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Working Paper

Mental Health Consequences of Working from Home during the Pandemic

GLO Discussion Paper, No. 960 [rev.]

Provided in Cooperation with:
Global Labor Organization (GLO)

Suggested Citation: Kim, Jun Hyung; Koh, Yu Kyung; Park, Jinseong (2022) : Mental Health Consequences of Working from Home during the Pandemic, GLO Discussion Paper, No. 960 [rev.], Global Labor Organization (GLO), Essen

This Version is available at:
https://hdl.handle.net/10419/248702

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Mental Health Consequences of Working from Home during the Pandemic*

Jun Hyung Kim†, Yu Kyung Koh‡, and Jinseong Park§

January 10, 2022

Abstract

This paper examines the effects of working from home on mental health, with particular attention to the role of home environments. Using unique real time survey data from South Korea collected during the COVID-19 pandemic, we find that working from home negatively affects the mental health of workers, with greater effects on women and those who are primarily responsible for housework while also maintaining market work. Surprisingly, workers who live with children in the household do not suffer from the negative effects of working from home. Our findings suggest that family-work interaction may be an important factor in the optimal design of working from home.

Keyword: Working from home, home working, remote work, COVID-19, mental health, subjective well-being

JEL: D13, L23, L84, M11, M54

*We would like to thank seminar/conference participants at the Institute for Economic and Social Research of Jinan University, Sogang University, Korea Academic Society of Industrial Organization Conference, 2021 Asian and Australasian Society of Labour Economics Conference for helpful feedback and comments. We gratefully acknowledge the financial support from Dong-A University. This study reports results from a survey that was approved by Columbia University IRB, Protocol number AAAT0180 (Y01M03).

†Institute for Economic and Social Research, Jinan University, Guangzhou, and GLO Fellow. kimjunhyung@jnu.edu.cn

‡Department of Economics, Columbia University, New York. yk2759@columbia.edu

§Department of Economics, Dong-A University, Busan, and GLO Fellow. parkjs@dau.ac.kr

1 Introduction

Since the beginning of the COVID-19 pandemic, between 25 to 50% of workers around the world reported working from home (WFH; Galasso and Foucault 2020; Brynjolfsson et al. 2020). This represents a dramatic increase in the proportion of workers WFH from the time before the pandemic. For instance, only 15% of working hours were performed at home in the United States between 2011 and 2018 (OECD, 2020a). Given that the pandemic brought about industry-wide jobs reallocation and investment in skills and technologies enabling remote work around the world (Barrero et al., 2021), WFH is likely to remain as a common form of work arrangement.

This rapid shift to WFH can generate both benefits and challenges to workers. WFH workers would be able to save time from commuting and more flexibly manage work and non-work responsibilities. In addition, spending more time with the family may generate positive spillovers that enhance work productivity and mental health (Greenhaus and Powell, 2006). On the other hand, WFH workers may have difficulties in securing workspace, communicating with peers, and setting a boundary between work and non-work activities. This work-family conflict can impose a huge psychological burden on WFH workers. These challenges could be exacerbated during the COVID-19 pandemic in which workers may spend longer time with other family members also working at home, provide childcare to their children attending schools remotely, and manage stress and social isolation due to the ongoing pandemic (Etheridge et al., 2020; Iqbal et al., 2020).

This paper explores how WFH affects workers' mental health, with particular attention to the role of home environments. While the effects of WFH on worker productivity has been investigated before in both pre-pandemic and mid-pandemic contexts (Bloom et al., 2015; Etheridge et al., 2020), there is relatively less understanding of the effects of WFH on mental health, and how they interact with home environments such as the distribution of household chores and childcare responsibilities. Since WFH is likely to become a more prevalent form of work in the near future, it is important to understand how WFH affects different workers.

We employ two empirical methods based on the propensity score to compare the mental health outcomes of WFH workers and office workers using unique real-time survey data from South Korea collected during the COVID-19 pandemic. The first method is kernel matching (Heckman et al., 1997), and the second method is doubly robust estimation that combines inverse probability weighting with regression adjustment (Słoczyński and Wooldridge, 2018). To account for selection on observables, we use a rich set of characteristics that predicts WFH status. In particular, the unique institutional setting which shaped workers' experience with respect to their work arrangement during the pandemic offers guidance on the choice of such predictors. First, feasibility for WFH during the pandemic varies substantially across industries (Dingel and Neiman, 2020). Second, the South Korean government's recommendation for the WFH arrangement was stronger in areas with many confirmed cases (MOHW, 2020). Moreover, individuals with public service occupations such as teachers and civil servants were often mandated to adopt WFH.

Our empirical methods rely on observable characteristics using cross sectional data, making it difficult to account for potential biases from selection on unobservables. It is not straightforward to anticipate the direction of the bias. On the one hand, most Korean workers have never worked from home before the pandemic, and thus had little opportunity to learn about whether WFH is suitable for them.[1] A study by Bloom et al. (2015) shows that about half of workers who initially opted in WFH returned to the office after experiencing productivity losses, suggesting that workers do not well anticipate the effects of WFH. If workers opt into the WFH arrangement based on their unobserved preferences for WFH, our estimates would likely understate the negative impact of WFH on mental health outcomes. On the other hand, our results would overstate the effects if individuals who have a stronger aversion to the COVID-19 infection risk choose to work at home in fear of the pandemic. While evidence in the literature suggests that that many workers did not have choice over whether to work at home or office, it is outside the scope of this paper to precisely determine

[1]For example, a survey in 2017 shows that only 3.2% of workers worked from home for more than once a week (KOSHA, 2017).

the relative magnitudes of these sources of bias.

Our results indicate that WFH workers are characterized by worse mental health, reporting more lethargy and sadness, but not anxiety or restlessness, compared to non-WFH workers. The negative impact of WFH is concentrated on female workers and (even more concentrated) on those who are primarily responsible for housework while also maintaining market work. Interestingly, contrary to conventional wisdom, we find the negative effect of WFH only for workers without children in the household. Those with children living in the same household do not suffer from worse mental health when they work from home, suggesting that family could provide a buffer against the negative effects of WFH.

Our study is among the first to primarily focuses on the mental health consequences of WFH during the pandemic. While economists investigated various aspects of different work arrangements (Garen, 2006; Mas and Pallais, 2017; Katz and Krueger, 2019), little is known about the impact of WFH on workers' psychological well-being. An exception is Bloom et al. (2015) in which workers learned through experience that WFH did not necessarily benefit everyone in terms of productivity and well-being.

Our study also contributes by exploring the role of family environment, specifically intra-household task allocation and the presence of children in the household, as potential moderators that affect the psychological burden of WFH workers. Previous studies focused on productivity and well-being of workers at home, but did not consider the importance of family environment (Beland et al., 2020; Etheridge et al., 2020; Felstead and Reuschke, 2020). Our findings emphasize home and family as important channels between WFH and workers' mental health.

The rest of this paper proceeds as follows. Section 2 presents background information regarding the COVID-19 pandemic in South Korea and the evolution of WFH before and during the pandemic. Section 3 explains our empirical strategy, how our setting affects the interpretation of our results, and the unique features of the real-time survey data used in the analysis. Section 4 presents the estimation results and Section 5 interprets our key findings.

Section 6 concludes.

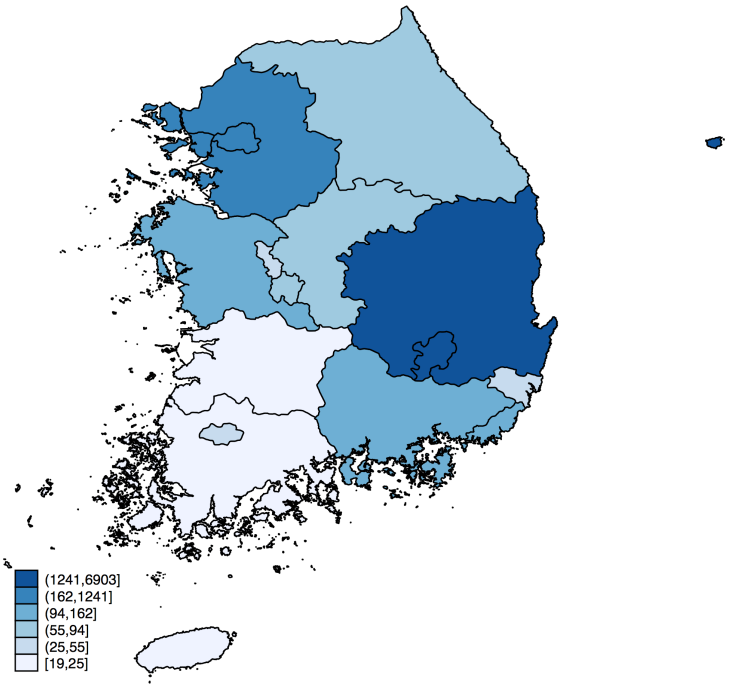
2 Background

The COVID-19 pandemic in Korea: Since the first case of COVID-19 was identified in South Korea on January 20, 2020, the number of cases increased to 3,150 by the end of February. By June 24, the date of the survey, the number of cases was at 12,535. Panel (a) of Figure 1 shows the geographic variation in the number of confirmed COVID-19 cases in Korea. Daegu metropolitan city is found on the right-hand side of the country, where the number of cases is much higher compared to other regions. 54.95% of the cases were in Daegu metropolitan city, and the greater Daegu area (Gyeongbuk province) had 11.03% of the cases. 9.95% of the cases were in Seoul city, and the greater Seoul area (Gyeonggi province) had another 9.12% of the cases. The cumulative incidence rate is 24.23 per 100,000 population (KCDC, 2020).

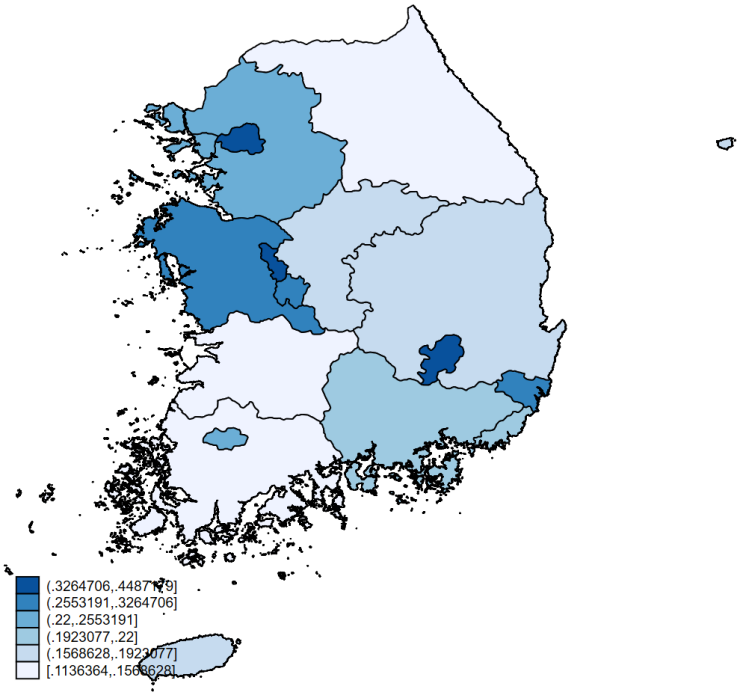
In response to the spread of COVID-19, the government strongly campaigned for voluntary social distancing, but avoided implementing mandatory lockdown. In addition, government tested those who showed symptoms and those who were in close contact with confirmed patients, and publicized local case data and the recent travel history of confirmed patients. Studies show that these measures significantly contributed to voluntary social distancing (Argente et al., 2020; Aum et al., 2021). Some businesses and institutions were shut down temporarily if they were deemed to pose serious infection risk, such as churches, gyms, karaokes, and clubs (MOHW, 2020).

Working From Home and the COVID-19 Pandemic: WFH during the COVID-19 pandemic is different from WFH before the pandemic, potentially providing new information on how workers' mental health can be affected while working remotely (Gorlick, 2020). First, WFH during the pandemic is strongly encouraged by the government. Therefore, the types of individuals WFH during the pandemic would be systematically different from those who

Figure 1: COVID-19 cases and Work From Home in Korea



(a) COVID-19 cases



(b) Work From Home

Note: Panel (a) shows the cumulative number of confirmed COVID-19 cases in Korea as of June 24, 2020, based on the KCDC official data. Panel (b) shows the proportion of individuals in the sample who reported any work from home experience between January 2020 and June 2020, based on authors' calculation.

have worked from home before the pandemic. Second, there exist other policies designed to contain the spread of COVID-19 such as school closures, which may pose additional challenges to WFH workers. Parents with children, in particular, would face dual responsibility as caregivers and workers at the same time. WFH would also reduce space available to each family member, adding to the psychological stress of workers and their families. Therefore, our study incorporates the effects of WFH on workers who would not have chosen the WFH arrangement otherwise, and the interaction of WFH and various family environments.

The contrast in WFH before and during the pandemic is especially stark in South Korea, where WFH was highly uncommon before the pandemic. In 2017, 94.8% of employees reported that they have never worked from home in the past 12 months, and only 2.2% of employees reported that they work from home more than once a month (KOSHA, 2017). These figures stand in contrast to other countries such as the US, where between 15 to 20% of employees reported working from home once a week or more (Mas and Pallais, 2017).

Since the beginning of the pandemic, however, the Korean government vigorously campaigned for workers to choose WFH and for employers to provide for and recommend WFH to their employees, especially in areas with high COVID-19 intensity (MOHW, 2020). WFH was often mandated for public sector jobs (OECD, 2020b). 77.4% of the public sector employers introduced WFH by the first half of 2020, an increase from 7.4% in 2019 (Park, 2020). In addition, 48.8% of the employers introduced some form of the WFH arrangement since the start of the pandemic (MOEL, 2020c). 34.1% of the employees reported that they took advantage of the WFH arrangement, a dramatic increase from 2.2% in 2017.

Evidence suggests that individual workers had limited choice over WFH at least during the first half of 2020. In a nationally representative survey in 2020 (MOEL, 2020a), the most often cited reason for not working remotely was "WFH is not offered by the employer," followed by "job characteristics make WFH difficult."[2] 93.1% responded that they were willing to try WFH if offered by the employer. Anecdotal evidence from a government assistance

[2]Allowing for multiple responses, 65.6% chose "WFH is not offered by the employer" and 29% chose "job characteristics make WFH difficult."

program for implementing WFH (MOEL, 2020b) also shows that main obstacles for employers were providing for personnel policies and technological infrastructure for WFH. Overall, the expansion of WFH in South Korea seems to be driven not by the willingness of workers to try WFH but by the availability of WFH option, which is in turn determined by regional COVID-19 intensity and work characteristics.

The geographic pattern of WFH is consistent with our assumption that WFH is determined by the pandemic intensity and observable work characteristics. Panel (b) in Figure 1 shows that WFH tends to be more common in areas with higher COVID-19 cases.[3] Furthermore, WFH prevalence is higher in the metropolitan area, where more workers are at office jobs, which allow easier transition to WFH.

Working From Home and Mental Health: It is unclear a priori whether WFH during the COVID-19 pandemic would have positive or negative mental health effects on workers. On the one hand, WFH can lead to worse mental health due to feelings of social isolation, as workers find it difficult to associate with their colleagues at work, or attend social events which were mostly canceled due to social distancing measures. In addition, workers may experience heightened conflict between market work and housework, adding to psychological pressure (Greenhaus and Powell, 2006). Being at home may subject workers to incessant demands for attention to domestic chores, distracting them from market work. Lower labor productivity can then lead to lower mental health of workers (Etheridge et al., 2020).

On the other hand, it is possible that WFH during COVID-19 leads to better mental health. Staying at home may allow workers to be more focused on work by reducing office-related distractions, or better balance work and home responsibilities. Furthermore, being able to spend more time with family may have complementary effects on workers' mental health. Literature on work-family enrichment (Greenhaus and Powell, 2006) suggest that some family interaction can enhance both productivity and the quality of life of workers.

[3]The correlation between the WHF share and the cumulative COVID-19 cases is 0.59. The variation in the number of COVID-19 cases explains about one third of the variation in the WFH share in the bivariate linear probability model.

Focusing on pre-pandemic periods, Denzer and Grunau (2021) found positive effects of WFH on workers' well being, with greater effects on men. Oakman et al. (2020) reviewed medical literature on WFH and found that the association between WFH and mental well being are not consistent across studies, in which organizational support and work-family conflict were important moderators. During the COVID-19 pandemic, Xiao et al. (2021) conducted an online survey in 2020 on WFH workers and found positive association between workers' mental well being and physical exercise, healthy diet, work productivity, and the presence of an infant at home.

3 Empirical Strategy

3.1 Empirical Model

We estimate the effects of WFH on mental health outcomes by comparing WFH workers and non-WFH workers. The key empirical challenge is to account for the non-random selection into the WFH arrangement. To account for selection on observables, we rely on two complementary methods based on the propensity score: kernel matching (KM) and doubly robust estimator that combines inverse probability weighting with regression adjustment (IPWRA). In this section, we lay out the potential outcomes framework and the *unconfoundedness* assumption that would allow our estimators to identify the causal parameter. We then discuss how unobservables would affect the identification assumption in our institutional setting.

Consider a potential outcomes framework where D_i equals 1 for individual i who works at home, and 0 otherwise. Y_i denotes the observed mental health outcome and $Y_i(D_i)$ denotes the potential outcome given WFH status, D_i. Our estimand of interest is the average treatment effect on the treated (ATT), $E[Y_i(1)|X_i, D_i = 1] - E[Y_i(0)|X_i, D_i = 1]$. In general, comparing the average outcomes between the treatment group and control group would not recover the

true ATT because selection into treatment introduces bias:

$$E[Y_i|X_i, D_i = 1] - E[Y_i|X_i, D_i = 0] = \quad \tau_{ATT} + \underbrace{E[Y_i(0)|X_i, D_i = 1] - E[Y_i(0)|X_i, D_i = 0]}_{\text{selection bias}}. \tag{1}$$

However, the selection bias term would disappear if we can assume that WFH status is independent of the potential mental health outcome for office workers conditional on covariates, $E[Y_i(0)|X_i, D_i] = E[Y_i(0)|X_i]$. This assumption is called *unconfoundedness* in the literature.

Although we cannot eliminate potential bias from unobservables, the importance of observable characteristics in determining the WFH status is likely to be greater during the pandemic in South Korea compared to other settings. First of all, existing evidence from the literature suggests that job characteristics determine which work can be done from home (Dingel and Neiman, 2020; Hensvik et al., 2020). The results from our determinant analysis presented in Sections 3.3 and in the Appendix also indicate that job characteristics such as firm size and industry are key predictors of WFH status in South Korea. Second, a sudden increase in the share of WFH workers is mainly caused by responses of governments or firms to help prevent the spread of the COVID-19 virus. Therefore, we expect that the severity of COVID-19 at the local level would also be an important determinant of WFH status during the pandemic. Lastly, many individuals working in the public sector, including teachers and government officials, were forced to work at home due to either school closures or the government guidelines, especially in March 2020 when a mass outbreak among the members of Shincheoji church occurred in Daegu.

What are some of the scenarios that can bias our estimators away from ATT? If people who prefer to work from home chose to do so, then our estimates would be biased in the positive direction, understating the negative effects of WFH (or overstating the positive effects). Also, if there were selective unemployment that made it more likely for those who enjoy WFH to keep their jobs, then our estimates would also be biased in the positive

direction.[4] Under these scenarios, our estimates can be interpreted as upper bound on the effects of WFH on mental health. On the contrary, if individuals who fear the COVID-19 infection risk most decide to work at home, our estimates might capture the direct impact of the COVID-19 on mental health to some extent. Although our review of the implementation of WFH in Section 2 suggests that workers had relatively little choice in whether they could work from home, our results should be interpreted with these concerns in mind.

We correct for selection on observables using the propensity score. To obtain the propensity score for WFH treatment, we estimate the following selection equation using a logit model:

$$D_i = \delta + Z_i\Gamma + u_i, \tag{2}$$

where Z_i contains a set of variables that determine WFH status, including indicators for age over 40, female, presence of children under age 18 in the household, marital status, education, firm size, earnings categories, industry, and area of residence.[5]

Because matching overcomes the curse of dimensionality by summarizing all information into the propensity score, its success crucially hinges on whether the selection equation is correctly specified (Smith and Todd, 2005). However, it is not feasible to examine the extent to which our preferred specification closely approximates the true selection process. In response, we estimate the IPWRA model which is robust to misspecification either in the selection equation or in the outcome equation (Wooldridge, 2010).[6,7] We do not favor one method over another, but apply both methods for robustness. In addition, we examine the

[4] A report by the Bank of Korea (Kim and Yoo (2021)) shows that one of the driving forces of high unemployment during the pandemic was due to low transition from out-of-the-labor-force to employment, suggesting that bias from selective unemployment may be small.

[5] Our results are robust to using a continuous measure of age. This result is available upon request.

[6] The outcome equation refers to a model describing the effect of WFH on mental health outcomes. Specifically, we weight the conditional expectation of of a mental health outcome by the inverse probability of treatment, $1/P(D_i = 1|X_i)$, or non-treatment, $1/(1-P(D_i = 1|X_i))$, multiplied by the estimated propensity score to get our ATT estimates.

[7] To select the variables that affect the treatment (WFH status), we select three variables from demographic and work characteristics variables that best predict WFH status. We estimate every possible linear model with all three variable combination out of potential variables. The best predicting model is the one that generates the lowest Bayesian Information Criterion (BIC). The selected variables are: indicators for small firm size, high income, and public sector job.

robustness of our results by estimating linear regression model using OLS estimator. OLS results are in Table A3 in the Appendix.

The use of propensity score requires the *overlap* assumption: $P(D_i = 1|X_i) < 1$, ensuring that matching estimator is defined throughout the sample. This would be violated if individuals with certain characteristics in the sample either never work from home or always work from home. We find support for this assumption in Figure A4 in the Appendix, showing that the distribution of propensity scores overlap for workers at home and not at home. Finally, we invoke stable-unit-treatment-value assumption (SUTVA) which implies that there should be no spillover effect from one worker's WFH status to another worker's mental health. While we cannot test this directly, it is an intriguing possibility that may be examined in future research.

3.2 Data

To study the impact of COVID-induced WFH on mental health, we collected real-time online survey data consisting of a sample of 2,000 households during June 24 - 30, 2020 in South Korea. Recruitment of participants and implementation of the survey were conducted by a professional survey firm in South Korea. All our participants were selected from the company's panel who regularly participated in the company's other online surveys.[8] We used a regional quota-based sampling to ensure that our sample is nationally representative. To be eligible for the survey, participants had to be the head of household or the spouse and be of age between 25 and 55. Mean age of respondents is 40.76. 86% of them are married at the time of the survey and the mean number of children per household is 1.61. 89% of the respondents had work experience in the past year.[9]

We collected a wide range of information on each respondent and the respondent's spouse. Some of the information we collected, such as housework and childcare arrangement, employment, and mental health, are seldom jointly available in other public data sets in South

[8] To incentivize participation in the survey, we provided some monetary benefits for completing the survey.
[9] See Table A1 in the Appendix.

Korea or elsewhere, especially in real-time. Hence, our study has a potential to help understand how the effects of the COVID-19 pandemic depend on demographic, work, and family characteristics that are difficult to observe otherwise. Below, we briefly summarize the key variables used in our analyses.

Employment and Earnings: We have a rich set of information on respondent's employment and earnings. We followed employment-related questions in the Current Population Survey and the South Korean Labor Force Survey. For example, we asked respondent's job status for the past week, number of current jobs held by the respondent, and unemployment experience for the past year. Respondents were also asked to provide details on job characteristics, such as industry, employer type, employer size, and earnings from their current main job.[10]

In order to capture possible disruptions in work arrangement and payment schedule due to the COVID-19 pandemic, we asked whether the respondent had unpaid leave and payment delay in 2020. We also asked respondents how hours of work, work intensity, and household income have changed since the pandemic started.

Working From Home: To understand the individual heterogeneity in WFH experience, we asked survey participants whether they have worked from home between January 2020 and June 2020, and in which months they worked from home. Out of 1,684 employed respondents, 417 of them (about 25%) reported that they worked from home at some point in 2020. Table A2 reports differences between respondents with WFH experience and those without in the non-matched sample during this time. It shows that WFH workers are more likely to be women, college graduates, and high-income earners. Moreover, having public or government sector job, working for a large firm, and living in metropolitan city[11] are positively associated with WFH experience. However, Table 1 shows that these differences in observed characteristics between the two groups of workers disappear in the matched sample.

[10] Main job is defined as the job where the respondent spent most hours of work.

[11] Metropolitan cities include Seoul and six other major cities: Busan, Daegu, Incheon, Gwangju, Daejeon, and Ulsan.

Table 1: Balance Table

Dependent Variable	WFH	Non-WFH	$p > \|t\|$
Female	0.448	0.440	0.816
Over age 40	0.509	0.509	0.995
Have kid(s)	0.622	0.631	0.789
Single	0.106	0.110	0.846
Some college	0.154	0.157	0.905
College graduate	0.587	0.587	0.996
Grad school	0.224	0.218	0.827
Firm size: 10 - 49	0.212	0.207	0.867
Firm size: 50 - 99	0.179	0.176	0.914
Firm size: 100 - 499	0.217	0.213	0.913
Firm size: 500+	0.149	0.149	0.981
Monthly wage: $2000 - 4000	0.416	0.410	0.877
Monthly wage: $4000 - 6000	0.280	0.278	0.948
Monthly wage: $6000 - 8000	0.121	0.121	0.993
Transportation, warehousing, rental industry	0.028	0.029	0.924
Wholesale/retail, service industry	0.078	0.079	0.958
Professional, scientific, management industry	0.209	0.214	0.855
Public administration, military industry	0.068	0.073	0.787
Education, health, social service industry	0.292	0.271	0.517
Arts, entertainment, recreation industry	0.040	0.046	0.711
Other industry	0.081	0.081	0.967
Busan	0.050	0.051	0.975
Daegu	0.088	0.080	0.684
Incheon	0.058	0.055	0.877
Gwangju	0.025	0.024	0.936
Daejeon	0.030	0.032	0.875
Ulsan	0.028	0.023	0.643
Sejong	0.013	0.011	0.804
Gyeonggi	0.244	0.243	0.956
Gangwon	0.013	0.012	0.91
Chungcheongbuk	0.015	0.017	0.797
Chungcheongnam	0.048	0.044	0.792
Jeollabuk	0.020	0.021	0.927
Jeollanam	0.020	0.022	0.883
Gyeongsangbuk	0.030	0.030	0.957
Gyeongsangnam	0.053	0.052	0.933
Jeju	0.013	0.012	0.904

Note: This table compares the average characteristics of WFH workers and non-WFH workers in the matched sample. WFH workers refer to survey respondents who reported to have worked from home in 2020. The third column displays p-values for the two-sample t-tests for equal means.

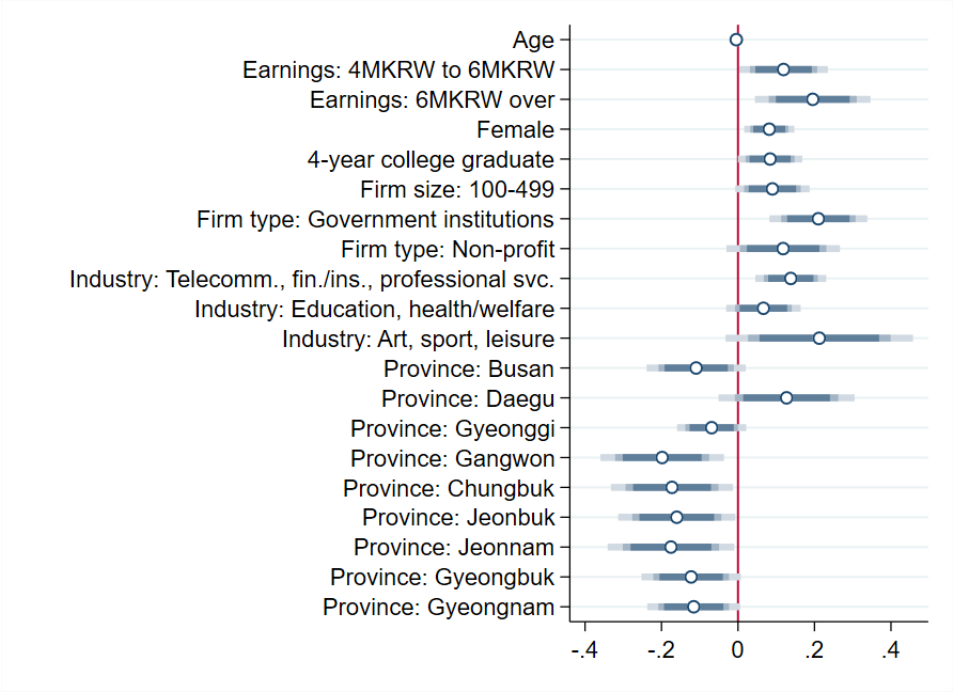
Mental Health: To measure the mental health outcomes of respondent, we follow Kessler's six-item scale of psychological distress (Kessler et al., 2002), which measures the current prevalence of depression symptoms. Specifically, respondents answered on a scale from 1 "Not at all" to 5 "Very True" regarding whether they felt (i) anxious; (ii) lethargic; (iii) restless; (iv) tired of everything; (v) sad; and (vi) worthless in the past month. To facilitate comparison with other measures in the literature, we created z-scores for each of the items as well as for the average score.

Housework Arrangement: Because housework can also affect mental health outcomes, we asked respondents about the allocations of housework within the household. We asked "who was mainly responsible for housework, such as cooking, laundry and cleaning, from January to May 2020?" The possible responses include: myself; my spouse; my parents; spouse's parents; and outside help.

3.3 Determinant analysis and matching quality tests

We present a plot of coefficient estimates from a logit model predicting WFH status in Figure 2. Consistent with the pattern reported in Dingel and Neiman (2020), high-earners, college graduates and those in skill-intensive industries are more likely to have worked from home during the pandemic. Workers in the public sector and in large employers are more likely to have worked from home, in part because they were under greater pressure to follow government guidelines (MOHW, 2020). Compared to the greater Seoul area (the reference group), only Daegu predicts higher chance of WFH. Daegu was the site of a highly publicized mass outbreak in mid-February, which led the local government to introduce strong social distancing measures (Kim et al., 2020).

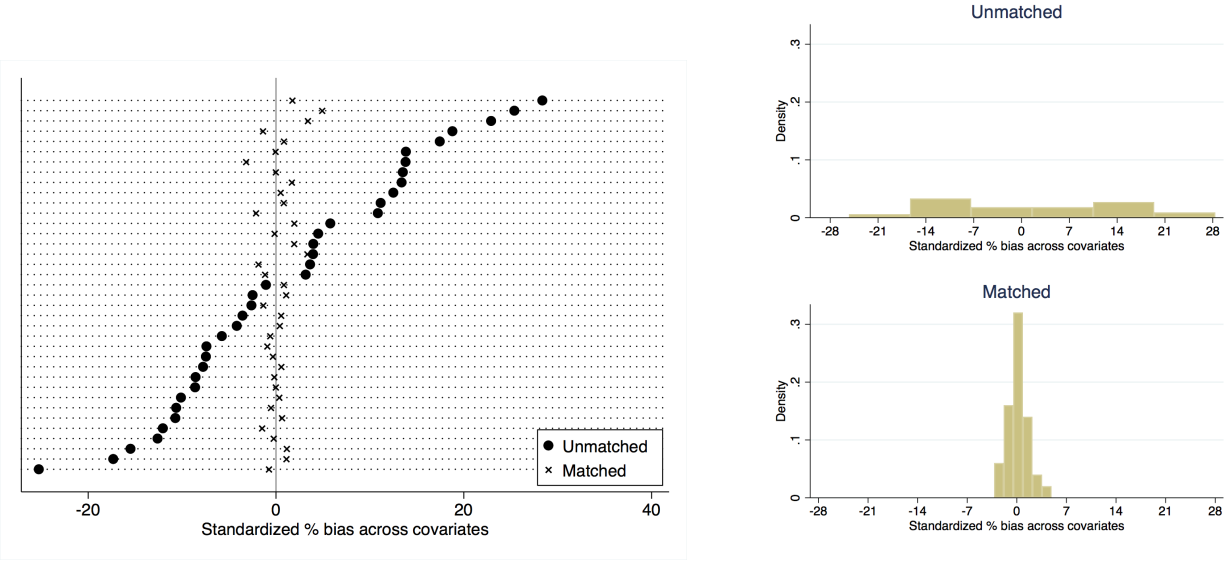
Figure 2: Determinants of Working From Home



Note: This figure summarizes the estimation result of a logit model where the dependent variable is the WFH status. A set of predictors contain individual age, and dummies for individual earnings, gender, having a child under age 18, firm size, firm type, being a regular employer, industry, and province of residence. The empty circle represents the marginal effect for each predictor and the associated horizontal bars represent 99%, 95%, and 90% confidence intervals based on robust standard errors, respectively. The coefficient estimates for predictors that are not statistically significant are excluded for brevity.

To adjust for the imbalance between the treatment and the control groups and ensure that comparisons are made between observations similar in the feasibility of choosing WFH, we include a rich set of demographic and work characteristics as conditioning variables in kernel matching. To evaluate match quality, we perform several balancing tests with respect to each covariate, following Rosenbaum and Rubin (1985). Figure 3a plots the standardized percentage bias of each conditioning variable before and after matching, and Figure 3b plots the same results as the averages of the full set of conditioning variables. Both plots show that matching reduces the covariate imbalance between WFH workers and office workers substantially. Table A2 in the Appendix further reports percentage figures for the reduction in bias for each conditioning variable.

Figure 3: Balance of conditioning variables before and after matching



(a) Graph (b) Histogram

Note: Estimates are obtained using 1,684 employed people in our survey data. Conditioning variables used in the match quality test are: indicators for age over 40, having children, marital status, education, firm size, earnings, industry, and province of residence.

4 Results

4.1 Baseline results

Table 2 shows the estimates of ATT in Equation 1 where outcome variables are various measures based on Kessler's depression scores. Estimates from Kernel Matching estimation are shown in Panel A while estimates from IPWRA estimation are shown in Panel B. Our set of matching variables include indicators for age over 40, female, presence of children under age 18 in the household, marital status, education level, firm size, earnings categories, industry, and area of residence. In Table A3 in the Appendix, we show that our results are robust to using linear regression model with OLS estimators.

Table 2: Baseline: Effect of Working From Home on Mental Health

(1) Avg.	(2) Factor	(3) Anxious	(4) Lethargic	(5) Restless	(6) Tired	(7) Sad	(8) Worthless	Obs.
Panel A: Kernel Matching								
0.105*	0.126*	0.054	0.141**	0.076	0.122*	0.125*	0.109*	1555
(0.055)	(0.066)	(0.066)	(0.066)	(0.066)	(0.066)	(0.065)	(0.065)	1555
Panel B: IPWRA								
0.116**	0.138**	0.072	0.160**	0.084	0.134**	0.127**	0.119*	1555
(0.053)	(0.063)	(0.065)	(0.063)	(0.063)	(0.064)	(0.063)	(0.063)	1555

Note:: Panels A and B report estimates of the average treatment on the treated effect (ATT). We restrict our estimation sample to employed individuals. For Column (1), the outcome variable is the average z-score of all mental health variables. For Column (2), the outcome variable is the factor score of all mental health variables, where we follow the methodology in Gensowski (2018). Columns (3) - (8) are for mental health z-score of individual items in Kessler's scale. All specifications include the following set of control variables: indicators for age over 40, female, presence of children under age 18 in the household, marital status, education, firm size, earnings categories, industry, and area of residence. Robust standard errors are reported in parentheses. ***, **, and * indicate significance of the coefficients at the 1%, 5%, and 10% levels respectively.

The estimates in Table 2 show that on average, WFH leads to a deterioration of mental health. Columns (1) and (2) show estimates based on average z-score and factor score, respectively, showing that the pandemic increased depression score by 0.105 to 0.138 in standard deviation unit.

Examining each of the subscales, the biggest impact is on the 'Lethargic' subscale, where the effect is 0.141 using KM and 0.160 using IPWRA, both significant at 5% level. Subscales titled 'Tired', 'Sad', and 'Worthless' also increased, the effects ranging from 0.109 and 0.134. Effects on subscales 'Anxious' and 'Restless' were small and not significantly different from zero. Overall, the effects seem greater on subscales related to feeling powerless or helpless, rather than on subscales related to being concerned or fearful.

4.2 Treatment effect heterogeneity

To further understand the negative effects of WFH on mental health, we investigate heterogeneity of effects by gender, housework responsibility, and the presence of children under age 18 in the household. Panels A and B in Table 3 presents a striking pattern: the negative

effects are entirely concentrated on women. The estimates on the average z-score and the factor score variables for women are large and significant in both KM and IPWRA models. Regarding the subscales for women, the effects are observed for 'Anxious', 'Lethargic', and 'Tired' subscales. Unlike the estimates for the entire sample, the effects are observed for 'Anxious' subscale. Effects on other subscales are positive and borderline significant. None of the effects are observed for men.

Panels C and D present evidence that the effect of WFH on mental health, and especially the bigger effect for women, may be driven by the home environment, specifically housework arrangement among family members. The subsample for Panel C consists of those who identified themselves as the main person responsible for household chores during this period, and the subsample for Panel D consists of those who identified someone other than themselves. Approximately 80% of the women identified themselves as being mainly responsible, while only 20% of the men did so. Rest of the men mostly identified their spouses as the one mainly responsible for housework.[12]

The results show that the negative effect of WFH is entirely concentrated on those who report that they are primarily responsible for housework. The magnitude of effects are greater and more significant in Panel C than in Panel A. Furthermore, the effects on "Sad" and "Worthless" subscales are significant in Panel C but not in Panel A. These suggest that unequal distribution of housework responsibility between men and women may be the explanation for the gender-specific effects of WFH on mental health.

Panels E and F show further evidence that the effect of WFH on mental health may depend on the home environment, comparing those who have children under age 18 living in the same household to those who do not. The negative effects of WFH on mental health is concentrated on those who do not have children living in the same household. None of the effects are large or significant when the respondents have children under the age of 18 living

[12]We provide descriptive statistics of responses to the question in Figure A3 of the Appendix. This designation did not change when asked about the housework done before the pandemic, suggesting that the placement of main housework responsibility may be a fixed household trait.

Table 3: Heterogeneous Effects of Working From Home on Mental Health

	(1) Avg.	(2) Factor	(3) Anxious	(4) Lethargic	(5) Restless	(6) Tired	(7) Sad	(8) Worthless
Panel A: Female. (N=621)								
KM	0.169**	0.195*	0.184*	0.200**	0.147	0.190*	0.155	0.139
	(0.083)	(0.101)	(0.097)	(0.100)	(0.101)	(0.104)	(0.106)	(0.106)
IPWRA	0.156**	0.179*	0.157*	0.184*	0.116	0.182*	0.157	0.138
	(0.078)	(0.095)	(0.093)	(0.095)	(0.094)	(0.097)	(0.101)	(0.101)
Panel B: Male. (N=934)								
KM	0.028	0.038	-0.033	0.075	0.011	0.021	0.050	0.041
	(0.072)	(0.087)	(0.089)	(0.087)	(0.086)	(0.085)	(0.084)	(0.084)
IPWRA	0.043	0.055	-0.016	0.094	0.021	0.045	0.057	0.059
	(0.072)	(0.086)	(0.091)	(0.085)	(0.084)	(0.086)	(0.083)	(0.083)
Panel C: Main Person Doing Housework. (N=581)								
KM	0.223**	0.262**	0.173	0.183*	0.157	0.277**	0.286**	0.259**
	(0.093)	(0.113)	(0.108)	(0.111)	(0.111)	(0.115)	(0.116)	(0.117)
IPWRA	0.213**	0.249**	0.150	0.183*	0.149	0.254**	0.262**	0.278**
	(0.089)	(0.107)	(0.103)	(0.104)	(0.105)	(0.111)	(0.107)	(0.108)
Panel D: Not Main Person Doing Housework. (N=721)								
KM	0.047	0.052	0.044	0.108	0.013	0.043	0.044	0.033
	(0.077)	(0.093)	(0.096)	(0.093)	(0.092)	(0.092)	(0.090)	(0.089)
IPWRA	0.037	0.038	0.031	0.111	-0.003	0.034	0.017	0.030
	(0.075)	(0.089)	(0.101)	(0.092)	(0.088)	(0.091)	(0.086)	(0.086)
Panel E: No Kids. (N=609)								
KM	0.131	0.158	0.033	0.228*	0.089	0.087	0.173	0.177
	(0.097)	(0.117)	(0.119)	(0.117)	(0.117)	(0.114)	(0.119)	(0.115)
IPWRA	0.172**	0.213**	0.050	0.284***	0.140	0.128	0.234**	0.197*
	(0.088)	(0.105)	(0.108)	(0.107)	(0.105)	(0.104)	(0.110)	(0.107)
Panel F: Have Kids. (N=946)								
KM	0.057	0.067	0.054	0.073	0.031	0.099	0.055	0.032
	(0.069)	(0.084)	(0.082)	(0.083)	(0.083)	(0.085)	(0.081)	(0.082)
IPWRA	0.065	0.073	0.075	0.074	0.046	0.111	0.043	0.041
	(0.066)	(0.080)	(0.082)	(0.079)	(0.080)	(0.083)	(0.078)	(0.078)

Note: KM: Kernel Matching; IPWRA: Inverse Probability Weighting with Regression Adjustment. We restrict our estimation sample to employed individuals. For Column (1), the outcome variable is the average z-score of all mental health variables. For Column (2), the outcome variable is the factor score of all mental health variables, where we follow the methodology in Gensowski (2018). Columns (3) - (8) are for mental health z-score of individual items in Kessler's scale. All specifications include the following set of control variables: indicators for age over 40, female, presence of children under age 18 in the household, marital status, education, firm size, earnings categories, industry, and area of residence. Robust standard errors are reported in parentheses. ***, **, and * indicate significance of the coefficients at the 1%, 5%, and 10% levels respectively.

in the household, as shown in Panel F. These results come as a surprise since we expect the additional burden of childcare would add to the difficulty of maintaining market work while WFH. They suggest that the work-family enrichment may be an important factor in explaining the effects of WFH on mental health, as discussed further in the next section.

5 Discussion

What do these results tell us? Our findings stand in contrast to the positive effects of WFH on workers' well being based on data before the pandemic (Bloom et al., 2015; Denzer and Grunau, 2021). A key difference may be that workers before the pandemic had more discretion in choosing to work from home, and were able to maintain social network outside of work. WFH workers during the pandemic must cope with social isolation in addition to other challenges of remote work. Consistent with our results, workers in the study by Bloom et al. (2015) mentioned loneliness as a major challenge while at home. A consistent interpretation of these results is that for many WFH workers during the pandemic, the cost of loneliness was greater than the benefits of working remotely.

Our study further suggests that the presence of children could counteract the negative effects of WFH, despite the additional burden of childcare the workers must bear. One explanation is that the utility benefit of having children sufficiently compensates for the negative effect of WFH. Giménez-Nadal et al. (2020) use a time-use survey in the UK and the US (both before the pandemic) to show that women are more likely than men to enjoy housework when performed with other family members and in the presence of children. Their simulation of the lockdown situation shows that the presence of children improves women's enjoyment of housework. Our findings confirm their predictions and further show that the benefit of being with children in the household can be significant enough to compensate for the negative effects of WFH on mental health.

In addition, we provide suggestive evidence that worse mental health suffered by women

during the pandemic (Beland et al., 2020; Etheridge and Spantig, 2020; Oreffice and Quintana-Domeque, 2021) may in part be explained by the psychological burden of having to manage both housework and market work. A series of papers show that most of the additional child-care and housework burden fell on women (Del Boca et al., 2020; Farré et al., 2020; Oreffice and Quintana-Domeque, 2021). We show that women in Korea bear a disproportionately large share of housework, even when they maintain market work. Moreover, women's dual responsibility of market work and housework while WFH seems to contribute to the worse mental health of women than of men during the COVID-19 pandemic.

Finally, our findings emphasize the importance of work-family enrichment in determining the effects of WFH on workers' mental health. Work-family enrichment is a positive spillover between work life and family life, where the interaction with family members can improve the mental well-being of workers and improve worker productivity (Greenhaus and Powell, 2006). Similarly, Xiao et al. (2021) found positive association between WFH worker's mental well being and having an infant at home. Inoue et al. (2021) also found that men working from home during the pandemic are more likely to spend time with the family and value family over work. Our findings suggest that the presence of young children and the distribution of housework responsibility may be important components of the home environment that can improve workers' experience while working remotely.

How can we interpret the magnitude of our estimates? Focusing on studies of mental health during the pandemic that use the same outcome measure as our own (Kessler et al., 2002), the effects of WFH we estimated are comparable to about one-tenth of the overall mental health difference in the US population between 2018 and 2020 (Twenge and Joiner, 2020), around half of the effects of a one standard deviation change in the probability of a reduction in annual income by at least 25% (Watson and Osberg, 2019), and more than a one standard deviation decrease in neighborhood ethnic diversity (Churchill et al., 2019).[13]

[13] Twenge and Joiner (2020) find that the average mental health scores of the US population in 2018 and 2020 are different by 1.48 in standard deviations. Watson and Osberg (2019) used a Canadian sample to show that a one standard deviation increase in the probability of experiencing an annual income decrease of at least 25% is associated with a 0.54 to 0.57 standard deviation increase in psychological distress, while

6 Conclusion

The COVID-19 pandemic led to an unprecedented increase in the prevalence of WFH in South Korea, creating a unique setting to examine the effects of WFH on workers' mental health. We find that the pandemic-driven WFH has negative effects on the mental health of workers as measured by lethargy and sadness, consistent with the interpretation that loneliness plays an important role in workers' WFH experience.

We emphasize the role of family environments in moderating the effects of WFH on workers' mental health. First, the negative effects are greater for women and those who assume dual responsibility of housework and market work, implying that the pressure to coordinate multiple responsibilities may partly explain women's greater mental health deterioration during the pandemic (Adams-Prassl et al., 2020). Second, workers who live with children at home do not experience more loneliness when they work from home, suggesting that interactions with family members can shield workers from the negative effects of WFH. These provide useful guidelines in analyzing or implementing WFH policies, which is likely to be an increasingly common form of work.

We point out a few limitations of our study. First, the rapid increase in the number of WFH workers coincided with the global pandemic. Although the spread of COVID-19 was relatively mild during our study period in South Korea, we cannot completely rule out that the negative impact of WFH may be attributable to the pandemic itself to some extent. Second, grueling work hours and collectivist corporate culture of South Korea may have affected our results (Cho et al., 2014; Park et al., 2010). However, anecdotal and survey evidence (MOEL, 2020b,a) suggests that WFH employees were not so much worried about social pressure to be in the office than about efficient work communication, a concern plausibly shared by WFH workers in other cultures as well (Siha and Monroe, 2006). Nevertheless, these concerns may limit the external validity of our results to other countries

an equivalent decrease in the same probability is associated with 0.16 to 0.35 standard deviation decrease in psychological distress. Churchill et al. (2019) shows that a one standard deviation increase in neighborhood ethnic diversity is associated with a 0.092-0.129 standard deviation decline in mental health.

and non-pandemic periods. Finally, our results are based on comparisons of mental health outcomes by WFH status using matching on observable characteristics. While we point out background characteristics that suggest unobservable factors played a relatively limited role, we emphasize that our estimates are only suggestive of causal effects.

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Appendix

A Determinants of Working From Home status

This appendix section provides further evidence regarding factors that predict individual WFH experience during the pandemic. This exercise would confirm whether we have a thorough understanding of the determinants of WFH status, which is crucial for our empirical methods to be successful (Caliendo and Kopeinig, 2008). Again, our descriptive evidence presented below is largely consistent with our expectations stated in Section 3.

We first examine the distribution of the share of individuals who have ever worked from home from January to June of 2020 across several work characteristics. Figure A1b shows that individuals working in public institutions or government-owned firms exhibit the highest share of WFH workers, while the share is lowest among sole proprietors. In terms of industries, individuals working in arts, sports, entertainment industries and industries producing professional and public services are more likely to work from home. Dingel and Neiman (2020) find similar evidence in the US.

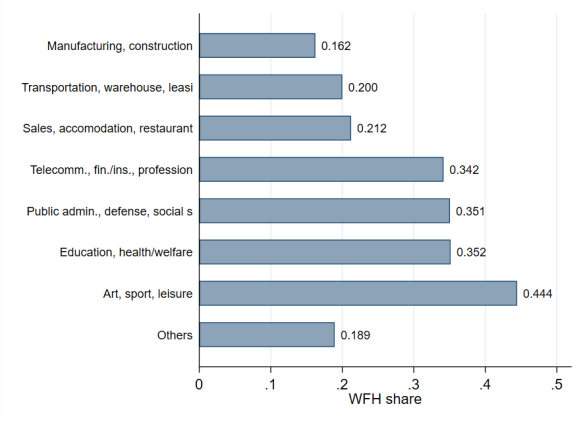
Figure A1b confirms our expectation that the share of WFH workers is higher among workers in public institutions and government-owned firms. In terms of firm size, employees working in relatively large-sized firms exhibit a higher share of WFH workers, which is consistent with the findings in Kawaguchi and Motegi (2021) for workers in Japan. This may reflect the fact that small firms lack the infrastructure or resources needed for smooth transition to WFH. Or, it may be that small businesses such as local restaurants and stores belong in industries where WFH is infeasible. The WFH experience also varies across geography, as shown in Figure A1d. The share of WFH workers is the largest in Daegu, where there was a mass outbreak. The share of WFH workers is the second largest in Sejong, a fast-growing city where the majority of government ministries and agencies are located.

Lastly, we examine the share of WFH workers across individual characteristics in Figure A2. It shows that high-income and college-educated individuals are more likely to work from home in South Korea. In general, the pattern is consistent with existing evidence from other countries.[14] We also find that the share of workers working at home is higher for females.[15]

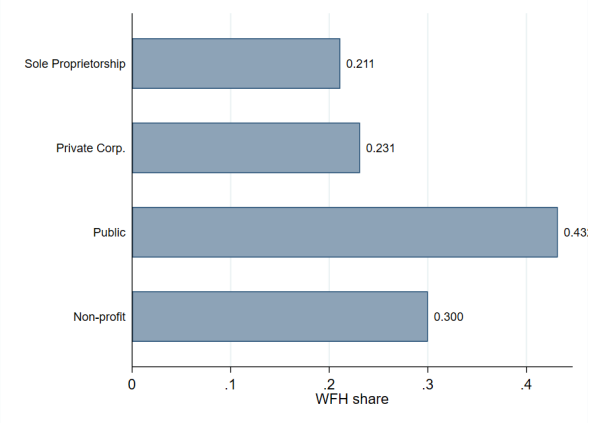
[14]For example, recent studies find similar patterns in the US (Brynjolfsson et al., 2020) and Japan (Kawaguchi and Motegi, 2021) to name a few. Galasso and Foucault (2020) also provide similar evidence from twelve countries.

[15]The share of home workers by gender differs across countries (Galasso and Foucault, 2020).

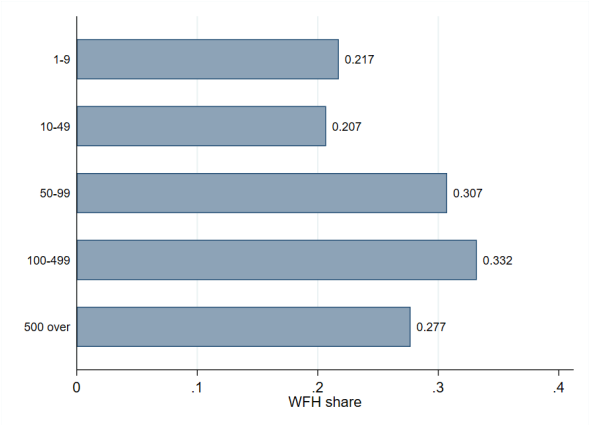
Figure A1: WFH Shares Across Work Characteristics



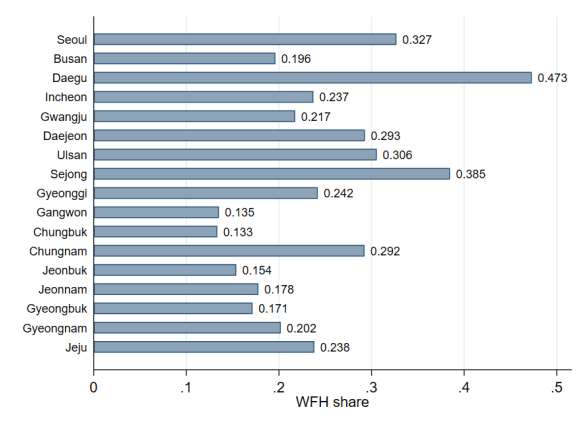
(a) Industry



(b) Firm Types



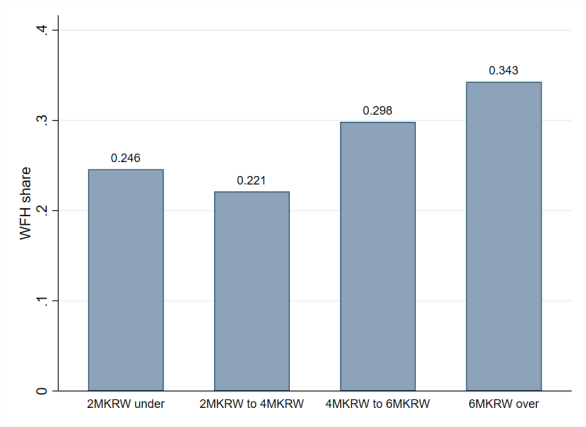
(c) Firm Size



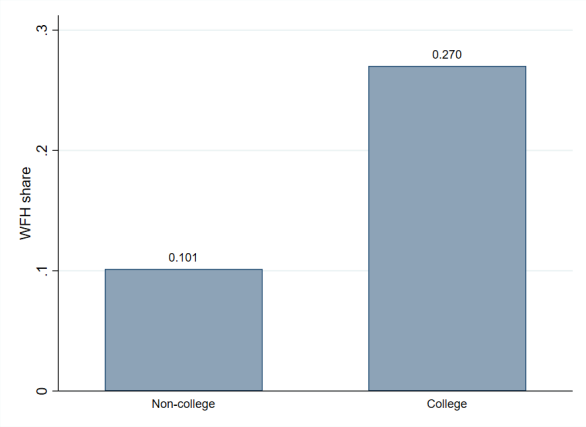
(d) Geography

Note: The WFH share represents the share of individuals who have ever worked from home since the beginning of 2020, which is calculated using 1,555 workers in our estimation sample.

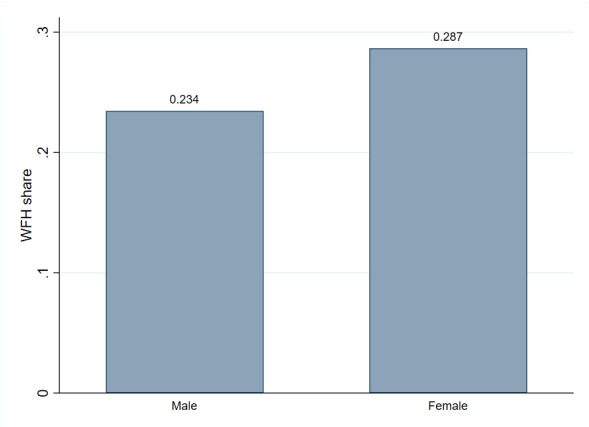
Figure A2: WFH Shares Across Individual Characteristics



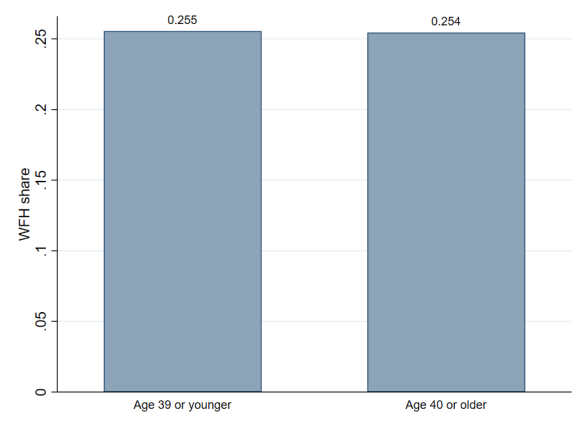
(a) Earnings



(b) College Education



(c) Gender



(d) Age Group

Note: The WFH share represents the share of individuals who have ever worked from home since the beginning of 2020, which is calculated using 1,555 workers in our estimation sample.

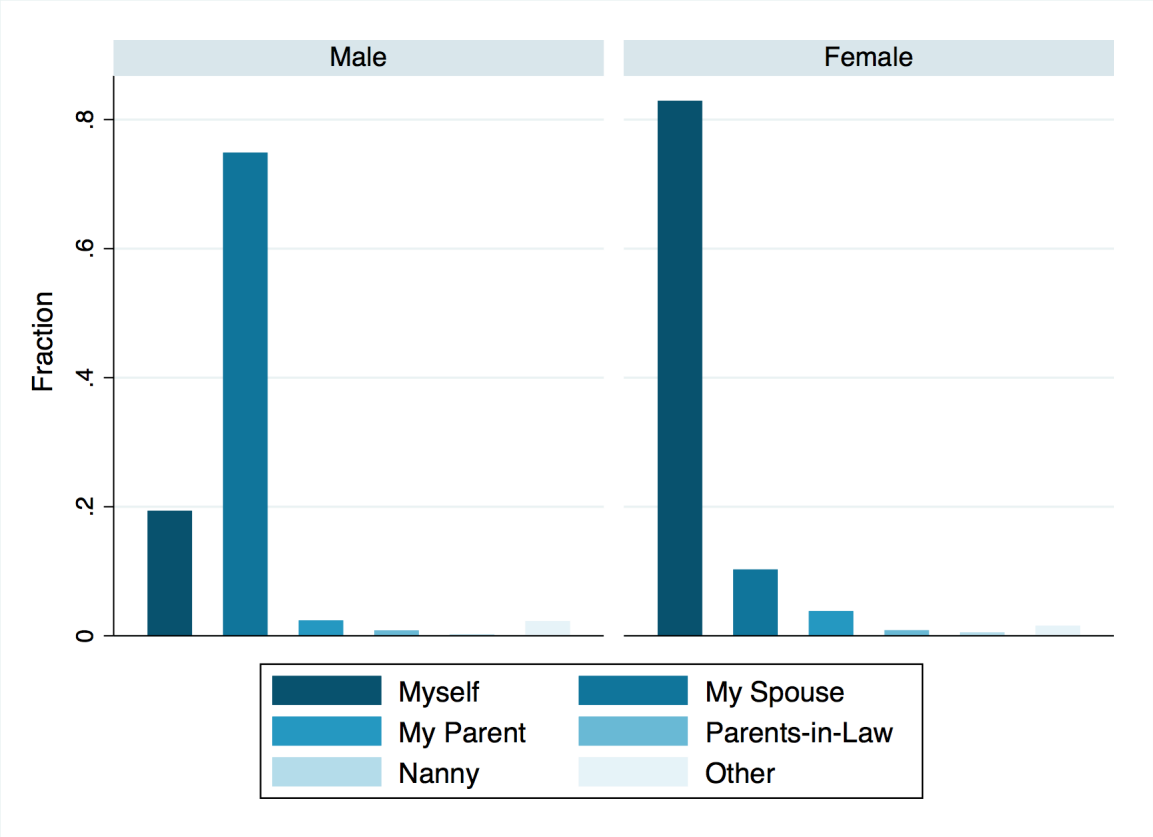
B Additional Descriptive Statistics

Table A1: Summary Statistics

	Mean	Std.Dev.
Female	0.49	0.50
Age	40.76	8.26
Married	0.86	0.35
Years of education	15.57	2.12
Number of HH members	3.27	1.08
Number of children in HH	1.61	0.62
Worked past year	0.89	0.31
Observations	2000	

Note: This table reports mean summary statistics of key demographic variables of full sample of our survey data. "HH" refers to household. Definition of children is those under age 18.

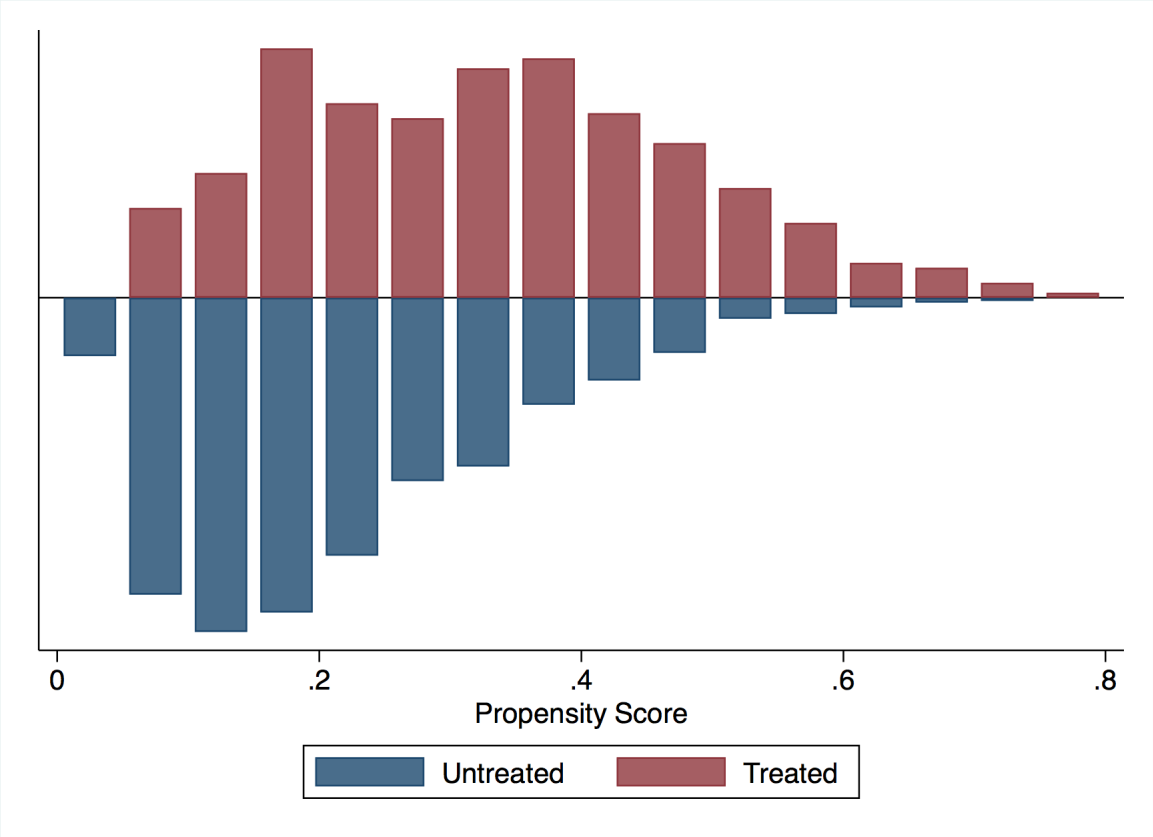
Figure A3: Who was mainly responsible for the housework



Note: This figure reports responses to our survey question that asks **who is mainly responsible for the housework**. We limit the sample to married, employed individuals.

As the Figure A3 shows, in most cases the women were mainly responsible for the housework, even when both of the spouses were employed. In a nationally representative survey of households between 2012 and 2018 (KWDI, 2018), for each category of domestic labor including cooking, dishwashing, laundry, grocery shopping, and cleaning, less 10% of the respondents said that husband performed these activities more than 4 days a week. The most frequent response was that the husband "never" engaged in these activities (27 to 44%). This pattern suggests that the allocation of housework is highly skewed and inflexible for most households in Korea. In our survey, we found that 75% of the respondents said that the distribution of housework before the pandemic remained the same during the pandemic, while 20% said that the burden increased for the main housework provider. Only approximately 5% responded that the housework distribution became more evenly distributed after the pandemic. Given this background, we think of the "main person responsible for the housework" in our sample as a fixed characteristics of the household rather than an outcome of the COVID-19 pandemic.

Figure A4: Propensity Score Distribution for Treated and Control Groups



Note: This figure shows the propensity score distribution for the treated and control groups for our main specification, which include the set of variables that determine WFH status.

Table A2: Test of Match Quality

Dependent Variable	Sample	T Mean	C Mean	% bias	% Reduct —bias—	t-stat	$p > \|t\|$
Female	Unmatched	0.44836	0.38256	13.4		2.31	0.021
	Matched	0.44836	0.44016	1.7	87.5	0.23	0.816
Over age 40	Unmatched	0.50882	0.55181	-8.6		-1.48	0.138
	Matched	0.50882	0.50902	0	99.5	-0.01	0.995
Have kid(s)	Unmatched	0.62217	0.60449	3.6		0.62	0.534
	Matched	0.62217	0.63135	-1.9	48.1	-0.27	0.789
Single	Unmatched	0.10579	0.11399	-2.6		-0.45	0.655
	Matched	0.10579	0.11009	-1.4	47.6	-0.19	0.846
Some college	Unmatched	0.15365	0.25475	-25.3		-4.16	0
	Matched	0.15365	0.15673	-0.8	97	-0.12	0.905
College graduate	Unmatched	0.5869	0.51986	13.5		2.31	0.021
	Matched	0.5869	0.5871	0	99.7	-0.01	0.996
Grad school	Unmatched	0.22418	0.11831	28.4		5.21	0
	Matched	0.22418	0.21773	1.7	93.9	0.22	0.827
Firm size: 10 - 49	Unmatched	0.21159	0.27807	-15.5		-2.61	0.009
	Matched	0.21159	0.20674	1.1	92.7	0.17	0.867
Firm size: 50 - 99	Unmatched	0.17884	0.13817	11.1		1.97	0.049
	Matched	0.17884	0.17589	0.8	92.8	0.11	0.914
Firm size: 100 - 499	Unmatched	0.21662	0.1494	17.4		3.11	0.002
	Matched	0.21662	0.21343	0.8	95.3	0.11	0.913
Firm size: 500+	Unmatched	0.14861	0.13299	4.5		0.78	0.435
	Matched	0.14861	0.14921	-0.2	96.2	-0.02	0.981
Monthly wage: $2000 - 4000	Unmatched	0.41562	0.50173	-17.3		-2.97	0.003
	Matched	0.41562	0.41018	1.1	93.7	0.16	0.877
Monthly wage: $4000 - 6000	Unmatched	0.2796	0.22539	12.5		2.19	0.029
	Matched	0.2796	0.27753	0.5	96.2	0.06	0.948
Monthly wage: $6000 - 8000	Unmatched	0.12091	0.07945	13.8		2.49	0.013
	Matched	0.12091	0.12111	-0.1	99.5	-0.01	0.993
Transportation, warehousing,	Unmatched	0.02771	0.038	-5.8		-0.96	0.339
rental industry	Matched	0.02771	0.02884	-0.6	89	-0.1	0.924
Wholesale/retail, service industry	Unmatched	0.07809	0.09931	-7.5		-1.25	0.211
	Matched	0.07809	0.07909	-0.4	95.3	-0.05	0.958
Professional, scientific,	Unmatched	0.20907	0.13817	18.8		3.37	0.001
management industry	Matched	0.20907	0.21437	-1.4	92.5	-0.18	0.855
Public administration, military	Unmatched	0.06801	0.04318	10.8		1.97	0.049
industry	Matched	0.06801	0.07292	-2.1	80.2	-0.27	0.787
Education, health,	Unmatched	0.29219	0.1848	25.4		4.54	0
social service industry	Matched	0.29219	0.27146	4.9	80.7	0.65	0.517
Arts, entertainment, recreation	Unmatched	0.0403	0.01727	13.8		2.64	0.008
industry	Matched	0.0403	0.04565	-3.2	76.8	-0.37	0.711
Other industry	Unmatched	0.0806	0.11831	-12.6		-2.08	0.037
	Matched	0.0806	0.0814	-0.3	97.9	-0.04	0.967

Table A2: Test of Match Quality–continued

Dependent Variable	Sample	T Mean	C Mean	% bias	% Reduct —bias—	t-stat	$p > \|t\|$
Busan	Unmatched	0.05038	0.07081	-8.6		-1.42	0.156
	Matched	0.05038	0.05086	-0.2	97.6	-0.03	0.975
Daegu	Unmatched	0.08816	0.03368	22.9		4.43	0
	Matched	0.08816	0.08012	3.4	85.2	0.41	0.684
Incheon	Unmatched	0.05793	0.0639	-2.5		-0.42	0.672
	Matched	0.05793	0.05539	1.1	57.3	0.16	0.877
Gwangju	Unmatched	0.02519	0.03109	-3.6		-0.6	0.55
	Matched	0.02519	0.02431	0.5	85.1	0.08	0.936
Daejeon	Unmatched	0.03023	0.02504	3.2		0.56	0.578
	Matched	0.03023	0.03217	-1.2	62.6	-0.16	0.875
Ulsan	Unmatched	0.02771	0.02159	3.9		0.7	0.484
	Matched	0.02771	0.02255	3.3	15.8	0.46	0.643
Sejong	Unmatched	0.01259	0.00691	5.8		1.07	0.283
	Matched	0.01259	0.0107	1.9	66.6	0.25	0.804
Gyeonggi	Unmatched	0.24433	0.26252	-4.2		-0.71	0.475
	Matched	0.24433	0.24266	0.4	90.8	0.05	0.956
Gangwon	Unmatched	0.01259	0.02763	-10.7		-1.7	0.09
	Matched	0.01259	0.01172	0.6	94.2	0.11	0.91
Chungcheongbuk	Unmatched	0.01511	0.03368	-12		-1.91	0.057
	Matched	0.01511	0.01742	-1.5	87.6	-0.26	0.797
Chungcheongnam	Unmatched	0.04786	0.03972	4		0.7	0.485
	Matched	0.04786	0.04393	1.9	51.7	0.26	0.792
Jeollabuk	Unmatched	0.02015	0.038	-10.6		-1.71	0.088
	Matched	0.02015	0.02108	-0.6	94.8	-0.09	0.927
Jeollanam	Unmatched	0.02015	0.03195	-7.4		-1.21	0.226
	Matched	0.02015	0.02165	-0.9	87.3	-0.15	0.883
Gyeongsangbuk	Unmatched	0.03023	0.05009	-10.1		-1.65	0.1
	Matched	0.03023	0.02958	0.3	96.7	0.05	0.957
Gyeongsangnam	Unmatched	0.0529	0.07168	-7.8		-1.29	0.196
	Matched	0.0529	0.05157	0.5	92.9	0.08	0.933
Jeju	Unmatched	0.01259	0.01382	-1.1		-0.18	0.856
	Matched	0.01259	0.01166	0.8	23.3	0.12	0.904

C Robustness

As a robustness exercise, we re-estimate the baseline results and the heterogeneity analyses using OLS, where the control variables are the same set of variables used as the variables

used for propensity score matching. Shown in Table A3, the results are comparable to those estimated using matching, both in terms of magnitude and in qualitative implications.

Table A3: OLS: Effect of Working From Home on Mental Health

	(1) Avg.	(2) Factor	(3) Anxious	(4) Lethargic	(5) Restless	(6) Tired	(7) Sad	(8) Worthless	Obs.
Panel A: Full Sample									
	0.089*	0.106	0.048	0.128**	0.067	0.066	0.112*	0.115*	1364
	(0.053)	(0.064)	(0.065)	(0.063)	(0.064)	(0.064)	(0.065)	(0.066)	1364
Panel B: By Gender									
Male	0.018	0.025	-0.041	0.070	-0.005	-0.014	0.049	0.050	832
	(0.074)	(0.089)	(0.089)	(0.086)	(0.087)	(0.087)	(0.086)	(0.087)	832
Female	0.145*	0.167*	0.158*	0.159*	0.136	0.128	0.148	0.139	532
	(0.078)	(0.094)	(0.093)	(0.094)	(0.095)	(0.099)	(0.102)	(0.106)	532
Panel C: By Housework									
Not Main Person	0.024	0.020	0.050	0.097	-0.026	0.002	0.022	-0.002	656
	(0.077)	(0.093)	(0.098)	(0.094)	(0.093)	(0.095)	(0.091)	(0.090)	656
Main Person	0.177**	0.201*	0.142	0.156	0.122	0.168	0.206*	0.270**	516
	(0.086)	(0.103)	(0.101)	(0.101)	(0.100)	(0.105)	(0.106)	(0.113)	516
Panel D: By Children									
No Kids	0.148*	0.185*	-0.008	0.241**	0.150	0.075	0.183*	0.250**	518
	(0.085)	(0.102)	(0.107)	(0.103)	(0.105)	(0.098)	(0.108)	(0.104)	518
Have Kids	0.015	0.014	0.027	0.028	-0.024	0.023	0.031	0.007	846
	(0.067)	(0.081)	(0.081)	(0.081)	(0.080)	(0.084)	(0.080)	(0.083)	846

Note: This table reports the OLS estimates of work from home. For Column (1), outcome variable is the average z-score of all mental health variables. For Column (2), outcome variable is the factor score of all mental health variables, where we follow the methodology in Gensowski (2018). Columns (3) - (8) are for mental health z-score of individual items in Kessler's scale. Control set includes: indicators for age over 40, presence of children under age 18 in the household, marital status, education, firm size, earnings categories, industry, province of residence. Robust standard errors are reported in parentheses. ***, **, and * indicate significance of the coefficients at the 1%, 5%, and 10% levels respectively.