 jobs 2027: 77310 jobs		
Liverpool, England $R_L(x) = 4.27(10^{-2})e^{0.00741x}$ 2022: 137237 jobs 2024: 139286 jobs 2027: 142417 jobs		
Barry, Wales $R_B(x) = 2.24(10^{-2})e^{0.00673x}$ 2022: 18203 jobs 2024: 18450 jobs 2027: 18826 jobs		

City/Year	2022 Percentage of Remote-Ready Jobs	2024 Percentage of Remote-Ready Jobs	2027 Percentage of Remote-Ready Jobs
Seattle, WA	0.28058	0.28336	0.28753
Omaha, NE	0.30860	0.31120	0.31510
Scranton, PA	0.30212	0.30504	0.30942
Liverpool, England	0.18396	0.18287	0.18123
Barry, Wales	0.300502	0.302184	0.304707

1.6 Strengths and Weaknesses

Although we found that the United States and the United Kingdom have similar population and occupation rates, our data distribution and final model could have been stronger if we had taken UK data into account when finding the percentages of each remote-ready occupation.

As the distribution of government occupations was not readily available, we had to assume it was uniform with the distribution of private sector occupations.

However, our data collection and calculation was very thorough with what we were given, as we tested our model multiple times for intuity and sensibility.

2 Part II: Remote Control

2.1 Restatement of the Problem

Although many occupations are able to work in-person, many still choose to work remotely, despite the decreasing numbers of coronavirus infections. People are starting to work from home now by choice rather than necessity, increasing the percentage of people who work in jobs that are remote-ready [3]. Thus, in this part, we were tasked with creating a model that predicts whether or not an individual worker whose job *is* remote-ready will choose to and/or be allowed to work from home.

2.2 Assumptions

1) *Each factor is independent of any other factor.* So, there is the same probability that a 15-year-old has childlike responsibilities (possibly in the form of siblings) as a 57-year-old.
2) *Every remote-ready person that is allowed to work remotely by their employer and chooses to work remotely will work remotely.* Unless extenuating circumstances are

involved, a remote-ready person has no reason not to work remotely if their employer allows them to and they choose to do so.

3) *The distribution of each circumstance is constant and uniform for both the US and UK.* While the distributions may change, they will not do so drastically within the next 10 years. The cities' distributions should also not significantly deviate from the national distributions for the categorical variables that we accounted for.

2.3 Variables

Name	Symbol	Units
Works remotely	**R**	Event
Remote ready	**A**	Event
Heuristic weight for category c of circumstance v	$\mathbf{W_{v,\,c}}$	Weight
A set of circumstances	**C**	A category number (or 0 if unknown) for each defined circumstance
The category listed for circumstance v in the set of circumstances C	$\mathbf{C_v}$	Category
Probability of a remote-ready individual with a set of circumstances C working remotely	**P(C)**	Probability

2.4 Model Development

2.4.1 Weighing Each Variable

We identified ten categorical variables - representing circumstances - which are correlated with a remote-ready person working remotely. Using the data found in table [8], we constructed a heuristic algorithm to determine the probability of a remote-ready person working remotely based on that person's values for the ten variables.

First, we calculated the probability that a person who falls into a specific category for a certain circumstance will work remotely given the ability, which we denoted as $P_{v,\,c}(R|A)$. This was done by dividing the proportion of remote-ready people in that category who worked remotely by the proportion of people in that category who were remote-ready.

eq(7)

$$P_{v,c}(R|A) = \frac{P_{v,c}(R \cap A)}{P_{v,c}(A)}$$

Next, we calculated the probability that a remote-ready person will work remotely assuming that the population was evenly distributed across the defined categories in a certain circumstance, $M_v(R|A)$. We did so by averaging the probabilities that a remote-ready person in each category will work remotely.

eq(8)

$$M_v(R|A) = \frac{\sum_{c=1}^{l} P_{v,c}(R|A)}{l}$$

With our next step, we used our previous results to calculate a heuristic weight for each category in each circumstance - $W_{v,c}$.

eq(9)

$$W_{v,c} = \frac{P_{v,c}(R|A)}{M_v(R|A)}$$

Finally, we found the probability that a remote-ready person with a certain set of circumstances will work remotely by multiplying .436, the national average probability that a remote-ready person will work remotely, by the weights of each category that the person falls under and performing an adjusted sigmoid function on the product. This probability was named P(C).

eq(10)

$$S(x) = \frac{2}{1+e^{-1.5x}} + 1$$

eq(11)

$$P(C) = S(0.436 \prod_{v=1}^{10} W_{v,C_v})$$

2.5 Results

We used Google Sheets to create a table of heuristic weights for each category of each categorical variable (circumstance). We then developed a program using Python which would calculate the probability of a remote-ready individual with a certain set of circumstances working remotely using the weight table as a reference and applying the product procedure found in eq(11).

For example, our model predicts that a remote-ready individual that falls into the following categories: some college or associate's degree, 55 years and older, has children, works part time, is female, is married, lives in a Metropolitan area with a population range of 500,000–1,000,000, is Non-Hispanic White, works in a sales or related occupation, and is in the financial activities industry, will have approximately a 64.27% probability of working remotely.

2.6 Strengths and Weaknesses

WEAKNESSES:

The data that we used was ultimately limited to 10 categorical variables, and fails to account for other factors such as commute time.

The number of categories for each variable was limited, making our outputs rough estimates of a remote-ready individual's probability of working remotely rather than precise predictions.

STRENGTHS:

We were able to account for 10 categorical variables which accounts for many of the factors influencing a remote-ready individual's probability of working remotely.

Our model is able to ignore any and all of the ten variables if it is unknown what category the individual would belong to for that variable.

The adjusted sigmoid function in eq(11) normalizes the final probability, offering both stability and a sense of continuity in the outputs of P(C).

3 Part III: Just a Little Home-work

3.1 Restatement of the Problem

Now that we have determined the number of remote-ready occupations in each of the cities AND the probability that an individual worker will be allowed to/choose to work from home, we can now create a mathematical model that predicts the percentage of workers who *will* work remotely. We are also asked to rank the "magnitude of impact" that remote work will have on each of the five given cities.

3.2 Assumptions

1) *We are defining impact as the amount of money saved in a given city*. Since so much weight on a city's success and reputation is put on their financial tendencies, we believe that comparing how remote-work affects the city financially would best represent the impact remote-work has on the city as a whole.

2) *Our model is treating every commuter as vehicle-driving*. The proportion of people who drive to people who use other transportation methods (i.e., walk, bike, or use public transportation) is roughly similar across all five cities, and therefore will not have a significant effect on their relative financial impacts.
3) *The state average data is accurate to use in terms of each given city* [13].
4) *We are using the average regular gas prices of each given city, not the premium or medium gas, to keep the data consistent.*
5) *All current data will remain constant through 2027*. We will treat them as constant because we are assuming variables, such as the average cost of gas, will increase proportionally in each city, and therefore will not affect their relative rankings to each other.
6) *The average person works a forty-hour work week, and works 48 weeks of the year.* To keep our calculations consistent amongst the different cities, we established a set work time for every considered worker.
7) *We are only considering the year 2027 when comparing the magnitude of impacts amongst each of the cities.*

3.3 Variables

We did not use concrete variables, but instead assumed values to consistent occurrences in the data, as can be seen in the data table in 3.4.3. Also, see how we would have improved our variable usage given more time in 3.6.

3.4 Model Development

3.4.1 Synthesis

1. Using the first model, we predicted the percentage of remote-ready jobs for a given city and year.
2. Using the second model, we calculated the percentage of remote-ready workers who are permitted to and chose to work remotely in a given city. We did this by finding data on each city and apportioning the population as an input to the second model (instead of finding the category that each variable of an individual corresponds to, we input the proportions of the population into their respective categories). To account for the lack of properly fitting data for each city, we used the second model's redundancy of assuming the US national average for missing inputs.
3. Then, we multiplied the percentage of remote-ready jobs calculated by the first model by the second model's output of percentage of remote-ready workers that were permitted to and chose to work remotely, getting the percentage of people who were working remotely in a given city and year.
4. To calculate the magnitude of impact remote work has on the city, we multiplied the predicted percentage of remote workers by the projected population to get the predicted number of remote workers. Then we calculated the magnitude of impact each person had using qualitative factors. Finally we multiply the predicted number of remote workers by the impact each person had to get the total impact remote work had on a city.

Then we can calculate the impact a single person will have if they work remotely in a given city.

City	**2022 (% of occupations done remotely)**	**2024 (% of occupations done remotely)**	**2027 (% of occupations done remotely)**
Seattle, WA	**403660**/1901953 = 21.2%	**413796**/1935491 = 21.4%	**429479**/1986911 = 21.6%
Omaha, NE	**91752**/505232 = 18.2%	**93485**/511229 = 18.3%	**96147**/520358 = 18.5%
Scranton, PA	**30653**/248878 = 12.3%	**30812**/247979 = 12.4%	**31022**/246636 = 12.6%
Liverpool, England	**43267**/801707 = 5.4%	**43913**/818394 = 5.4%	**44900**/844077 = 5.3%
Barry, Wales	**6109**/59432 = 10.3%	**6192**/59903 = 10.3%	**6318**/60617 = 10.4%

The bolded values in the table above represent the number of people in each of the remote-ready jobs that WILL be working from home. These values will be used to calculate the money values in 3.4.4. The unbolded values in the table above represent the total number of jobs. The percentage is the percentage of workers that will work from home.

3.4.2 Qualitative Factors

With more remote-ready occupations available, more people will be taking said remote-ready opportunities. Thus, less people will be commuting to and from work, which will minimize their carbon footprint, money spent on gas, CO_2 emission in the air, and time spent commuting. All of these factors can be converted into dollar amounts in order to accurately compare the economic benefits of each city.

3.4.3 Relevant Data

City	Avg. Commute Time (Round-Trip) in min	Avg. Commute Distance (Round-Trip) in miles	Avg. Gas Prices in USD	Avg. Annual Salary (USD)
Seattle, WA	63.2 min [1]	14 miles [13]	$4.167 [16]	$92,100 [22]
Omaha, NE	42.2 min [1]	12.4 miles [13]	$3.381 [16]	$77,900 [22]
Scranton, PA	47.4 min [1]	13.4 miles [13]	$3.746 [16]	$54,872 [22]
Liverpool,	58 min [1]	23 miles [15]	$7.37 [17]	$60,922.35 [23]

England				
Barry, Wales	50.8 min [1]	20.74 miles [14]	$7.192 [18]	$90,366.57 [22]

We assumed the average miles per gallon to be 25.34 mpg [21].

3.4.4 Calculating Values

We calculated the amount of money saved on gas, time saved on commuting (which we converted to a monetary amount in terms of opportunity cost), and money saved on lessening CO_2 emissions (in terms of the predicted damage to the economy in dollars based on the pollution's effect on the environment).

Here is our calculating process for Seattle, which we applied to every other city listed:

Time Saved on Commuting Converted to Opportunity Cost

First, we calculated the number of hours one person in Seattle commutes to work in a year using the average round trip commute time which is 63.2 minutes [1]:

$$\frac{63.2\ minutes\ x48\ weeks \times 5\ days}{60\ minutes} = 252.8\ hours$$

Second, using the economic concept of opportunity cost, we assigned a monetary value to the time saved by not commuting in order to effectively weigh the importance of saving time with our other variables, such as money saved on gas. We decided that uniformity of units, in this case dollars, between the variables is the best way to compare the impact of working from home on each city.

We solved this by multiplying the average hours saved by the average hourly salary in a given city. We solved for average hourly wage by taking the average salary in a city and dividing by annual total hours worked by an average worker, which is 1920 hours. Opportunity cost in this scenario is defined as the money a person could be making annually by working instead of spending their time commuting, which, for Seattle, is solved by the equation:

$$252.8\ hours\ \times\ \$92,100/1920\ hours = \$12,126.82.$$

Therefore, based on our models, the annual economic gain the average person living in Seattle who works from home will experience due to saving time from not commuting is $12,126.82. The total amount of economic benefit for the city as a whole in terms of only time saved is calculated by multiplying this number by the number of people who are going to work from home in 2027, which equates to **$\$5.21\times10^9$**.

Money Saved on Gas

First, we must find the total number miles the average worker commutes to work in Seattle per year:

$$14\ mi/day \times 48\ weeks/year \times 5\ days/week\ = 3360\text{ mi/year}$$

In order to calculate the money one worker saves on gas by working at home instead of commuting to work, one must use dimensional analysis:

$$\frac{3360\ mi/year}{25.34\ mi/gal} = 132.597\ gal/year,$$

$$\frac{132.597\ gal/year}{} \times \frac{\$4.167}{1\ gal} = \$552.23 \text{saved on gas PER YEAR.}$$

We had to first find the total gallons the average Seattle worker used to drive ONLY to and from work in a year. Then we had to use that gallon amount and multiply it by the price per gallon to find the total amount the average Seattle worker spent on gas to drive to and from work.

Thus, if this average Seattle worker were to start working from home, he or she would not have to spend \$552.23 on gas, and is thus <u>saving</u> **\$552.23 on gas**.

To find how much money Seattle would be saving in gas IN TOTAL, we just have to multiply this value, \$552.23, and the total number of people who will be working from home based on our models from Part II and Part III, 429,479.

$$429{,}479 \times \$552.23 = \$2.37 \times 10^8$$

Finally, here is the total amount of money the city of Seattle will save in gas in 2027: **\$237,000,000.**

Carbon Footprint (CO_2 emission in air)

To determine the amount of money that each city will save in terms of their emission of CO_2, one will need to compare the gallons the average car in the given city uses in a year to travel to and from work to the ratio of pounds of CO_2 gas that is emitted per gallon and the economic impact of per ton of CO_2. Gallons used per year times pounds of CO_2 used per gallon times dollars of environmental damage per ton of CO_2 gives the total environmental damage in dollars caused by the average individual per year due to commuting, which is modeled by the equation:

$$\frac{132.597\ gal}{1\ year} \times \frac{20.35\ lbs}{1\ gal} \times \frac{\$50}{2000\ lbs} = \$67.46,$$

where the average Seattle commuter will prevent \$67.46 in environmental damages if they were to stop driving to work, and instead work from home.

To find the total amount of money Seattle will save in CO_2 emissions, we just multiply \$67.46 by the total number of remote-ready workers in Seattle in 2027, which leads us to a total amount of money saved as **$\$2.90 \times 10^7$.**

The following data table presents the numerics we arrived at for Seattle along with the rest of the cities.

Opportunity Cost for Commute	Money Saved for Gas	Money Saved in

Time (saved)		Environmental Impacts (CO_2 emission)
Seattle - $5.21×10^9$	Seattle - $2.38×10^8$	Seattle - $2.90×10^7$
Omaha - $6.56×10^8$	Liverpool - $7.21×10^7$	Omaha - $5.75×10^6$
Liverpool - $3.31×10^8$	Omaha - $3.82×10^7$	Liverpool - $4.98×10^6$
Scranton - $1.68×10^8$	Scranton - $1.48×10^7$	Scranton - $2.00×10^6$
Barry - $6.04×10^7$	Barry - $8.94×10^6$	Barry - $6.32×10^5$

3.5 Results

To find out the ultimate ranking of each of the five cities, we must add all of the dollar amounts and compare them. This is the final ranking of each city in order of most total economic benefit to least:

1) Seattle - $5.5x10^9$
2) Omaha - $7.0x10^8$
3) Liverpool- $4.1x10^8$
4) Scranton - $1.8x10^8$
5) Barry - $7.0x10^7$

In the end, Seattle had the highest amount of money saved due to time commuted, the highest amount of money saved in gas, and the highest amount of money saved in CO_2 emission. Also, by adding up the total money saved by each city as a whole, Seattle is still the city that would benefit the most from remote work, having the highest magnitude of (positive) impact.

3.6 Strengths and Weaknesses

If we had more time, we would have liked to create variables for each city to input to determine their magnitude of impact. For example, we had to assume an average mileage per gallon value, although it is not a fair depiction of every car in the cities listed.

However, we were able to use extensive dimensional analysis and our intuition to create a model that makes sense since we used such a common denominator as our magnitude of impact: money. Overall, we utilized something from every part and intertwined each model to end up with a qualitative ranking system, based on quantitative values.

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5 Appendix - Code

```python
import numpy as np
import math

def modifiedSigmoid(x):
    return (2 / (1 + math.exp(-1.5*x)))-1

s = """
1   1   1   1   1   1   1   1   1   1
0.4498919214    0.5763961339    0.9366636931    1.204430532 1.117943281 0.8880541857    0.4824668053    1.217400223 2.830802112 0.888337992
0.6848964413    1.405410327 1.063336307 0.7955694679    0.8820567188    1.111945814 0.7748709297    1.11698352  2.680939337 1.140546337
0.9753323144    1.018193539 0   0   0   0   1.265286979 0.6656162569    0.7244667178    0.5733053507
1.889879323 0   0   0   0   0   0.6173796038    0   2.780907511 1.370262789
0   0   0   0   0   0   0.9791238107    0   0.9828843224    0.8384139023
0   0   0   0   0   0   1.148265929 0   0   0.960008135
0   0   0   0   0   0   1.401053391 0   0   1.599829225
0   0   0   0   0   0   1.331552552 0   0   1.282199628
0   0   0   0   0   0   0   0   0   1.768377952
0   0   0   0   0   0   0   0   0   0.6829505725
0   0   0   0   0   0   0   0   0   0.562840102
0   0   0   0   0   0   0   0   0   0.6155996865
0   0   0   0   0   0   0   0   0   0.7173283275
"""
a = np.fromstring(s, sep=' ')
a.shape = (14,10)
def function(input):
    ans = 0.436
    for i,val in enumerate(input):
        ans *= a[val][i]
    return ans,modifiedSigmoid(ans)

# arr = [3,3,2,2,2,2,5,1,4,8] # Example used
# print(function(arr))
cities=[1.017041261,0.8950262189,0.5668838457,0.4351903752,0.4655526036]
citiesOut = [(i,modifiedSigmoid(i)) for i in cities]
print(citiesOut)
```