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Summary of Findings

Overview

The work-from-home (WFH) conversation is one that has gained considerable traction in recent years, and has inspired organizational restructuring of different industries and sectors towards the functionality of work away from the office. While some companies utilize WFH strategies to minimize operational costs or shut down underutilized office spaces, others explore WFH policies as a response to employment patterns and employee behaviors, as is applicable in the case of interest.

For the company of interest, a Chinese travel agency referred to as company *XYZ*, employee retention has been flagged as a business concern, likely due to unmanageable commute times to the central office. Ultimately, *XYZ* is interested in making decisions on WFH policies based on its effect on employee retention and their satisfaction. While the costs of commuting can be mitigated by WFH policies, *XYZ* wants to be mindful of possible impacts of WFH on worker productivity as offices provide spaces for team building, networking, and focused work. This productivity is quantified by a performance score which is measured based on the average number of calls per hour and total monthly score. Based on the nature of their work, trial WFH policies were enacted on the call center employees who assist customers with booking orders and resolving issues over the phone.

Participants were randomly divided into treatment and control groups evenly with the only difference between both groups being their location of work (home vs. the central office). The data provided to our consulting team on performance was panel data, and thus we used differences-in-differences to uncover an unbiased estimate of causal effect of WFH policies on performance.

To analyze the effect of WFH on retention, we used data provided by the company on the employees in the sample group who had quit from their roles during the study period. Our outcome variable *quitjob* took on binary values of 1 if the employee quit during the study period and 0 if they retained their position. The resulting regression produced a linear probability model where the coefficient of the treatment variable gives an estimated prediction of the effect of WFH policies on employee retention.

Data Cleaning

Data set	Observation	Variable(s)	Value(s)	Change and reason for change
EmployeeCharacteristics.dta	personid = 5018	age, tenure	-99, -99	Impossible values. Age and tenure cannot be negative. Changed to missing value.
EmployeeCharacteristics.dta	personid = 26618	age, tenure	-99, -99	Impossible value. Age and tenure cannot be negative. Changed to missing value.
Performance.dta	personid = 29216	performance_score	176.3382	Impossible value. Avg performance evaluation on a scale of (0-100). Changed to missing value.
Performance.dta	personid = 29996	performance_score	278.1695	Impossible value. Avg performance evaluation on a scale of (0-100). Changed to missing value.
Performance.dta	personid = 21710	total_monthly_calls, calls_per_hour	0, 18.97752	Total monthly calls cannot be zero if calls_per_hour is non-zero. Changed to missing value.
Performance.dta	personid = 38046	total_monthly_calls	-108951.9	Total monthly calls cannot be negative. Changed to missing value.
Performance.dta	personid = 39530	total_monthly_calls, calls_per_hour	0, 21.15223	Total monthly calls cannot be zero if calls_per_hour is non-zero. Changed to missing value.
Attitudes.dta	No problem values			
QuitDate.dta	No problem values			

As a part of the data cleaning and organization process, many data files were also merged using STATA as needed throughout the analysis using *personid* as the variable to link multiple datasets together. STATA was also used to run all regression models and create visualizations.

Exploratory Data Analysis

The treatment and control groups were randomly selected which eliminates any selection bias present in this experiment. To confirm this, a balance table (Figure 1) was constructed to determine whether or not receiving a treatment was correlated with any employee characteristics, and the analysis found that there is no significant correlation between treatment and any characteristic at the 1% significance level. There was a correlation between *treatment* and *married* at the 5% significance level, but this will be disregarded as the relationship is not significant at the 1% level, and the treatment group was randomized, so this is likely due to chance. Because there is no correlation between receiving the treatment and any of the provided employee characteristics (excluding whether or not an employee is married), heteroskedasticity is not a major concern when determining the effect of the treatment on both employee performance and retention.

Additionally, before conducting any statistical tests, we created histograms to visualize the number of employees that quit in each month of the period when the treatment was being implemented for both the treatment and control groups. It appears that the data was not normally distributed for either group as seen in Figures 2a and 2b. It is interesting to note that for the control group, the distribution is positively skewed; for the treatment group, the distribution is negatively skewed.

Histograms (Figures 3 a-c) were also made for each of the performance metrics to visualize the distribution of data among all employees in both the treatment and control groups. Outliers were minimal: one employee had a performance score in the 50s range, compared to an average in the 70s. Another employee yielded a perfect performance score (100). Regardless, these values were still within the possible ranges for each measurement, so they were included in calculations as we were unable to confirm that these measurements were in fact errors.

Effects of Working from Home on Employee Performance

Because information on employee performance was provided before and after the implementation of the WFH policy, a difference-in-differences approach was used to analyze this panel data. The purpose of this method is to determine if there is a significant effect on a treatment (in this case, changing the working policy to four days at home and one day in-office per week for some employees as opposed to the original policy of five days working in-office) by comparing changes in a measured variable (in this case, the three performance metrics were used) between the group that received the treatment and the group that did not (the control group) over time. This approach requires the assumption that the treatment and control group have parallel trends in the measured variables before the treatment/policy is implemented; this assumption was verified with the balance table showed in Figure 1 as the two groups do not have any statistically significant differences in characteristics, and therefore, are expected to have parallel trends in the performance metrics during the pre-treatment periods.

To determine the effect of receiving the treatment (being selected to participate in the new WFH model) *after* the treatment went into effect on each of the three performance measurements (performance score, calls per hour, and total monthly calls), the following three regression models were created:

$$\widehat{performance\ score} = \hat{\beta}_0 + \widehat{\beta_{treatment}}\, treatment + \widehat{\beta_{post}}\, post + \widehat{\beta_{treatment*post}}\,(treatment * post)$$

$$\widehat{total\ monthly\ calls} = \hat{\beta}_0 + \widehat{\beta_{treatment}}\, treatment + \widehat{\beta_{post}}\, post + \widehat{\beta_{treatment*post}}\,(treatment * post)$$

$$\widehat{calls\ per\ hour} = \hat{\beta}_0 + \widehat{\beta_{treatment}} treatment + \widehat{\beta_{post}} post + \widehat{\beta_{treatment*post}} (treatment * post)$$

Based on the results of these regressions (Figure 4), it appears that the differential effect of being selected for the WFH working model and after this policy went into effect has a significant effect on performance score (very significant, at the 1% significance levels), total monthly calls (at the 5% significance level), and calls per hour (at the 5% significance level).

It also appears the the average performance score and average total monthly calls metrics decreased for the control group after the policy was implemented (as seen from the negative value for the "post" variable coefficient in those two regressions shown in Figure 4), and it is expected that the same would have happened for the treatment group over time if the WFH policy had never gone into effect. The average calls per hour increased for the control group even after the policy went into effect, so this metric would have increased over time, but the presence of the treatment caused the average calls per hour to increase at a higher rate (the coefficient for "post" - 0.325 - is less than the coefficient for "post x treatment" - 0.578).

From this analysis, **we can conclude that working from home did have a positive significant effect on the three performance metrics**, especially for performance score and total monthly calls which both would have decreased from December 2010-August 2011 in comparison to pre-December 2010 data for both the treatment and control groups (i.e., all employees at the company).

It should also be noted that we checked for correlation between each performance variable from the pre-treatment period data and several employee characteristics (age, tenure, cost of commute, rental, male, married, and high_school) as seen in Figure 5, and no statistically significant relationship was found between any of these variables, so omitted variable bias is not a major concern for this analysis. The wage characteristics were not included in this correlation test because we know that the bonus (and, resulting, the gross wage) is determined using an employee's performance metrics.

Effects of Working from Home on Employee Retention

Data on whether or not an employee quit was not available for the pre-WFH policy period, so a difference-in-differences approach was not appropriate for analyzing the effect of working from home on employee retention.

Instead, a linear probability model was used to determine the probability of an employee quitting from December 2010-August 2011 (the WFH experiment period) depending on whether that employee is in the treatment or control group. The following linear probability model equation was used:

$$P(quitjob = 1 \mid treatment) = 0.3474576 - 0.1871523 treatment$$

Using this model, it can be concluded that the predicted probability of quitting is 16% for those working from home four days per week and in-office one day per week, and the predicted probability of quitting for those working in-office all five days per week is 34.75%; both of these predicted probabilities are statistically significant (Figure 6). As a result, **it can be concluded that working from home does have a statistically significant and positive impact on retention**.

It is important to note that a logit model can also be used to predict the probability of employees in the treatment and control groups quitting during the duration of the experiment; however, a linear probability model was utilized in this instance due to easier interpretability when communicating the findings to the client. The logit model also yields the same conclusion that working from home does have a statistically significant and positive impact on retention (Figure 7). However, using the logit model, the predicted probability of employees in the control group (those working in-office five days per week) quitting is 65.25%, and the predicted probability of employees in the treatment group (those working from home four days per week and in-office one day per week) quitting is 40.24%.

The logit model predicted probabilities were derived using the coefficients in Figure 7 and the following equation:

Probability that employees that worked from home and subsequently quit their job during the study period = p_i

$$p_i = \frac{1}{1 + e^{-(0.6302334\,-\,1.025725(0))}}$$

$$p_i = \frac{1}{1 + e^{-(0.6302334\,-\,1.025725(1))}}$$

It is important to note that omitted variable bias is a possible source of error. We checked for any correlation between *quitjob* and what we assumed to be time-constant employee characteristics for the course of the experiment such as age, rental, male, married, and high_school, and we found no statistically significant correlations (Figure 8). However, we were unable to check whether base wage, bonus, and/or gross wage have a significant effect on probability of quitting because we do not have any post-treatment data on these variables, and we can assume that these vary as they are dependent on performance, and the treatment was found to have a causal effect on the performance metrics.

Additional Analysis and Future Direction

In addition to analyzing the effects of receiving the treatment (being placed into the WFH group), we also analyzed the effect of receiving the treatment on employees' satisfaction levels at work. This relationship was examined using the difference-in-differences model because panel data was provided (we were provided with satisfaction data in both the pre- and post-treatment periods for each employee in the sample, so a similar approach to how the performance data was analyzed was implemented). From these findings, **we can see that working from home had a statistically significant and positive impact on employee satisfaction levels after the WFH**

policy went into effect (December 2010-August 2011) at the 1% significance level (Figure 9). From this regression, we can also see that just being selected into the treatment group did not have a statistically significant effect on the average satisfaction at work per employee (pre-treatment going into effect), and the average satisfaction at work did not have a statistically significant change for employees in the control group after the WFH policy was implemented.

Furthermore, another regression was done to see if there is a relationship between average employee satisfaction during the treatment period and probability of quitting after the treatment was implemented across all employees; this relationship was found to not be statistically significant (Figure 10).

Additionally, a regression with an interaction term that combines the "satisfaction" and "treatment" variables into "satisfaction * treatment" (because we saw that treatment is correlated with satisfaction as seen from the regression output in Figure 9) was conducted to see if this interaction term shows an effect on the probability of quitting after the WFH policy was implemented. As seen in Figure 11, there is no significant relationship between satisfaction*treatment and the probability of quitting. This was a surprising result, as we had initially predicted satisfaction at work to have a statistically significant effect on employee retention. If more time and data are available, we would be interested in investigating this relationship further as well as seeing if any other variables contribute to retention and how satisfaction at work may potentially be used as an instrument variable or other contributor towards studying retention trends among employees in both the short- and long-term.

It may also be interesting to perform this experiment at other offices locations within the company (if there are multiple) to determine whether commute times are a company-wide major concern for employees and/or whether a hybrid in-office/WFH model works well for all employees across all of the company's locations. It may also be beneficial to allow participants to choose whether or not they want to fully WFH, work in a hybrid model, or work fully in-person; while this will cause selection bias, the ability to choose a working model may have a significant impact on both performance and retention, and this effect may potentially be even greater than the treatment effect studied in this experiment.

Conclusion

As mentioned above, the treatment, working from home for four out of five shifts, had a significant causal effect on both employee performance (measured by performance score, average total monthly calls, and average calls per hour for each worker) and employee retention (measured by whether or not an employee quit in a specified period). Based on the current findings, it is recommended that the client expands the work from home policy to other departments in the company where necessary to reduce the burden of commuting and improve employee satisfaction. However, as mentioned previously, it may be beneficial to run alternative experiments (such as allowing participants the option to self-select into different working model groups) and/or examine other variables more in-depth before implementing this policy and requiring all employees to WFH four days per week.

Appendix:

Figure 1. Balance Table using the Employee Characteristics data

	Control	Treatment	Difference between Groups
age	24.347	24.403	0.056
	(3.536)	(3.572)	(0.453)
tenure	28.254	25.674	-2.580
	(21.938)	(21.547)	(2.769)
basewage	1,562.799	1,539.864	-22.935
	(185.397)	(136.157)	(20.480)
bonus	1,092.587	1,030.901	-61.685
	(655.717)	(597.664)	(79.430)
grosswage	3,003.362	2,949.730	-53.632
	(825.599)	(758.050)	(100.362)
costofcommute	8.338	7.892	-0.446
	(5.554)	(8.031)	(0.884)
rental	0.203	0.244	0.041
	(0.404)	(0.431)	(0.053)
male	0.466	0.466	-0.000
	(0.501)	(0.501)	(0.064)
married	0.322	0.221	-0.101*
	(0.469)	(0.417)	(0.056)
high_school	0.864	0.824	-0.040
	(0.344)	(0.382)	(0.046)
Observations	118	131	249

Figure 2. Histograms of the distribution on quit month for all employees that quit in (a) control group and (b) the treatment group.

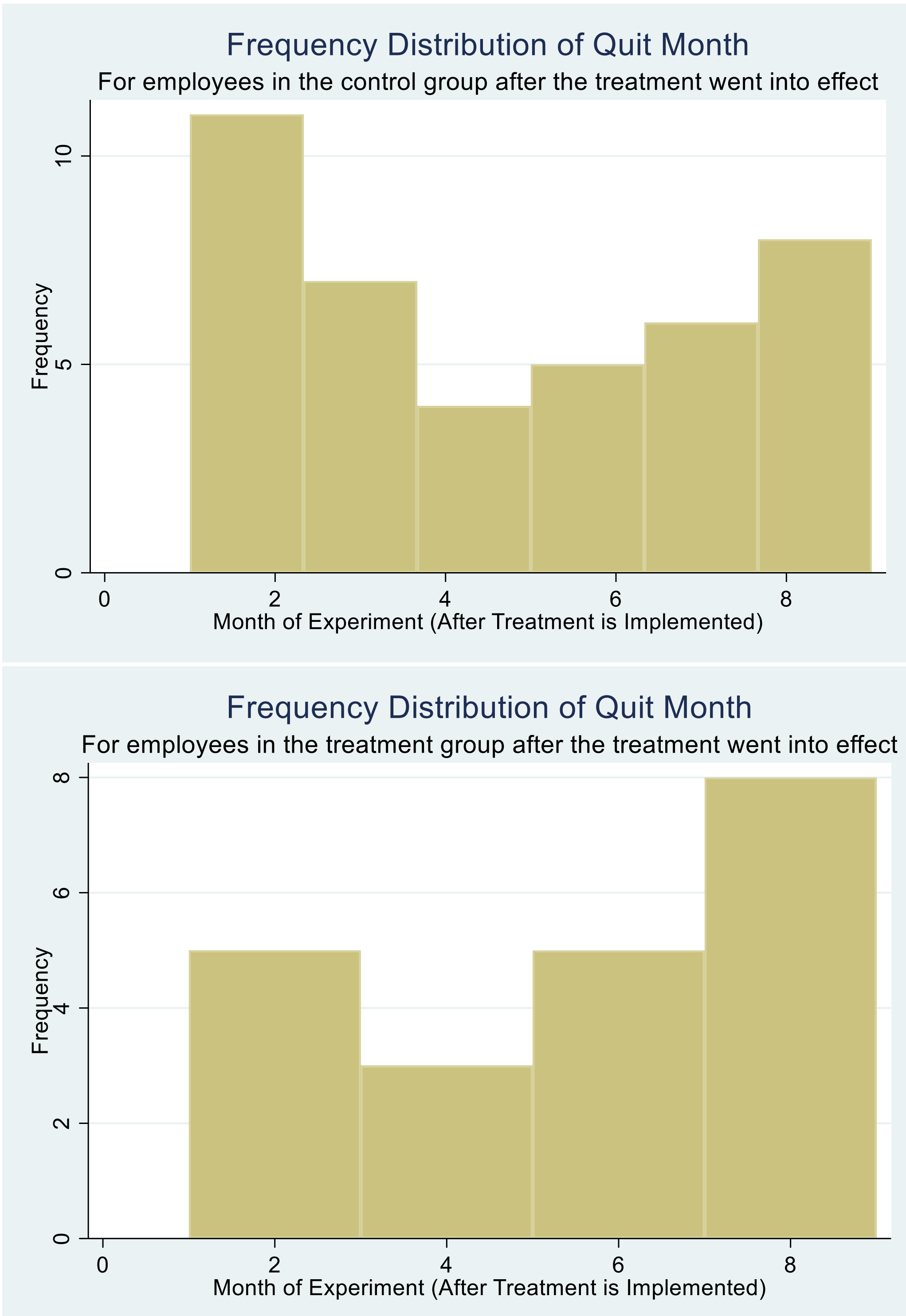
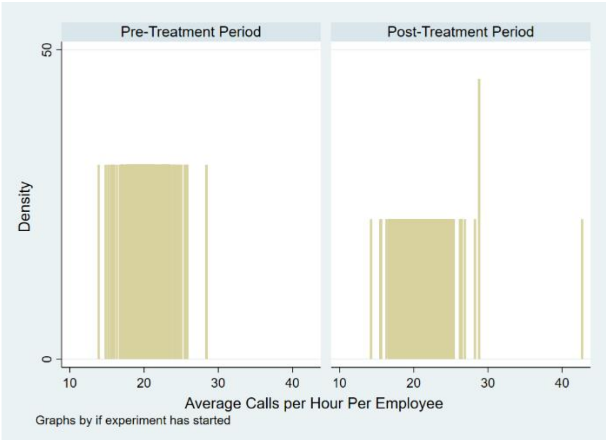
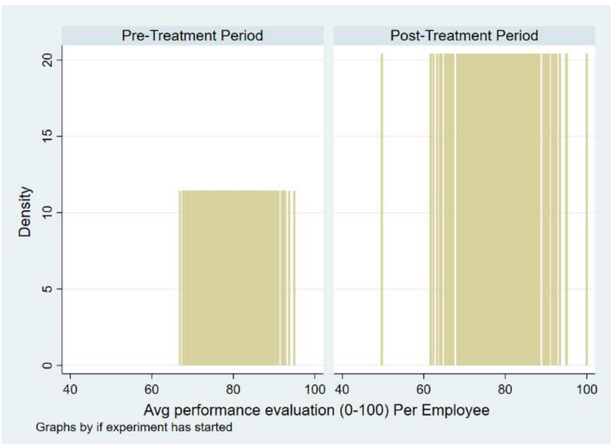


Figure 3. Distribution of Performance Metrics During Pre- and Post-Treatment Periods for Both Treatment and Control Groups Combined

a) Distribution of Employees' Average Calls per Hour



b) Distribution of Employees' Average Performance Evaluation



c) Distribution of Employees' Total Monthly Calls

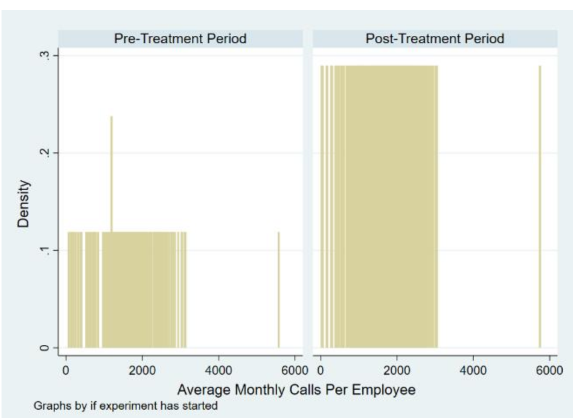


Figure 4. Difference-in-Differences Regression Results for Each Performance Metric

	(1) performance_score	(2) total_monthly_calls	(3) calls_per_hour
treatment	0.259	5.298	-0.312
	(0.35)	(0.07)	(-1.05)
post	-3.052***	-105.5**	0.325**
	(-5.64)	(-2.67)	(2.64)
treatmentXpost	2.824***	127.3*	0.578*
	(3.97)	(2.35)	(2.44)
_cons	79.12***	1771.6***	20.53***
	(156.62)	(35.12)	(92.54)
N	496	495	498

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Figure 5. Employee Characteristics Regressed on Pre-Treatment Period Performance Score

	(1) performance_score
age	0.112
	(0.80)
tenure	0.0204
	(0.98)
costofcommute	0.00395
	(0.08)
rental	0.869
	(0.96)
male	-3.007***
	(-4.02)
married	1.109
	(1.18)
high_school	-2.515*
	(-2.59)

_cons	79.02***
	(23.79)
N	247

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Figure 6. Relationship Between Treatment and Quitting using the Linear Probability Model

	(1)
	quitjob
treatment	-0.187***
	(-3.48)
_cons	0.347***
	(8.90)
N	249

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Figure 7. Relationship Between Treatment and Quitting using the Logit Model

	(1)
	quitjob
quitjob	
treatment	-1.026***
	(-3.34)
_cons	-0.630**
	(-3.26)
N	249

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Figure 8. Relationship Between Probability of Quitting and Fixed Employee Characteristics (using Logistic Regression)

	(1)
	quitjob
age	0.00564
	(1.89)
rental	0.0217

	(0.33)
male	0.0275
	(0.49)
married	0.0351
	(0.54)
high_school	0.130
	(1.74)
_cons	0.0902
	(0.92)
N	249

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Figure 9. Relationship Between Average Satisfaction at Work and Treatment using the Difference-in-Differences Methodology

	(1) avg_satisfaction
post	-0.195
	(-1.30)
treatment	0.0575
	(0.31)
treatmentXpost	0.564^{**}
	(2.82)
_cons	4.531^{***}
	(33.04)
N	342

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Figure 10. Probability of Quitting Based on Average Satisfaction (Logit Model using Post-Treatment Implementation Data)

	(1) quitjob
quitjob	
avg_satisfaction	0.239
	(0.51)
_cons	-4.657^{*}
	(-1.98)
N	171

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Figure 11. Probability of Quitting Based on an Interaction Term With Treatment and Average Satisfaction (Logit Model using Post-Treatment Implementation Data)

	(1)
	quitjob
quitjob	
satisfactionXtreatment	0.0406
	(0.22)
_cons	-3.633***
	(-4.78)
N	171

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$