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Claremont McKenna College

A Case Study on the Impacts of COVID-19 on Remote Work and Compensation in the San Francisco Bay Area

Submitted to
Professor Ozbeklik
And
Professor Batta

By
Carson Stubstad

For
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Abstract

COVID-19 has changed the way that organizations conduct business. Stay-at-home orders shifted many workers, who traditionally worked in-person, to remote work. Research has been done to understand the macro impacts and organization impacts of remote work, but very little research has been conducted on the impact of wages. This paper studies the effects of remote work during and after COVID-19 lockdowns on wages. This thesis uses the San Francisco Bay Area as a case study. The findings suggest that remote workers are being paid higher after the lockdown in the area. I analyze these trends by controlling for a variety of compensation factors using Payscale Crowdsourced Data, which acts as an employee survey. The analysis extends to gender and top industries in the San Francisco Bay Area. The implication of this thesis suggests that remote work will be valued higher in the future and that more research should be done to follow these trends.

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I. Introduction

In 2020, Coronavirus (COVID-19) caused a worldwide pandemic. Across the planet, countries, businesses, and people were faced with finding a way to continue working while operating in a different world. For most of 2020, the majority of the world completely shut down their economies by calling for stay-at-home orders to prevent the spread of COVID-19. This sparked a dramatic shift in companies that conducted their business in person. Whether it was a service business, that needed to figure out contactless delivery, or a business that utilizes offices and employee interaction, without time to adjust, businesses and employees were thrust into remote work environments.

The discussion of remote work began to seem more indefinite than temporary when organizations noticed the success of remote work. Platforms like Zoom kept employees connected while saving on office space and utilities. In fact, Bloom (2015), a Stanford study found that remote workers had a 13% increase in performance and a 9% increase in minutes worked per shift. This showed the success of remote work despite initial hesitancy.

While the discussion was around performance and the organization, the question remained of how this shift in work conditions impacted the workers, particularly in wages. This study utilizes employee data from Payscale, Inc. to measure the impact of COVID-19 lockdowns on the earnings of the workers in the San Francisco Bay Area. I find that, relative to during the COVID-19 lockdowns, the wages of a remote worker (mostly telecommuting) are 2% higher after the lockdowns that took place in the San Francisco Bay Area. Expanding on the analysis, I look at the changes in wages based on gender and by industry. Similarly, I concluded that females' wages after the lockdowns (relative to during) were 2% higher. These findings are in line with the belief that remote work creates a higher level of productivity for organizations and other possible factors; however, these analyses are not complete. For example, looking by industry produced only some significant results reflecting the differences in attitude toward telecommuting and wages but not all. Industries including Information; Profession, Scientific, and Technical Services; and Management of Companies and Enterprises; Administrative and Support West Management and Remediation Services saw a difference of 3% for mostly telecommuters after the COVID-19 lockdown compared to during the COVID-19 lockdown, but the Manufacturing industry saw a -4% difference. More time to collect data is needed to create definitive conclusions about the impact on wages for other industries and genders. Many factors impact the wages of an individual, so this thesis focuses only on one factor, telecommute status while acknowledging the larger, more complex picture of labor markets during and after the COVID-19 pandemic.

In the remaining paper, I will be discussing these findings. In section 2, I discuss the current literature regarding compensation and remote work during COVID-19. Then in section 3, I will discuss the data provided by PayScale Inc. Next, in section 4, I will fully discuss the methodology and results of all analyses including gender and industry. Lastly, section 5 will conclude with thoughts of future research and the impact of the results.

II. Literature Review

Originating at the beginning of the COVID-19 pandemic sent a shock across labor markets around the world. It didn’t take long for shelter-in-place orders to be placed. Specifically in the San Francisco Bay Area, all 6 Bay Area Counties — San Francisco, Santa Clara, San Mateo, Marin, Contra Costa, Alameda — began their shelter-in-place orders on March 17, 2020.[1] All non-essential workers were sent home and the labor market was disrupted. By the end of April 2020, the unemployment rate rose 3.5% to 14.8%, which is the worst unemployment rate since the Great Depression.[2] This resulted in over 30 million people without work and industries like leisure and hospitality, education and services, and government crippled (Falk 2021). It affected employment status, businesses, work conditions, and wages in a way that no previous recession had done.

Within a month of the pandemic, the United States saw dramatically more unemployment claims than any month of the Great Recession (Coibion et al. 2020). Unusual to a typical recession that sees a larger impact on men, women took the toughest blow from layoffs. Albanesi and Kim (2021) studied this trend and found that roughly 66% of the aggregate decline was brought by women in spring 2020 and 63% in summer of 2020. This change was attributed to the overrepresentation of women in high-contact and inflexible occupations (typically service occupations), which were impacted the most. The impact of these unemployment numbers on households was large. With programs like Unemployment Insurance (UI) and the Coronavirus Aid, Relief, and Economic Security Act (CARES), the recovery was cushioned. Martin, Markhvida, Hallegatte, and Walsh (2020) model the poverty rates and recovery period during the COVID-19 Pandemic in the San Francisco Bay Area using a two-period crisis model. They predicted an increase in poverty rates from 17.1% to 25.9% and a recovery period

[1] San Francisco Bay Area COVID-19 timelines, sfchronicals.com
[2] A Bureau of Labor Statistics report, bls.gov

of 11.8 to 6.7 months. These impacts demonstrate the irregularity that the pandemic has brought and further reason to explore the impacts on the labor market.

COVID-19 heavily impacted the businesses that employ across the United States. Of these businesses, 99.7% of them were small businesses. Alekseev, Amer, Gopal, Kuchler, Schneider, Strobel, and Wernerfelt (2020) set out to determine how small businesses were impacted. With a 136-question survey and 66,000 responses, they found that 32.9% of firms closed operations due to COVID-19 and, 42% reported more outflows than inflows as of the end of April 2020. As a result, 44.5% of employers reduce their number of employees contributing to the unemployment numbers. However, throughout the pandemic layoffs were not the only factor contributing to shifts in employment. As 2020 continued, a "great resignation" began with quit rates increasing up to about 6%.[3] Workers began to grasp their destiny as work conditions changed and opportunities opened. This puts pressure on companies to adjust to changing work preferences and enthusiasm in the office.

The changing work preferences came primarily as a product of unsafe working conditions or more importantly, the shift to remote work. Brynjolfsson, Horton, Ozimek, Rock, Sharma, and TuYe (2020) conducted two surveys during the 2020 shelter-in-place and discovered that 35.2% of workers previously commuting were now working from home. That came to a total of 50% of the workforce working from home. This shift allowed for drastic changes in how companies thought about work. The businesses that moved to remote work began to invest in it and find that it paid off for the employee and the employer. Payscale's *2021 State of Remote Work Report* (2021) surveyed 682

[3] *2021 Wage and Labor Market Trends*, Payscale, 2021

companies and found that 50% expect remote or hybrid work to be offered after the pandemic. That number increases to 70% for occupations like marketing and IT. 73% of total organizations predict that remote work will change the competitive landscape of attracting and retaining talent. This is evident with the rise in quit rates. Remote work is becoming more attractive to employees that want to cut out commute time and stay home, and now, it is proven that employers can provide that.

Another form of remote work is hybrid offices. Payscale's *Remote Work Report* (2021) says that 47% of organizations say they will exercise by coming to the office 2-3 times a week. This means that not only fully remote work is now being offered but also hybrid conditions. This gives the employee flexibility for those who want to interact in person as well. Upwork's Chief Economist, Asam Ozimek, surveyed 1,500 hiring managers in April of 2020 and 40% believe that the benefits of remote work include lack of commute, fewer unnecessary meetings, and reduced distractions at the office (Ozimek, 2020). Remote work shows clear benefits for both the employee and the employer with a potential improvement in productivity. In fact, a working report states that the US labor productivity per hour grew by 3.2% in 2020 compared to 2019, which is the largest year-over-year growth since 2010 (Bloom et al. 2020). With these discoveries and changes in the labor market from COVID-19, the question remains as to how compensation has changed.

The focus of this paper is to discover the changes in compensation from fully remote (Mostly Telecommute) and somewhat remote work (Some Telecommute) throughout the pandemic. As we are still amid COVID-19, there is not any current research on the specific area of interest, but there are some tangential studies done by

Payscale that reflect the expectations and realities of wage changes coming out of the 2020 shelter-in-place. Payscale's *State of Remote Work Employer Survey* (2021) finds that 81% of organizations do not have a compensation strategy that encompasses remote work and 69% of organizations do not plan to lower pay for current employees that work remotely. This shows the uncertainty as to how the shift in working conditions will change wages; though 14% of organizations believe that they will pay lower for fully remote work if the employee is in a lower-cost area than the office. In the San Francisco Bay Area after the shelter-in-place was lifted on January 28, 2021, it is unknown how these wages have changed by the specific working conditions.[4] Holistically, there are larger trends from 2020 on the impact of COVID-19 on wage growth.[5] In the San Francisco-Oakland-Fremont area wage growth decreased from 5.4% in 2019 to 1.0% in 2020, and in the San Jose-Sunnyvale-Santa Clara area wage growth decreased from 2.4% to -0.5%. This can be related to the slowed economic growth and the need for companies to cut pay in response. However, industries vary like Technology. The industry grew by 3.4% in 2020 whereas Accommodations and Food Services shrunk by -10.2%. With some industries more impacted by others from COVID-19 and/or the shift to remote work, it raises the question of changes in wages by industry.

Through my analyses, we can contribute to this literature by addressing the 2% higher wages that mostly telecommuting workers have received after the COVID-19 lockdown. This potentially can be attributed to the increasing demand for that type of work and the benefits in productivity that it produces. For gender and industry, not

[4] News release for the stay-at-home order lifted, sfmayor.org
[5] *The impact of current economy on Wage Growth*, Payscale, 2021

enough can be definitively concluded to contribute, but we can see that the value in wages for telecommuters vary by industry as addressed in section 1.

III. Data

Payscale is a compensation company that specializes in software and data. Their software products allow for compensation professionals to accurately set wages based on market data provided by Payscale or other compensation data sources. Traditionally, this data comes from companies that participate in compensation surveys and share their data. The aggregated data is then used to price jobs. [6] The downside to this method is that the data is collected quarterly, and it is hard to find real-time changes in salaries. Lucky for the industry and this analysis, Payscale has pioneered a new data source called Crowdsourced Data.[7] Payscale collects thousands of profiles daily from individuals who fill out their survey online to discover their job's price. This data can be aggregated to research wage trends using hundreds of characteristics.

I obtained data on October 21, 2021, for all 6 San Francisco Bay Area counties from Payscale, Inc. This data collected all job profiles under the conditions that they are in the Bay Area and filled out the telecommute question. The first variable of interest lies within the telecommute question:

Are you able to telecommute / work from home?

I. Yes, I telecommute 100% of the time
II. Yes, I telecommute most of the time
III. Yes, I telecommute some of the time
IV. Yes, I telecommute as an as-needed basis only (e.g., furniture delivery)

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[6] Payscale calls this data, Company Sourced data. Similarly, companies like Mercer, Aon-Radford, and Willis Towers Watson are similar companies that produced these types of compensation surveys.
[7] Crowdsourced Data survey location, payscale.com

V. No, I can't telecommute

In the analysis, I consolidate into three dummy variables: *telecommute_yes*, *telecommute_some*, and *telecommute_no*. I designated "Yes, I telecommute 100% of the time" and "Yes, I telecommute most of the time" as an occupation that mostly telecommutes (Mostly Telecommute); "Yes, I telecommute some of the time" as an occupation that sometimes telecommutes (Some Telecommute); "No, I can't telecommute" and "Yes, I telecommute as an as-needed basis only (e.g., furniture delivery)" as an occupation that does not telecommute (No Telecommute).

The second variable of interest is the time period. The data is collected from January 1, 2016, to October 20, 2021. To measure the effect of remote work (telecommuting) during the COVID-19 shelter-in-place, I create three dummy variables: *pre lockdown*, *during lockdown*, and *post lockdown*. *Pre lockdown* is all data collected before the Bay Area shelter-in-place on March 17, 2021, *during lockdown* is all data collected during in the shelter-in-place until January 28, 2021, and *post lockdown* is all the data collected after. I also create nine interaction variables between time period dummies and remote work status to measure the differences in compensation trends based on the extent of telecommuting.

Table 1

Descriptive Statistics of All Variables

Key Variables

Variable	Percentage of Data
Telecommute Status	
Never telecommute (no)	68.44%
Some telecommute (some)	18.35%

Mostly telecommutes (yes)	13.21%

Continuous Control Variables

Variable	Mean	SD	Range
Total Cash Compensation ($)	92823.54	53104.51	12000 - 750000
Years of Experience (years)	8.96	8.25	0 - 55
Age (years)	36.50	11.32	16 - 99

Categorical Control Variables

Variable	Percentage of Data
Gender	
Male	49.80%
Female	50.21%
Education Status	
High School Diploma	17.64%
No Degree	7.26%
Associate Degree	7.05%
Bachelor's Degree	47.45%
Master's Degree or Higher	20.60%
Labor Market	
Napa	1.37%
Oakland-Hayward-Berkeley	23.09%
San Francisco-Redwood City-South San Francisco	42.23%
San Jose-Sunnyvale-Santa Clara	28.22%
Santa Rosa	5.08%
Business Size (Employee #)	
Size Class 1 (1-4)	8.94%
Size Class 2 (5-9)	5.54%
Size Class 3 (10-19)	6.51%
Size Class 4 (20-49)	9.88%
Size Class 5 (50-99)	8.94%
Size Class 6 (100-249)	12.95%
Size Class 7 (250-499)	7.48%
Size Class 8 (500-999)	6.88%
Size Class 9 (1000+)	32.88%

Note: N = 35208

These variables are used as key independent variables for the analysis of wages. In addition to these variables, there is the dependent variable, *tcc*. *Tcc* represents the total cash compensation of a given occupation. This will be used as the proxy for wages due to a lack of data consistency in base salary. Total cash compensation is the combination of base salary and short-term incentives such as bonuses and sales commissions.

Table 1 shows the average wage of all historical data in the Bay Area. For the regression to reflect the percent change in *tcc* I have decided to use the natural log of total cash compensation, so *tcc*'s value is reflected as Ln(*tcc)*.

The data contained a variety of control variables including years of experience, age, gender, race, location, industry, and others shown in Table 1. The final regression contained 38 coefficients due to the large number of binary variables created for the categorical variables in the data set. Table 1 contains the summary statistics of key and control variables. Some dummy variables included will later be excluded to prevent a dummy variable trap.

The variables in Table 1 are broken into continuous and binary variables. Other than *tcc,* two other continuous variables are age and years of experience. As most fields are, the compensation survey keeps most questions optional. Deciding whether to include the *NA* values or not had an impact on the analysis. In the case of continuous variables, all *NA* values are omitted from the regression. That removes 9,156 observations from the total 59,658 observations.

The binary variables used in this analysis consist of categorical information that makes up the identity of each individual: gender, education level, industry, business size, metropolitan area, skills, certifications, and race. Due to the lack of completion (large number of *NA)*, skills, certifications, and race have been removed for the final analysis. As for the rest of the categorical variables turned to binary variables, it goes as follows:

Gender has been filtered for "male" and "female" responses to avoid *NA*s or the low number of "Prefer to self-define" (200 observations). This is also relevant for the extension of this analysis based on gender.

Education level represents the education level of the individual. To clean up the education data, all responses with *NA* have been removed and the responses were consolidated into the 5 categories seen in Table 1. This uncovered the large percentage of individuals that have completed higher education in this dataset.

Business size reflects the U.S. Bureau of Labor Statistics classification of business size depending on total employee count.[8] NA values were removed to accurately control for business size. The largest two levels are levels 6 and 9 which can be reflected by a large number of technology companies (Code 5 other) within the region.

Labor markets represent the metropolitan or labor market within the greater San Francisco Bay Area that the individual's occupation. These dummy variables act as a control for the local labor markets within the area.

Additionally, this analysis contains an industry fixed effect. The data represents the NAICS 50 classification for the employer's industry.[9] *NA* values are included as a binary variable in this analysis to be used as the omitted dummy variable for industries. Of the 20 different classifications, I consolidated the industries into 12 codes utilizing the

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[8] Businesses are broken up into 9 classes by number of employees (range): Level 1 (1-4), Level 2 (5-9), Level 3 (10-19), Level 4 (20-49), Level 5 (50-99), Level 6 (100-249), Level 7 (250-499), Level 8 (500-999), Level 9 (1000+), bls.gov

[9] For a complete breakdown of NAICS codes and industry titles, naics.com.

first digit of the two-digit code and prior knowledge of the area. Later in this analysis, I will discuss the changes in wages for the top five highest represented industry groups.

IV. Estimation Methodology and Results

To estimate the relationship between telecommute status and wages (total cash compensation) during and post COVID-19 shutdowns, I estimate the following regression equation,

$$
\begin{aligned}
ln\ tcc_{ijt} = \beta_0 + \ \beta_1\, DURING_t + \ \beta_2\, POST_t + \ \beta_3\, TELE_{SOME} + \ \beta_4\, TELE_{YES} \\
+ \ \beta_5\,(TELE_{SOME} \times DURING_t) + \beta_6\,(TELE_{SOME} \times POST_t) \qquad (1) \\
+ \beta_7\,(TELE_{YES} \times DURING_t) + \beta_8\,(TELE_{YES} \times POST_t) \\
+ X_i'\,\mu + \gamma_j + \varepsilon_{ij}
\end{aligned}
$$

where $ln\ tcc_{ijt}$ the natural log of total cash compensation for individual *i* in industry *j* at time *t*; $DURING$ and $POST$ are binary variables taking the value of 1 for the time period during and after the COVID-19 shutdowns, respectively; $TELE_{SOME}$ and $TELE_{YES}$ are binary variables taking the value of 1 for individuals who telecommute some of the time and most of the time/always, respectively; X_i' is the vector of controls including gender, age, years of experience, education level, labor market, and business size; and γ_j are the industry fixed effects.. The variables of interest are the 4 interaction variables, YES × DURING ($TELE_{YES} \times DURING_t$), YES × POST ($TELE_{YES} \times POST_t$), SOME ×

DURING ($TELE_{SOME} \times DURING_t$), and SOME × POST ($TELE_{SOME} \times POST_t$). [10] The coefficients for these interaction binary variables capture percent the difference-in-differences in total compensation relative to the excluded category (individuals who do not telecommute) and time period (pre-COVID 19 lockdowns). For example, the coefficient estimate for $TELE_{SOME} \times DURING_t$, β_5 , measures the percent difference in total compensation between individuals who can telecommute some of the time and individuals who could not telecommute during the COVID-19 lockdowns relative to the corresponding difference before the lockdowns. Similarly, for $TELE_{YES} \times POST_t$, β_8 , the coefficient estimate measures the percent difference in total compensation between individuals who can telecommute most of the time and individuals who could not telecommute after the COVID-19 lockdowns relative to the corresponding difference before the lockdowns.

As an extension of this analysis, I conducted an analysis on the differences of wages based on telecommute status for gender and some of the industries in the San Francisco Bay Area.

For gender, the same regression was run but in two iterations. The two iterations separate the data between males and females. These two regressions are referred to as Male Only and Female Only regressions as seen in Table 3, Column 2 and 3.

The next is the industry analysis, based on the number of observations, I analyzed the top 5 industry sub-sections that were grouped based on NAICS codes. In order of largest to smallest:

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[10] YES × DURING – Mostly telecommute and during lockdown; YES × POST – Mostly telecommute and post lockdown; SOME × DURING – Sometimes telecommute and during lockdown; SOME × POST – Sometimes telecommute and post lockdown

Table 2

Industry Sub-Sections

Variable Name	Industries
Code 5 (Other)	Information; Professional, Scientific, and Technical Services; Management of Companies and Enterprises; Administrative and Support and Waste Management and Remediation Services
Code 3	Manufacturing
Code 6 (Health Care)	Health Care and Social Assistance
Code 5 (Real Estate and Finance)	Finance and Insurance; Real Estate and Rental and Leasing
Code 2	Mining, Quarrying, and Oil and Gas Extraction; Utilities; Construction

The same regression was run like the original for all 5 industries, however, each data set was filtered to only contain individuals that marked their employer under that industry group. Results in Table 4 will be discussed later in this section.

As previously stated, the goal of this analysis is to begin understanding the impacts of telecommuting on compensation. Now looking at the results, I can pick up on some new trends, but it left some questions unanswered. Potentially due to the limited number of observations (among a variety of unforeseen factors) in the *during lockdown* and *post lockdown* time period relative to *pre lockdown*, which spans across multiple years, I see that some of the results are not significant enough to make confident conclusions. Nevertheless, the data produces some trends that can begin to be measured for future analyses.

The main results are presented in Table 3, Column 1. There is a complete list of key variables used to predict the natural log of total cash compensation. Looking at the coefficients for telecommute status, we can assume a positive coefficient means that wages are higher than the excluded non-telecommuters. For example, seeing that some telecommuters have 14% higher wages than non-telecommuters, then I can assume that these jobs are typically higher-paying jobs on average than the other category.

Table 3

Complete and Gender Regressions Results

	All Data	Male Only	Female Only
Some Telecommute	0.14*** (0.01)	0.14*** (0.01)	0.14*** (0.01)
Mostly Telecommute (YES)	0.05*** (0.01)	0.05*** (0.01)	0.04*** (0.01)
During Lockdown	0.03*** (0.01)	0.02 (0.01)	0.05*** (0.01)
Post Lockdown	0.03* (0.01)	0.02 (0.02)	0.04* (0.02)
YES × DURING	0.08*** (0.02)	0.09*** (0.02)	0.07*** (0.02)
YES × POST	0.10*** (0.02)	0.09*** (0.03)	0.10*** (0.02)
SOME × DURING	0.01 (0.02)	0.01 (0.02)	0.00 (0.02)
SOME × DURING	0.01 (0.02)	0.02 (0.03)	0.01 (0.03)
Other Controls	Yes	Yes	Yes
Constant	10.45*** (0.01)	10.61*** (0.02)	10.45*** (0.02)
Observations	35208	17530	17678
Adjusted R^2	0.52	0.52	0.47

Note: Significance: *0 '***' 0.001 '**' 0.01 '*' 0.05 ' · ';*
Heteroskedastic robust standard errors are used in this analysis;
N = 35209

Unfortunately, I cannot confidently conclude how Some Telecommuters significantly change during and after the lockdown, but maybe that is due to the lack of data. The shift to hybrid work has just begun and that potentially will show a larger change in sometimes telecommuting individuals.

In Table 3, Column 1, there are significant findings to highlight. In general, mostly telecommuters have, historically, had 5% higher wages than non-telecommuters in the time period before the COVID lockdowns. Wages for all workers during and after the COVID-19 lockdown are 3% higher wages than before the COVID-19 lockdown, and the two interaction variables, YES × DURING and YES × POST*,* are 8% and 10% higher than non-telecommuters before the lockdown. This shows that mostly telecommuters had higher wages increasingly higher wages than non-telecommuters before the lockdowns.

In order to understand the change in wages for mostly telecommuters after the COVID-19 lockdown relative to during, I must add the coefficients of the interaction variables to the individual coefficients of each variable and subtract the two. For example, to understand the complete change in mostly telecommuters during COVID-19, I must add the coefficient for mostly telecommuters, the coefficient for the time period during, and the interaction variable between the two. Once finding that, I can subtract it from the total change in wages for mostly telecommuters after the COVID-19 lockdowns. Following these steps, the difference between the two, 2%, reveals that wages increased by 2% for mostly telecommuting individuals from during the lockdown to after. This difference reveals that there is indeed a premium for remote workers coming out of the San Francisco Bay Area lockdown. This can point to the increasing trend and organizational emphasis on remote work. Though Payscale's State of Remote Work Employer Survey (2021) finds that 81% of organizations do not have a compensation strategy that encompasses remote work, it seems that there is significant enough evidence to say that there is a small premium coming out of the lockdown. It is worth noting that this shows a positive correlation for remote workers having higher wages, however, it is not causation as there are many other unforeseen factors.

To further dig deeper, I explore if these trends for telecommuters are the same among male and female genders. Looking at Table 3, there is inconclusive evidence of these trends remaining the same among males and females. For starters, though not all significant, I can see that in the Male Only regression, men have 9% higher wages for both interaction variables, during and after the quarantine, where telecommute is yes. Looking at the interaction variables, we can see that mostly telecommuters during, and post COVID-19 lockdown were paid 9% higher than non-telecommuters before COVID-19. In the female regression, I find 7% higher wages for females that are mostly telecommuting during the lockdown and 10% higher wages for females that are mostly telecommuting remote after the lockdown (relative to non-telecommuters before COVID). Using the method of adding up interaction and respective individual coefficients and subtracting the two, in the Female Only Regression, that mostly telecommuting females saw an increase of 2% in wages after the lockdown relative to during the lockdown. This is reflective of the larger finding that telecommuters produce a premium after the lockdown.

Lastly, I look at the difference in telecommuters based on the top 5 represented industry groups (see Table 2 for industry names). These regressions (shown in Table 4) unfortunately do not produce significant enough findings to draw conclusions. The only variable that contains significance across all industry groups is Some Telecommute. For interpretation, I can say with 95% certainty that Code 2 has the lowest increase in wages of 6% for Some Telecommuters relative to non-telecommuters before the COVID-19 lockdowns.

Focusing now on the key interaction variables, individually, Code 5 (Other) and

Table 4

Industry Regressions

	Code 5 (Other)	Code 3	Code 6 (Healthcare)	Code 5 (Real Estate and Finance)	Code 2
Some Telecommute	0.12*** (0.01)	0.13*** (0.02)	0.14*** (0.03)	0.14*** (0.02)	0.06· (0.03)
Mostly Telecommute (Yes)	0.06*** (0.01)	-0.01 (0.02)	-0.01 (0.03)	0.08*** (0.03)	-0.03 (0.03)
During Lockdown	0.03· (0.02)	0.01 (0.02)	0.06· (0.03)	0.06 (0.04)	0.07* (0.03)
Post Lockdown	0.01 (0.02)	0.01 (0.03)	0.12*** (0.03)	-0.03 (0.05)	0.10* (0.04)
YES × DURING	0.07* (0.03)	0.16*** (0.05)	0.08 (0.06)	-0.03 (0.06)	0.01 (0.07)
YES × POST	0.10*** (0.03)	0.12* (0.05)	0.03 (0.07)	0.13· (0.07)	0.00 (0.08)
SOME × DURING	0.01 (0.03)	0.07 (0.04)	-0.06 (0.06)	-0.02 (0.06)	0.03 (0.06)
SOME × DURING	0.03 (0.03)	0.03 (0.05)	-0.05 (0.07)	0.10 (0.08)	-0.01 (0.07)
Other Controls	Yes	Yes	Yes	Yes	Yes
Constant	10.71*** (0.02)	10.56*** (0.03)	10.37*** (0.03)	10.55*** (0.04)	10.48*** (0.04)
Observations	13544	4284	3267	2828	2235
Adjusted R^2	0.46	0.56	0.46	0.46	0.48

Code 3 have significant interaction variables for mostly telecommuters. Looking at Code 5 (other), relative to pre lockdown, we can see that the interaction coefficient for after the lockdown is 3% higher than the interaction for during. For mostly telecommuters during the lockdowns, they had 7% higher wages relative to non-telecommuters before the lockdowns and after the lockdowns they had 10% higher wages (relative to non-telecommuters before the lockdowns). Comparatively, Code 3 has 4% lower wages which may show that mostly telecommuters were valued less after the lockdown. However, trends show that wages were 16% higher for mostly telecommuters during the COVID-19 lockdowns and 12% higher after the COVID-19 lockdowns (relative to non-telecommuters before the lockdowns). This can show the difference in importance of telecommuting by industry like discussed in section 2, but also could indicate an increasing value of being a mostly telecommuting worker even in an industry like Code 3 (manufacturing).

The lack of significance for the rest can be partially attributed to the limited number of data posts spread across 6 different binary variables that further segment the data. Looking at the number of observations in each regression, I can begin to understand the lack of significance. For example, at the most Code 5 (other) has 13544 observations and at the least Code 2 has 2235. Looking at the time periods, the observation begins to split more which could lessen the significance in the results, however, that provides a future opportunity for more data after the lockdowns to be collected.

V. Conclusion

This thesis attempts to measure the changes of compensation for mostly telecommuters (remote workers) during and after the San Francisco Bay Area COVID-19 lockdown taking place from March 17, 2020, to January 28, 2021.

After controlling for a variety of compensation factors such as age, gender, years of experience, industry, company size, and more, I can to conclude that remote workers have been paid higher after the lockdown. This may suggest that remote workers will be valuable in the future. As the "Great Resignation" continues and new variants of COVID-19 prevent a full return to the office, companies will begin to face the decision of how to attract new workers. They could be offering higher wages for employees that are best while fully telecommuting, or the premium could be simply product of needing to attract new talent.

Through the analyses conducted on gender and industry, we can conclude that there is a potential difference between gender and industry as predicted. Though there is not complete confidence in this analysis, it shows promise that future work can find the differences in preference for remote work by the two categories and the impact on wages.

Going into the future as more data is collected, this analysis can be replicated to utilize more up-to-date data that can contain a larger sample size for the *post lockdown* time period group. As companies begin to get a grip on the impact of remote work on their business, these changes will boil down to the wages of the workers. As was attempted with the industry analysis, it is known that this workplace trend will not heavily impact all industries because some like the Accommodation and Food Service industry, which traditionally requires in-person work. Further analysis can be a vital indicator as to how the future of work will shift holistically and by industry.

Another extension of this analysis could be utilizing, traditional compensation data that is collected by companies like Payscale through company-sourced data instead of employee-sourced data. This could allow for more complete sets of data due to the requirements that companies have while reporting their compensation data. The only downside is the lack of timely data as these data sets are usually completed quarterly or annually and the data is limited to the requirements.

The San Francisco Bay Area is a large expanse area containing 5 metropolitan areas and a variety of industries. Utilizing the data of this region, I can conclude that there is evidence of remote work having higher wages after the COVID-19 lockdown in 2020, and the United States may have felt a similar impact. Particularly in metropolitan areas that are dense in population, remote work may be seen as the more streamlined form of work for the future that in turn produces higher wages for the workers.

VI. References

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