Kim, Jun Hyung; Koh, Yu Kyung; Park, Jinseong

Working Paper

Mental Health Consequences of Working from Home during the Pandemic

GLO Discussion Paper, No. 960

Provided in Cooperation with:
Global Labor Organization (GLO)

Mental Health Consequences of Working from Home during the Pandemic

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

October 21, 2021

Abstract

This paper examines the effects of working from home on mental health, 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 in the first half of 2020. Furthermore, we find substantial heterogeneity across gender and home environment. The negative impact of working from home is concentrated on women, and on 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

*Institute for Economic and Social Research, Jinan University, Guangzhou, and GLO Affiliate. 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

COVID-19 pandemic has dramatically changed the landscape of work. Before the pandemic, only a small proportion of workers worked from home.[1] In contrast, between 25 to 50% of workers around the world reported working from home since the beginning of the pandemic (Galasso and Foucault, 2020; Brynjolfsson et al., 2020).[2] This rapid shift to working from home can generate benefits, but also challenges, to workers and employers.

From the employers' perspective, working from home would greatly reduce the overhead costs associated with running offices, including rents and utilities costs. However, labor productivity could suffer when managers have limited control over their employees working from home. From the workers' perspective, working from home removes the hassles from commuting and allows more flexibility in allocating workers' time between work and non-work activities. 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, workers working from home may have difficulties in securing work space, communicating with peers, and setting a boundary between work and non-work activities. This work-family conflict can impose a huge psychological burden on workers working from home (Etheridge et al., 2020; Iqbal et al., 2020).

This paper explores how working from home (WFH) affects workers' mental health, using unique real-time survey data from South Korea collected during the COVID-19 pandemic. 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 on the effects of WFH on mental health. Since WFH is likely to become a more prevalent form of work in the near future, it is important to understand

[1] For instance, in the US, only 15% of working hours were performed at home in the US between 2011 and 2018 (OECD, 2020a).

[2] Dingel and Neiman (2020) and Gottlieb et al. (2021) show that the ability to work from home differs widely across countries, based on job compositions and the communication technology infrastructure. Nonetheless, the proportion of workers working from home likely increased in all countries affected by the pandemic.

the benefits and costs of working from home.

Working-from-home during the COVID-19 pandemic is quite different from its pre-pandemic form, allowing us to learn new and different aspects of WFH that can affect workers' mental health (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 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 a caregiver and worker 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 WFH arrangement otherwise, and how their experience interacts with family environment and responsibilities.

To estimate the average effect of WFH on individuals with the WFH experience (i.e. treatment effects on the treated), we employ two empirical methods based on propensity score. The first method is kernel matching proposed by Heckman et al. (1997), and the second method is doubly robust estimation that combines inverse probability weighting with regression adjustment. Our identification relies on the *unconfoundedness* assumption, which means that potential mental health outcomes of individuals who have never worked from home are independent of WFH status, conditional on observable characteristics.[3] In essence, the assumption implies that the mental health outcomes of WFH workers during the pandemic would be similar to those of office workers had they not worked from home.

We acknowledge that unconfoundedness is a strong assumption. However, we believe that the COVID-19 context and the institutional background of South Korea mitigates concerns about the potential violation of the assumption, while also helping us understand the nature of selection into WFH during the pandemic. First of all, the severity of COVID-19 infections

[3] Caliendo and Kopeinig (2008) note that this assumption is variously called exogeneity, selection on observables, or the conditional independence assumption in the literature.

across localities would matter because an abrupt switch to WFH was partly driven by an effort to contain the virus. Workers in areas with higher confirmed cases were strongly encouraged to work from home, and employers were asked to make WFH feasible (Ministry of Health and Welfare, 2020). Moreover, individuals with public service occupations such as teachers or civil servants were mandated to adopt WFH depending on the circumstances. Second, job-level or firm-level feasibility for WFH would also play an important role in determining WFH status during the pandemic (Dingel and Neiman, 2020). Lastly, most Korean workers have never worked from home before the pandemic, and thus have little opportunity to learn about whether WFH is suitable for them.[4] Bloom et al. (2015) show that about half of workers who initially opted in WFH returned to the office after experiencing productivity losses. This evidence suggests that the realized mental health might not necessarily reflect workers' preferences for WFH.

Nevertheless, we would not be able to remove the omitted variable bias completely. For example, our estimate would understate the negative effects of WFH on mental health if workers sorting into WFH indeed enjoyed it. On the other hand, we would overstate the detrimental impact of WFH on mental health if employees living in areas with higher infection rates were forced to switch to WFH. In this case, our estimates may reflect the negative impact of the pandemic to some extent, although we control for regional differences in the COVID-19 confirmed cases in all specifications.[5]

Our results indicate that WFH during the pandemic deteriorates individual mental health. In particular, WFH workers have a greater chance of feeling lethargic and sad than non-WFH workers of similar characteristics. We also find evidence that there exists substantial treatment effect heterogeneity. The negative impact of working from home is concentrated on female workers. In addition, the negative effect is stronger for those who are primarily responsible for housework while also maintaining market work. Finally, contrary

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

[5] We provide further evidence supporting our unconfoundedness assumption in Sections 5.1 and A.1.

to conventional wisdom, we find 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.

Our contributions are twofold. First, our study is the first that primarily focuses on the mental health consequences of WFH during the pandemic. While WFH has become increasingly common during the pandemic, little is known about the impact of WFH on workers' psychological well-being. We provide evidence from South Korea whose COVID-19 infection rate was modest at the time compared to other countries. This is worth emphasizing because in general the direct impact of the pandemic would complicate the interpretation of results. Although we do not claim to completely eliminate such concerns, studying the case of South Korea would help mitigate the confounding effects of pandemic to some extent. Second, we explore 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. The importance of family environment was not considered in the previous studies of WFH (Felstead and Reuschke, 2020; Beland et al., 2020; Etheridge et al., 2020).

This paper speaks to two strands of literature. The first strand of literature explores potentials of WFH as a form of alternative work arrangements. While economists investigated various aspects of different work arrangements (Garen, 2006; Mas and Pallais, 2017; Katz and Krueger, 2019), only a few studies explored the benefits and costs of working from home before the COVID-19 pandemic, especially in relation to worker's mental health. One notable exception is Bloom et al. (2015) who explored the potentials of WFH using a field experiment. The authors show that working from home leads to higher productivity, greater work satisfaction, and lower attrition. Importantly, they show that WFH is not necessarily beneficial for everyone. Workers in their sample learned over time whether they were a good fit for WFH, and some workers chose to work in the office even when given an opportunity to continue working from home.

As the widespread COVID-19 virus called for a dramatic shift in working environment, several studies examine how working from home shapes our working life in many dimensions. Studies document that certain types of jobs can be done from home relatively easily than other jobs (Dingel and Neiman, 2020; Hensvik et al., 2020; OECD, 2020a). In general, these jobs belong to education, management, finance and insurance, and information industries, where tasks can be relatively easily done at home compared to other jobs. Adams-Prassl et al. (2020) find that higher suitability for home working is negatively associated with the probability of losing a job. Women and less-skilled workers are under-represented in these jobs, and thus bear higher risk of being unemployed. As a result, WFH during the pandemic led to widening income inequality (Bonacini et al., 2021).

The second strand of literature explores the link between the spread of COVID-19 and individual mental health. Studies find evidence that the pandemic deteriorated individual mental health in Europe and the US (Brodeur et al., 2021), the UK (Etheridge and Spantig, 2020), Canada (Beland et al., 2020), and Singapore (Cheng et al., 2020), among others. In general, women and the less educated experienced more serious deterioration of mental health during the pandemic (Beland et al., 2020; Etheridge and Spantig, 2020).

A few recent studies provide some evidence regarding the mental well-being of WFH workers during the COVID-19 pandemic. First, Felstead and Reuschke (2020) document a comprehensive description of WFH in the UK and its impact on productivity and mental health. Felstead and Reuschke (2020) find that WFH leads to lower mental well-being on average, consistent with our results. They further show that the effects faded over time as workers adjusted to the new environment. Second, Beland et al. (2020) investigate the effect of COVID-19 on the Canadian labor market, showing that workers who cannot work from home suffered lower mental health due to COVID-19 than those who could easily work from home. In other words, the authors emphasize on the role of WFH in mitigating the negative effects of the pandemic on mental health. Finally, Etheridge et al. (2020) investigate the productivity of WFH workers in the UK. The authors provide suggestive evidence that women with children may suffer worse mental health due to lower productivity compared to women without children. While their finding focuses on the channel from WFH to mental health via productivity, our study shows that the overall effect of having children at home is not negative, suggesting that there may be channels other than productivity decline that connect WFH to mental health.

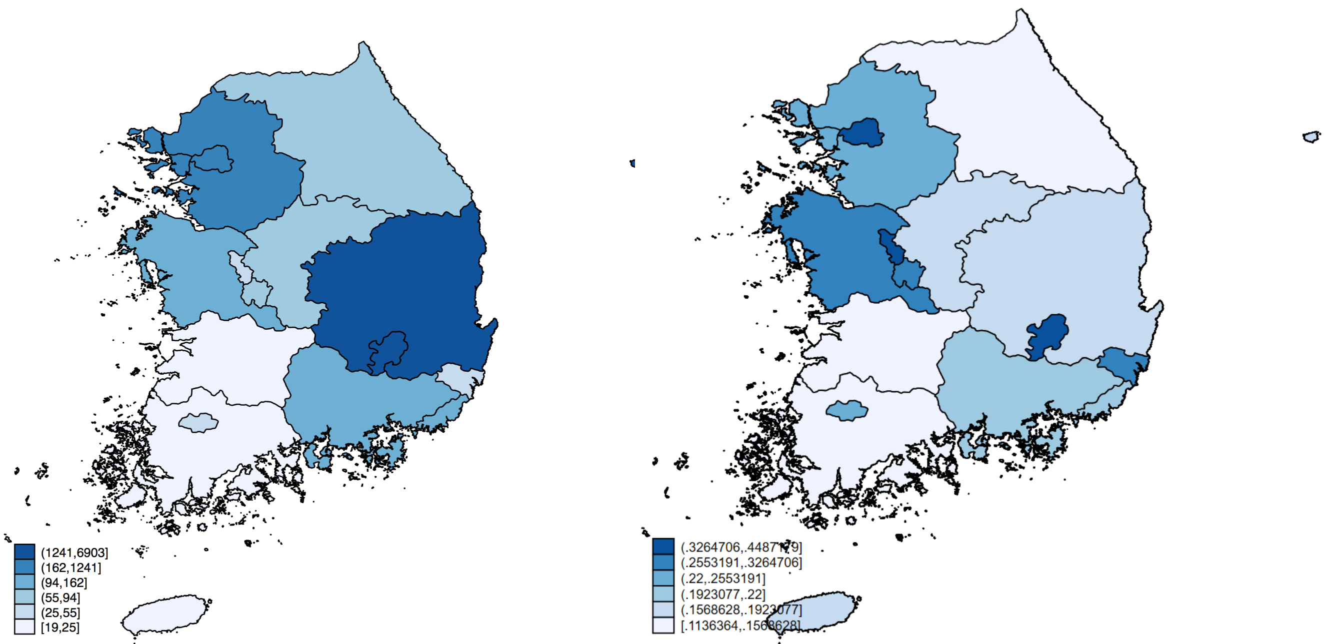
The rest of this paper proceeds as follows. Section 2 presents background information regarding the COVID-19 pandemic in South Korea and the evolution of home working before and during the pandemic. Section 3 discusses the unique features of the real-time survey data used in the analysis and Section 4 explains our empirical strategies and potential threats to identification. Section 5 presents the estimation results and Section 6 interprets our key findings. Section 7 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 (Ministry of Health and Welfare, 2020).

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.

Working From Home and the COVID-19 Pandemic in Korea: Before the COVID-19 pandemic, very few workers experienced WFH in Korea. According to a nationally representative survey of workers 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).

However, work arrangements changed dramatically for Korean workers since the beginning of the pandemic. The government put out statements strongly encouraging WFH in order to reduce the spread of COVID-19 (Ministry of Health and Welfare, 2020), while mandating WFH for many public sector jobs (OECD, 2020b). Reports show that 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, a survey by the Ministry of Employment and Labor shows that 48.8% of the employers introduced some form of WFH arrangement since the start of the pandemic. 34.1% of the employees reported that they took advantage of the work-from-home arrangement, a dramatic increase from 2.2% in 2017 (MOEL, 2020).

The pattern of WFH reflects both the regional COVID-19 intensity and the job characteristics of workers, 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.[6] 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

[6] 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.

health. Staying at home may allow workers to be more focused on work by reducing office-related distractions, or better balance housework and market work. 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 Data

To study the impact of COVID-induced WFH on mental health, we use real-time online survey data that we collected on 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 are selected from the company's panel who regularly participated in the company's other online surveys.[7] We used a regional quota-based sampling to ensure that our sample is geographically representative. To be eligible for the survey participation, participants had to be the head of household or the spouse and be of age between 25 and 55. Table A1 shows the summary statistics of some demographic variables. 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.

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 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 em-

[7] To incentivize participation in the survey, we provided some monetary benefits for completing the survey.

ployment and earnings. We followed employment-related questions in the Current Population Survey (CPS) and the South Korean Labor Force Survey (LFS). 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.[8]

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 this year. We also asked respondents how hours of work, work intensity, and household income have changed after the pandemic started.

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

Table 1: Balance Table

Variable	(1) Never WFH N	(1) Never WFH Mean/SE	(2) WFH N	(2) WFH Mean/SE	T-test Difference (1)-(2)
Age	1206	40.979	417	40.269	0.711
		(0.238)		(0.392)	
Gender	1206	0.386	417	0.460	-0.074***
		(0.014)		(0.024)	
Married	1206	0.856	417	0.871	-0.015
		(0.010)		(0.016)	
Have Kids	1206	0.605	417	0.619	-0.013
		(0.014)		(0.024)	
Years of Education	1206	15.435	417	16.391	-0.956***
		(0.060)		(0.103)	
College Graduate	1206	0.517	417	0.583	-0.066**
		(0.014)		(0.024)	
High Income	1182	0.304	410	0.393	-0.089***
		(0.013)		(0.024)	
Public Sector Job	1206	0.113	417	0.240	-0.127***
		(0.009)		(0.021)	
Firm Size: Under 100 Employees	1180	0.719	403	0.633	0.086***
		(0.013)		(0.024)	
Residence: Metro City	1206	0.428	417	0.528	-0.100***
		(0.014)		(0.024)	

Notes: The value displayed for t-tests are the differences in the means across the groups. WFH refers to the survey respondents who have reported to work from home this year. ***, **, and * indicate significance at the 1, 5, and 10 percent critical level.

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 1 reports differences between respondents with and without WFH experience during this time. It shows that women, college graduates, and high-income earners are more likely to have worked from home. Moreover, having public or government sector job, working for a large firm, and living in metropolitan city[9] are positively associated with WFH experience.

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

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 is widely used self-reported scale that 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. The information we use in our analyses include who mainly took care of housework this year. Figure A3 reports the responses to these questions for respondents who are both married and employed. Responses reveal that over 80% of female respondents identified themselves the main person who takes care of housework, whereas less than 20% of male respondents did so.

4 Empirical Strategy

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 causes biases:

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

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.

There are several reasons to believe that WFH status during the pandemic is primarily determined by a set of characteristics observed in our data. 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 5.1 and A.1 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.

Because our research design does not allow us to completely eliminate the threats to our identification assumption, our estimates may still be biased by unobservable characteristics that affect both WFH status and mental health. If, for example, 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.[10] Under these scenarios, our estimates can be interpreted as upper bound on the effects of WFH on mental health.

Under the unconfoundedness assumption, we rely on two complementary methods based

[10]A report by the Bank of Korea (Kim and Yoo (2021)) show 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.

on the propensity score: kernel matching (KM) and doubly robust estimation that combines inverse probability weighting with regression adjustment (IPWRA) (Wooldridge, 2010). In both models, the use of the propensity score helps correct for the imbalance in covariates between WFH workers and office workers. 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.[11]

Nonparametric methods such as single nearest neighbor matching do not rely on the functional form assumption. However, such pair matching is not efficient because the method does not use information on control units that are not matched, but share similar characteristics to the treated units. The efficiency loss would be particularly problematic in small samples where the number of available matches is limited (Imbens, 2004). In contrast, KM uses information in all control observations within a fixed bandwidth, and thus would be more efficient relative to single nearest neighbor matching (Huber et al., 2013).[12]

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. To allow for potential misspecification in the selection equation, we estimate the IPWRA model which is robust to misspecification either in the selection equation or in the outcome

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

[12] While our estimation sample is relatively small, especially considering a large number of covariates, we also employ nearest neighbor matching as an additional check. The results are qualitatively similar, but many of the estimates are not statistically significant due to large standard errors. The results are available upon request.

equation (Wooldridge, 2010).[13,14] We do not favor one method over another, but apply both methods for robustness.

The use of propensity score requires two additional assumptions. The second assumption, the *overlap* assumption, excludes the possibility that individuals of certain characteristics will receive the working-from-home treatment for sure: $P(D_i = 1|X_i) < 1$. This assumption is needed since matching estimator is undefined for the subsample where $P(D_i = 1|X_i) = 1$. There is no valid comparison group if everyone with characteristics X are in the treatment group. Figure A4 shows the distribution of the estimated propensity scores for workers in the treatment and the control group, confirming that the overlap assumption is satisfied in our sample. Lastly, we need a stable-unit-treatment-value assumption (SUTVA) which implies that one worker's mental health should not be affected by another worker's WFH status. We believe this assumption is unlikely to be a serious concern in our sample.

5 Results

5.1 Determinant analysis and matching quality tests

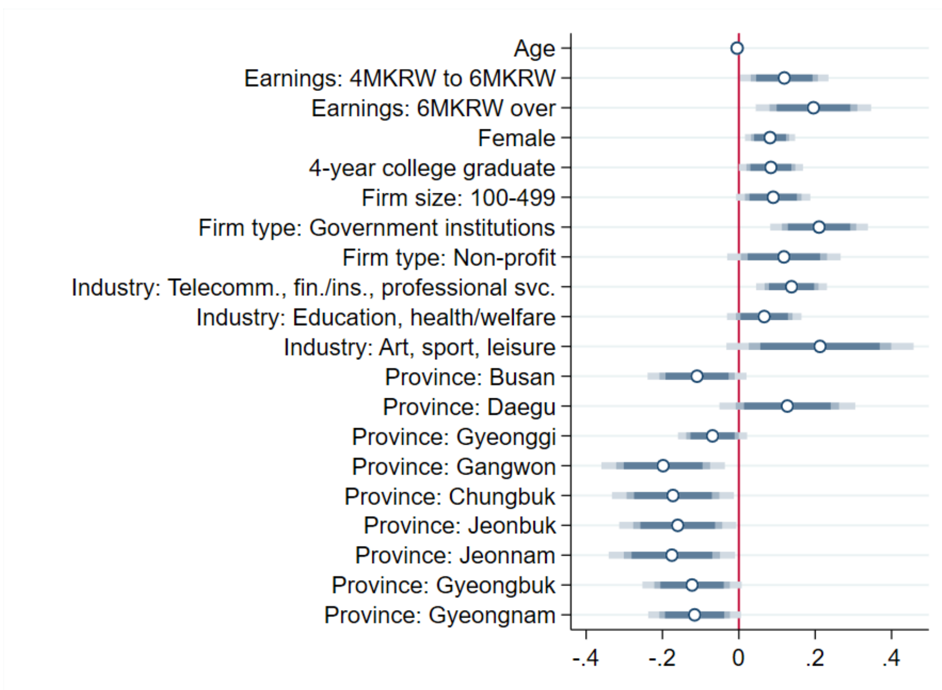
We begin by presenting a plot of coefficient estimates from a probit model predicting WFH status in Figure 2. Overall, the result is in line with our expectations as well as existing evidence from the literature. Consistent with the pattern reported in Dingel and Neiman (2020), high-earners, college 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

[13]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.

[14]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.

greater pressure to follow government guidelines (Ministry of Health and Welfare, 2020). Those in the city of Daegu are more likely to have worked from home. Daegu was the site of a highly publicized mass outbreak in mid-February, where the local government responded by introducing strong social distancing measures (Kim et al., 2020). Women are more likely to have worked from home than men. It is yet unclear whether this difference reflects preferences, job characteristics, or other factors.

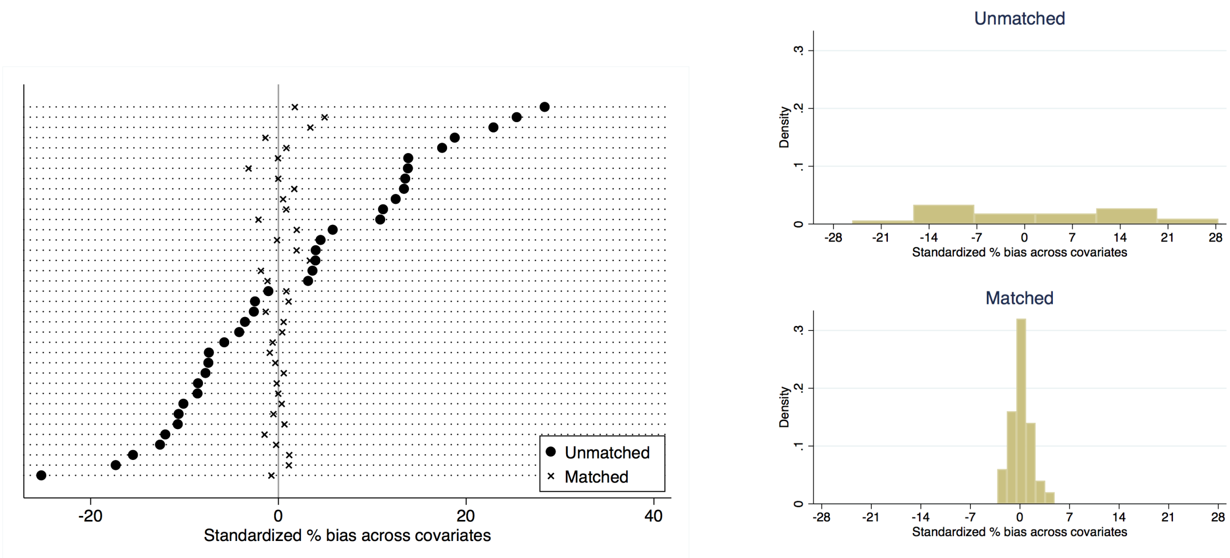
Figure 2: Determinants of Working From Home



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 this imbalance between the treatment and the control groups, 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. Appendix Table A2 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.

5.2 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 the appendix, we show that our results are robust to the inclusion of potentially endogenous variables that might affect mental health outcomes.[15]

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. Each column denotes dependent variable used in each regression. 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 0.1 and 0.13. Effects on subscales 'Anxious' and 'Restless' were between 0.05 and 0.07, 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.

[15]These variables include indicators for whether or not the respondent experienced unpaid leave, late payment, and decrease in household income due to the COVID-19 pandemic. In the main analyses, we excludes those variables to avoid the 'bad control' problem.

5.3 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. 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, ranging from 0.156 to 0.195.

Regarding the subscales, the effects are large and significant for the 'Lethargic' and 'Tired' subscales. The effects on 'Sad' and 'Worthless' subscales are sizable but borderline insignificant. The effect on 'Anxiety' subscale, which is not significant in the overall sample, is significant at 10% level for women. The effect on 'Restless' subscale is borderline insignificant and smaller in magnitude than others, but remain sizable compared to the effects for men. In summary, the effects for women are consistent with the estimates for the overall sample shown in Table 2, but larger in magnitude.

In contrast, the estimated effects for men are below 0.1 in absolute value and insignificant in all specifications.

Next, Table 4 presents 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. In Table 4, we divide our estimation sample into two groups based on the response to the question "who was mainly responsible for housework, such as cooking, laundry and cleaning, from January to May 2020?" Panel A presents estimates from the subsample of individuals who himself or herself was mainly responsible for housework during this period, and Panel B presents estimates from all other individuals.[16] The results show that the negative effect of WFH is entirely concentrated on those who

[16]The subsample of workers used in Panel B consists of individuals who responded "My spouse," "My parents," "Spouse's parents," or "Outside help" to the question. We provide descriptive statistics of responses to the question in Appendix Figure A3. We interpret this designation as a fixed trait of a household in our study and explain our reasoning in the appendix.

Table 3: Heterogeneity by Gender: 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: Male									
Kernel Matching									
	0.028	0.038	-0.033	0.075	0.011	0.021	0.050	0.041	934
	(0.072)	(0.087)	(0.089)	(0.087)	(0.086)	(0.085)	(0.084)	(0.084)	934
IPWRA									
	0.043	0.055	-0.016	0.094	0.021	0.045	0.057	0.059	934
	(0.072)	(0.086)	(0.091)	(0.085)	(0.084)	(0.086)	(0.083)	(0.083)	934
Panel B: Female									
Kernel Matching									
	0.169**	0.195*	0.184*	0.200**	0.147	0.190*	0.155	0.139	621
	(0.083)	(0.101)	(0.097)	(0.100)	(0.101)	(0.104)	(0.106)	(0.106)	621
IPWRA									
	0.156**	0.179*	0.157*	0.184*	0.116	0.182*	0.157	0.138	621
	(0.078)	(0.095)	(0.093)	(0.095)	(0.094)	(0.097)	(0.101)	(0.101)	621

Note: Panels A and B report estimates of the average treatment on the treated effect (ATT). We restrict our estimation sample to employed individuals. Each column denotes dependent variable used in each regression. 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.

report that they are primarily responsible for housework. The effects on the average mental health outcomes (Columns 1 and 2) in Panel B of Table 4 range between 0.213 and 0.262, and are greater than the corresponding effects for women in Panel B of Table 3. The effects are large and significant for 'Lethargic', 'Tired', 'Sad', and 'Worthless' subscales, larger than the corresponding effects for the women subsample in Table 3. Estimates for 'Anxious' and 'Restless' subscales are borderline insignificant and smaller in magnitude compared to the effects for other subscales, but are nonethelss sizable. On the other hand, the effects in Panel A, based on those who are not mainly responsible for housework, are small in magnitude and insignificant in all specifications.

Table 4: Heterogeneity by Housework: 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: Not Main Person Doing Housework								
Kernel Matching								
0.047	0.052	0.044	0.108	0.013	0.043	0.044	0.033	721
(0.077)	(0.093)	(0.096)	(0.093)	(0.092)	(0.092)	(0.090)	(0.089)	721
IPWRA								
0.037	0.038	0.031	0.111	-0.003	0.034	0.017	0.030	721
(0.075)	(0.089)	(0.101)	(0.092)	(0.088)	(0.091)	(0.086)	(0.086)	721
Panel B: Main Person Doing Housework								
Kernel Matching								
0.223**	0.262**	0.173	0.183*	0.157	0.277**	0.286**	0.259**	581
(0.093)	(0.113)	(0.108)	(0.111)	(0.111)	(0.115)	(0.116)	(0.117)	581
IPWRA								
0.213**	0.249**	0.150	0.183*	0.149	0.254**	0.262**	0.278**	603
(0.089)	(0.107)	(0.103)	(0.104)	(0.105)	(0.111)	(0.107)	(0.108)	603

Note: Panels A and B report estimates of the average treatment on the treated effect (ATT). We restrict our estimation sample to employed individuals whose information on housework responsibility is available. Each column denotes dependent variable used in each regression. 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.

Table 5 shows 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. Surprisingly, the negative effects of WFH on mental health is concentrated on those who do not have children living in the same household. The effects are significant for the average z-score, factor score, 'Lethargic' subscale, 'Sad' subscale, and 'Worthless' subscale, when estimated using IPWRA. The effects are borderline insignificant when estimated using KM, except for 'Lethargic' subscale where the effect is significant at 10%. While the differences are not as stark as those found in Tables 3 and 4, the estimated effects on mental health for WFH workers without children (in Panel A) are still two to three times larger than the corresponding effects for WFH workers with children (in Panel B). None of the effects shown in Panel B are significant, where respondents have children living in the same household. These results come as a surprise since we expect the additional burden of childcare would add to the difficulty of maintaining a career while WFH. We discuss further on these findings in Section 6.

Table 5: Heterogeneity by Presence of Children: 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: No Kids								
Kernel Matching								
0.131	0.158	0.033	0.228*	0.089	0.087	0.173	0.177	609
(0.097)	(0.117)	(0.119)	(0.117)	(0.117)	(0.114)	(0.119)	(0.115)	609
IPWRA								
0.172**	0.213**	0.050	0.284***	0.140	0.128	0.234**	0.197*	609
(0.088)	(0.105)	(0.108)	(0.107)	(0.105)	(0.104)	(0.110)	(0.107)	609
Panel B: Have Kids								
Kernel Matching								
0.057	0.067	0.054	0.073	0.031	0.099	0.055	0.032	946
(0.069)	(0.084)	(0.082)	(0.083)	(0.083)	(0.085)	(0.081)	(0.082)	946
IPWRA								
0.065	0.073	0.075	0.074	0.046	0.111	0.043	0.041	946
(0.066)	(0.080)	(0.082)	(0.079)	(0.080)	(0.083)	(0.078)	(0.078)	946

Note: Panels A and B report estimates of the average treatment on the treated effect (ATT). We restrict our estimation sample to employed individuals. Each column denotes dependent variable used in each regression. 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, which we follow the methodology in Gensowski (2018). Columns (3) - (8) is for the individual mental health z-score. All specifications include the following set of control variables: indicators for age over 40, presence of underage children, 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.

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 A7, the results are comparable to those estimated using matching, both in terms of magnitude and in qualitative implications.

5.4 The role of negative labor market shocks

Thus far, our results indicate that social isolation and difficulties that arise from work-family management are drivers of the mental health deterioration experienced by WFH workers. Would it be possible that our findings reflect the impact of negative labor market experiences during the pandemic? In our preferred specification, we do not include factors that are potentially affected by WFH status to avoid the bad control problem. Caliendo and Kopeinig (2008) also recommend researchers to exclude endogenous variables when modeling the selection equation.

However, our baseline estimates would be biased if those omitted factors that might influence mental health outcomes are correlated with WFH status. According to Adams-Prassl et al. (2020), the COVID-19 pandemic had an impact on the incidence of unpaid leaves, late payments, and income loss in the US, the UK, and Germany. To examine the extent to which our estimates are confounded by the effects of financial loss or concerns related to future labor market experiences, we add indicators for experiencing unpaid leaves, late payments, and income loss to all specifications and re-estimate our models.[17] If this additional exercise produces estimates that substantially diverge from our baseline estimates, the psychological burden from WFH may in part reflect the impact of the negative labor market shocks caused by the pandemic rather than social isolation and the difficulties of work-family management.[18]

The results are summarized in Table A3 in the appendix.[19] The inclusion of the three COVID-19 related variables reduces the magnitude of the effects of WFH on the average z-score by slightly more than 20% in both KM and IPWRA estimations and reduces statistical

[17]We construct those COVID-related indicators using responses to the following three questions: "whether the respondent experienced unpaid leave between January and June 2020", "whether the respondent experienced a delay in payments between January and June 2020", and "whether household income decreased between January and June 2020".

[18]It is worth mentioning that this exercise is only valid when the incidence of unpaid leaves, late payments, and income loss work as determinants of WFH status. If these variables are affected by WFH status, the inclusion of those endogenous variables would lead to underestimation of the true effect.

[19]We also explore treatment effect heterogeneity with those additional controls in Table A4, A5, and A6 in the appendix.

significance. As for the subscales, the estimates are now smaller in magntiude and most are borderline insignificant, although 'Lethargic', 'Tired', 'Sad', and 'Worthless' estimates are larger than 'Anxious' and 'Restless' estimates, consistent with the baseline results. Overall, the results indicate that the negative labor market shocks can at least partially explain our findings, assuming that those shocks are the causes of WFH rather than the consequences. Nevertheless, we still find suggestive evidence that WFH status, even conditional on labor market shocks, had a negative impact on workers' mental health during the pandemic.

6 Discussion

What do these results tell us? Our findings stand in contrast to those reported in Bloom et al. (2015) which showed that working from home had positive effects on workers' productivity and work satisfaction. However, it is important to account for some key differences between our study and Bloom et al. (2015). The workers in the sample of Bloom et al. (2015) consisted of volunteers, many of whom had children and had longer commutes. In addition, these workers did not experience the difficulties associated with the global pandemic, which created unique challenges to all WFH workers. In our study, the pandemic affected all the workers, regardless of their preferences with respect to WFH. In addition, workers had to cope with social distancing both inside and outside the context of work, contributing to social isolation workers must have experienced in our sample. Finally, it is interesting to note that many workers in Bloom et al. (2015) mentioned loneliness as a major difficulty while WFH. Consistent with this result, we also show that the negative effects of WFH is concentrated on feelings of lethargy and sadness, which are arguably more similar to the feeling of loneliness than to the feelings of anxiety and restlessness, where we find no effects. Accounting for these differences, a consistent interpretation of the findings of the two studies is that loneliness is a major challenge to WFH.

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 have had to 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 the predictions of Giménez-Nadal et al. (2020) 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 people during the pandemic, and especially women (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 childcare and housework burden fell on women (Oreffice and Quintana-Domeque (2021), in the UK; Farré et al. (2020), in Spain; Del Boca et al. (2020), in Italy). 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 are consistent with the results from the literature in psychology and management that discuss the effects of work-family enrichment. 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). Our findings suggest that the presence of young children may be an important component of the home environment that can improve workers' experience while WFH, even with the additional burden of childcare. In addition, whether or not the spouse shares housework burden seems to be an important component of the home environment that determines workers' mental health while WFH.

How can we interpret the magnitude of our estimates? Studies on the mental health of workers at home during the pandemic (Beland et al., 2020; Etheridge et al., 2020; Felstead and Reuschke, 2020) use different models and outcome measures from our own, making direct comparisons difficult. Studies that use the same outcome measure as our own (Kessler et al., 2002; 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) use 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 an equivalent decrease in the same probability is associated with 0.16 to 0.35 standard deviation decrease in psychological distress. Awaworyi Churchill et al. (2019) show that a one standard deviation increase in neighborhood ethnic diversity is associated with a 0.092-0.129 standard deviation decline in mental health. 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 significant reduction in annual income (Watson and Osberg, 2019), and more than a one standard deviation decrease in neighborhood ethnic diversity (Awaworyi Churchill et al., 2019).

7 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. In particular, the negative effects are concentrated on women, those who assume dual responsibility of housework and market work, those who do not live with children in the same household. The negative effects were primarily on measures of lethargy and sadness rather than on measures of anxiety and restlessness. These are consistent with the interpretation that loneliness plays an important role in workers' WFH experience.

Our evidence suggests that the pressure to coordinate multiple responsibilities may partly explain women's greater mental health deterioration during the pandemic (Adams-Prassl et al., 2020). If so, gender disparity in mental health effects due to WFH would be smaller in societies where the housework responsibilities are more equally shared among family members. We leave investigating this possibility for future research.

Our evidence also provides guidance to policymakers and managers with respect to WFH, which is likely to be an increasingly important type of work arrangement in the future. The effects of the home environment should be seriously considered when introducing WFH policies, since negative effects of WFH are shown to be highly dependent on the home environment such as the distribution of housework and the presence of children. Finally, further research into the interaction between different aspects of the home environment and WFH is of high importance from both managerial and public policy perspective.

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 estimation 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, South Korea is known for its grueling work hours and collectivist corporate culture (Cho et al., 2014; Park et al., 2010), which may affect our results. However, Korean corporations are increasingly becoming employee-friendly in response to global competition. Firms would be willing to adopt WFH during the pandemic if they saw it as the best response to the pandemic. Furthermore, anecdotal evidence (KBS, 2020) 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). Nonetheless, we acknowledge that these possibilities may limit the generalizability of our results to the effects of WFH on mental health in the non-pandemic period and in other countries. Finally, we cannot rule out the possibility that the unconfoundedness assumption is violated in our sample. While we point out background characteristics that suggest limited roles played by unobservable factors, we emphasize that our estimates are only suggestive of causal effects.

References

Adams-Prassl, A., T. Boneva, M. Golin, and C. Rauh (2020). Inequality in the impact of the coronavirus shock: Evidence from real time surveys. *Journal of Public Economics 189*, 104245.

Argente, D. O., C.-T. Hsieh, and M. Lee (2020). The cost of privacy: Welfare effect of the disclosure of covid-19 cases. Technical report, National Bureau of Economic Research.

Aum, S., S. Y. T. Lee, and Y. Shin (2021). Covid-19 doesn't need lockdowns to destroy jobs: The effect of local outbreaks in korea. *Labour Economics 70*, 101993.

Awaworyi Churchill, S., L. Farrell, and R. Smyth (2019). Neighbourhood ethnic diversity and mental health in Australia. *Health Economics 28*(9), 1075–1087.

Beland, L.-P., A. Brodeur, D. Mikola, and T. Wright (2020). Covid-19, occupation tasks and mental health in canada. *Working paper*.

Bloom, N., J. Liang, J. Roberts, and Z. J. Ying (2015). Does Working from Home Work? Evidence from a Chinese Experiment. *The Quarterly Journal of Economics 130*(1), 165–218.

Bonacini, L., G. Gallo, and S. Scicchitano (2021). Working from home and income inequality: risks of a 'new normal' with covid-19. *Journal of Population Economics 34*, 303–360.

Brodeur, A., A. E. Clark, S. Fleche, and N. Powdthavee (2021). Covid-19, lockdowns and well-being: Evidence from google trends. *Journal of public economics 193*, 104346.

Brynjolfsson, E., J. J. Horton, A. Ozimek, D. Rock, G. Sharma, and H.-Y. TuYe (2020, June). Covid-19 and remote work: An early look at us data. Working Paper 27344, National Bureau of Economic Research.

Caliendo, M. and S. Kopeinig (2008). Some practical guidance for the implementation of propensity score matching. *Journal of Economic Surveys 22*(1), 31–72.

Cheng, T. C., S. Kim, and K. Koh (2020, September). The impact of covid-19 on subjective well-being: Evidence from singapore. Working Paper 13702, IZA Institute of Labor Economics.

Cho, Y.-H., G.-C. Yu, M.-K. Joo, and C. Rowley (2014). Changing corporate culture over time in south korea. *Asia Pacific Business Review 20*(1), 9–17.

Del Boca, D., N. Oggero, P. Profeta, and M. Rossi (2020). Women's and men's work, housework and childcare, before and during covid-19. *Review of Economics of the Household 18*(4), 1001–1017.

Dingel, J. I. and B. Neiman (2020). How many jobs can be done at home? *Journal of Public Economics 189*, 104235.

Etheridge, B. and L. Spantig (2020, June). The Gender Gap in Mental Well-Being During the Covid-19 Outbreak: Evidence from the UK. *Covid Economics 33*, 46–72.

Etheridge, B., L. Tang, and Y. Wang (2020, October). Worker Productivity during Lockdown and Working from Home: Evidence from Self-Reports. *Covid Economics 52*, 118–151.

Farré, L., Y. Fawaz, L. González, and J. Graves (2020). How the covid-19 lockdown affected gender inequality in paid and unpaid work in spain.

Felstead, A. and D. Reuschke (2020). Homeworking in the UK: Before and during the 2020 lockdown. Working paper, Wales Institute of Social and Economic Research.

Galasso, V. and M. Foucault (2020). Working during covid-19: Cross-country evidence from real-time survey data. (246). https://doi.org/10.1787/34a2c306-en.

Garen, J. (2006). Use of employees and alternative work arrangements in the united states: a law, economics, and organizations perspective. *Labour Economics 13*(1), 107 – 141.

Gensowski, M. (2018). Personality, iq, and lifetime earnings. *Labour Economics 51*, 170–183.

Giménez-Nadal, J. I., J. A. Molina, and J. Velilla (2020). Should we cheer together? gender differences in instantaneous well-being during joint and solo activities: An application to covid-19 lockdowns. Technical report, GLO Discussion Paper No. 736.

Gorlick, A. (2020, March 30). The productivity pitfalls of working from home in the age of covid-19. https://news.stanford.edu/2020/03/30/productivity-pitfalls-working-home-age-covid-19/.

Gottlieb, C., J. Grobovšek, M. Poschke, and F. Saltiel (2021). Working from home in developing countries. *European Economic Review 133*, 103679.

Greenhaus, J. H. and G. N. Powell (2006). When work and family are allies: A theory of work-family enrichment. *Academy of Management Review 31*(1), 72–92.

Heckman, J. J., H. Ichimura, and P. E. Todd (1997). Matching as an econometric evaluation estimator: Evidence from evaluating a job training programme. *The Review of Economic Studies 64*(4), 605–654.

Hensvik, L., T. L. Barbanchon, and R. Rathelot (2020, May). Which Jobs Are Done from Home? Evidence from the American Time Use Survey. Working Paper 13204, IZA Institute of Labor Economics.

Huber, M., M. Lechner, and C. Wunsch (2013). The performance of estimators based on the propensity score. *Journal of Econometrics 175*(1), 1–21.

Imbens, G. (2004). Nonparametric estimation of average treatment effects under exogeneity: A review. *The Review of Economics and Statistics 86*(1), 4–29.

Iqbal, S., J. Suh, M. Czerwinski, G. Mark, and J. Teevan (2020, August). Remote work and well-being. Working paper, Microsoft.

Katz, L. F. and A. B. Krueger (2019). The rise and nature of alternative work arrangements in the united states, 1995–2015. *ILR Review 72*(2), 382–416.

Kawaguchi, D. and H. Motegi (2020). Who can work from home? the roles of job tasks and hrm practices. Technical report, Center for Research and Education in Program Evaluation.

KBS (2020, March). 재택근무 막상 해 보니... "눈치 안 보지만 고용은 불안"[working from home... no tacit pressure but concerned about employment]. Howpublished: https://news.kbs.co.kr/news/view.do?ncd=4399764. Note: Updated 12 March 2020.

KCDC (2020). Updates on covid-19 in republic of korea(as of 25 june). http://ncov.mohw.go.kr/en. Press Release, Korea Center for Disease Control & Prevention.

Kessler, R. C., G. Andrews, L. J. Colpe, E. Hiripi, D. K. Mroczek, S.-L. T. Normand, E. E. Walters, and A. M. Zaslavsky (2002). Short screening scales to monitor population prevalences and trends in non-specific psychological distress. *Psychological Medicine 32*, 959–976.

Kim, B. G. and M. J. Yoo (2021, April). Unemployment rate decomposition through employment status transition analysis [in Korean]. Technical report, Bank of Korea. *Josatong-gyewolbo*.

Kim, J.-H., J. A.-R. An, P.-k. Min, A. Bitton, and A. A. Gawande (2020). How south korea responded to the covid-19 outbreak in daegu. *NEJM Catalyst Innovations in Care Delivery 1*(4).

KOSHA (2017). Korean working conditions survey. https://kosis.kr/statHtml/statHtml.do?orgId=380&tblId=DT_380002_D008&conn_path=I3. Korea Occupational Safety & Health Agency.

KWDI (2018). Korean longitudinal survey of women & families. https://klowf.kwdi.re.kr/portal/mainPage.do. Korean Women's Development Institute.

Mas, A. and A. Pallais (2017). Valuing alternative work arrangements. *American Economic Review 107*(12), 3722–59.

Ministry of Health and Welfare (2020). (3.22.) stronger social distancing for 15 days, starting with the government! https://www.mohw.go.kr/eng. Press Release, Ministry of Health and Welfare.

MOEL (2020). 재택근무 업무효율과 직무만족 모두 높게 나타나[work from home associated with high productivity and worker satisfaction]. http://www.moel.go.kr/news/. Updated 24 Sept 2020, Press Release, Ministry of Employment and Labor.

OECD (2020a, September). Productivity gains from teleworking in the post covid-19 era : How can public policies make it happen? Technical report.

OECD (2020b). Public servants and the coronavirus (covid-19) pandemic: emerging responses and initial recommendations. Updated 27 April 2020, OECD.

Oreffice, S. and C. Quintana-Domeque (2021). Gender inequality in covid-19 times: Evidence from uk prolific participants. *Journal of Demographic Economics 87*(2), 261–287.

Park, J., Y. Yi, and Y. Kim (2010). Weekly work hours and stress complaints of workers in korea. *American Journal of Industrial Medicine 53*(11), 1135–1141.

Park, S. (2020). 올 상반기 공공기관 재택근무 7만5천명..작년의 53배[75,000 public sector workers work from home in the first half of this year, 53-fold increase from the previous year]. *Yonhap News*.

Rosenbaum, P. R. and D. B. Rubin (1985). Constructing a control group using multivariate matched sampling methods that incorporate the propensity score. *The American Statistician 39*(1), 33–38.

Siha, S. M. and R. W. Monroe (2006). Telecommuting's past and future: a literature review and research agenda. *Business Process Management Journal*.

Smith, J. A. and P. E. Todd (2005). Does matching overcome lalonde's critique of nonexperimental estimators? *Journal of Econometrics 125*(1-2), 305–353.

Twenge, J. M. and T. E. Joiner (2020). Mental distress among us adults during the covid-19 pandemic. *Journal of Clinical Psychology 76*(12), 2170–2182.

Watson, B. and L. Osberg (2019). Can positive income anticipations reverse the mental health impacts of negative income anxieties? *Economics & Human Biology 35*, 107–122.

Wooldridge, J. M. (2010). *Econometric analysis of cross section and panel data.* MIT press.

A Appendix

A.1 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 expectation stated in Section 4.

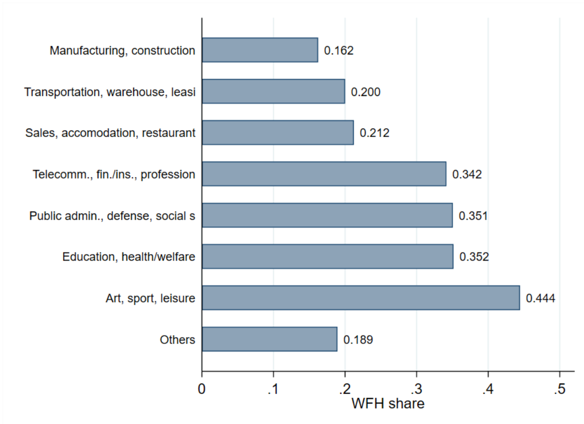
We first examine the distribution of the share of individuals who have ever worked from home from January to June of 2020 across several work characteristics. Figure A1b shows that individuals working in public institutions or government-owned firms exhibit the highest share of WFH workers, while the 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, 2020) 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 including 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.

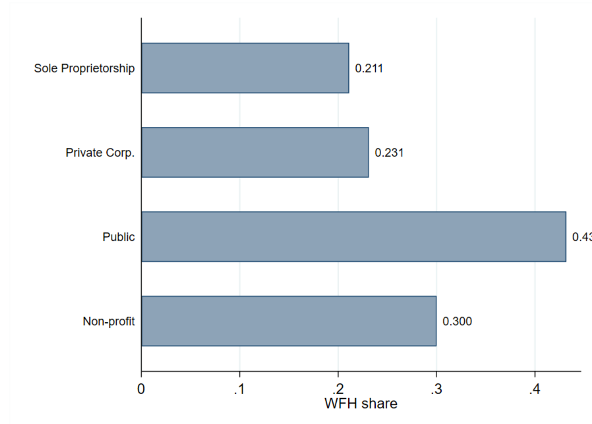
Lastly, we examine the share of WFH workers across individual characteristics in Figure A2. It shows that high-income and college-educated individuals are more likely to work from home in South Korea. In general, the pattern is consistent with existing evidence from other countries.[20] We also find that the share of workers working at home is higher for females.[21]

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

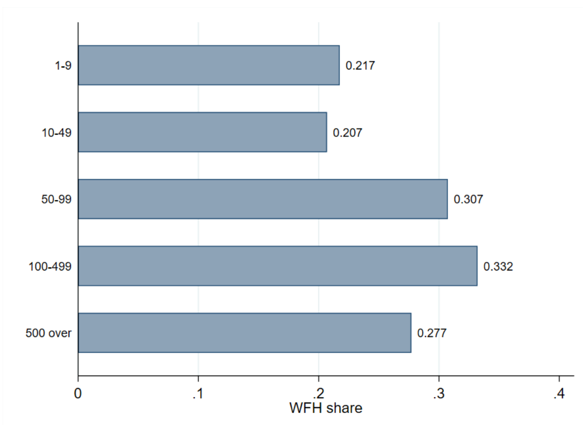
[21] The share of home workers by gender differs across countries (Galasso and Foucault, 2020).



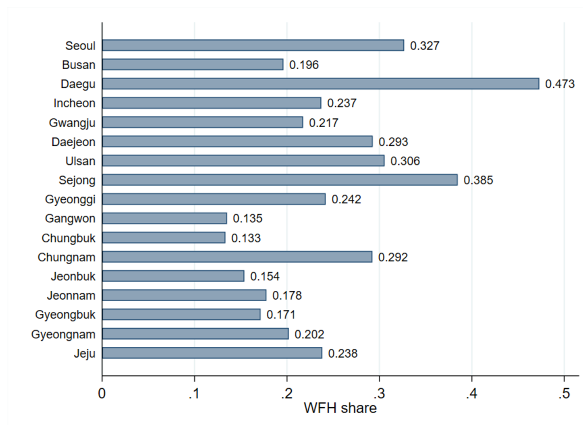
(a) Industry



(b) Firm Types



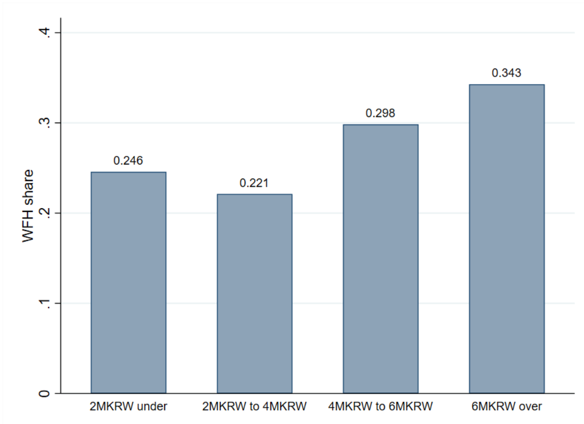
(c) Firm Size



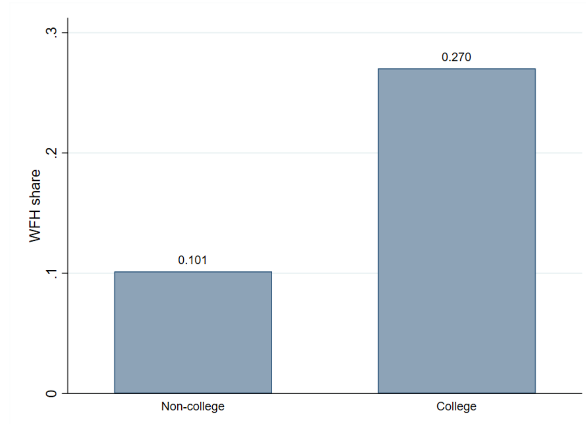
(d) Geography

Figure A1: WFH Shares Across Work Characteristics

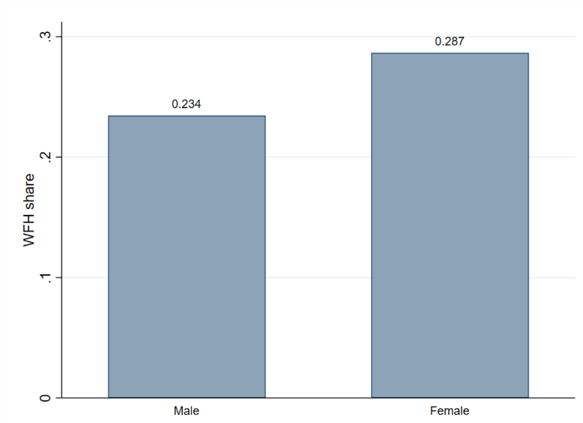
Note: The WFH share represents the share of individuals who have ever worked from home since the beginning of 2020, which is calculated using 1,555 workers in our estimation sample.



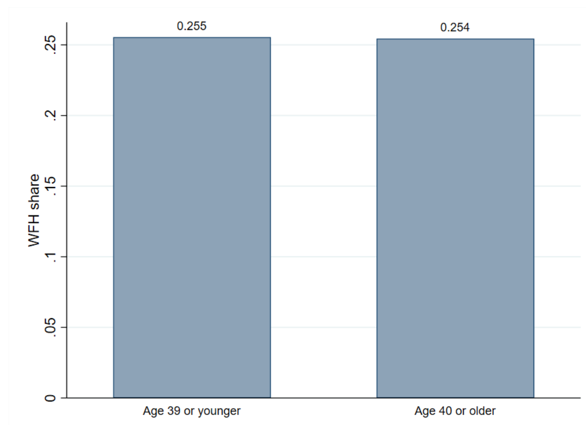
(a) Earnings



(b) College Education



(c) Gender



(d) Age Group

Figure A2: WFH Shares Across Individual Characteristics

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.

A.2 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.

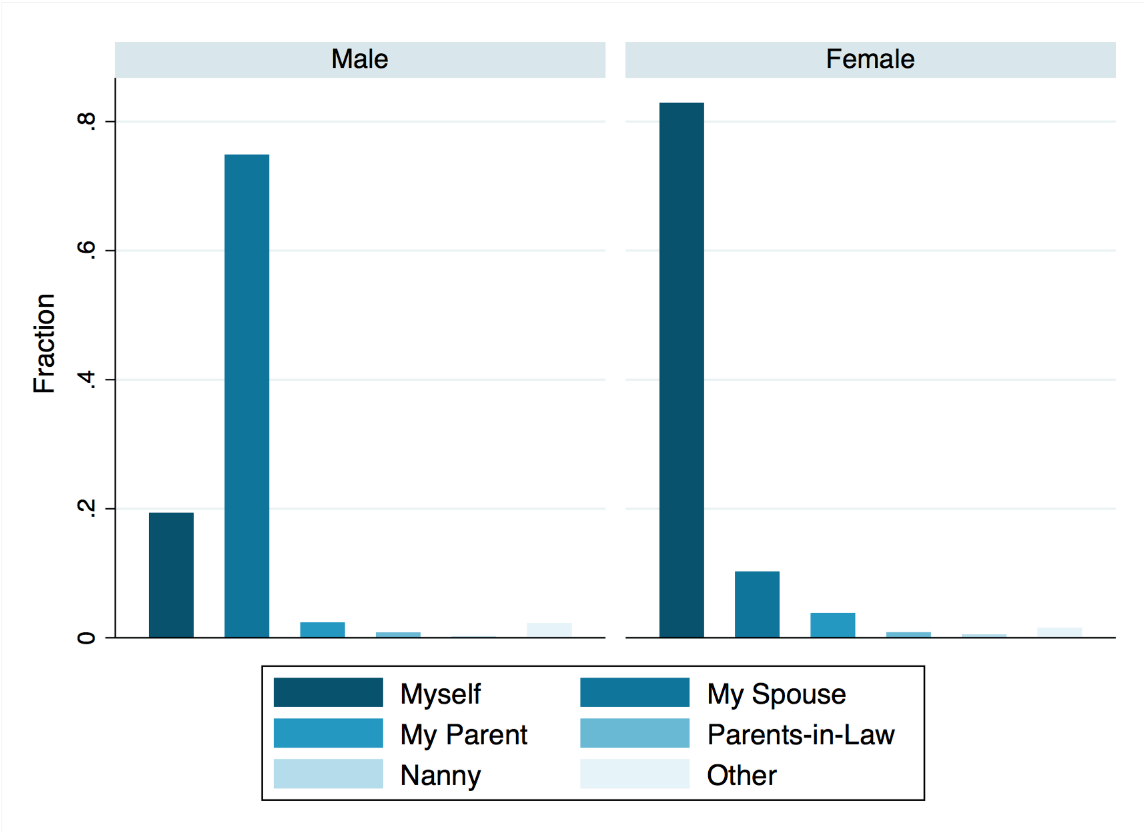
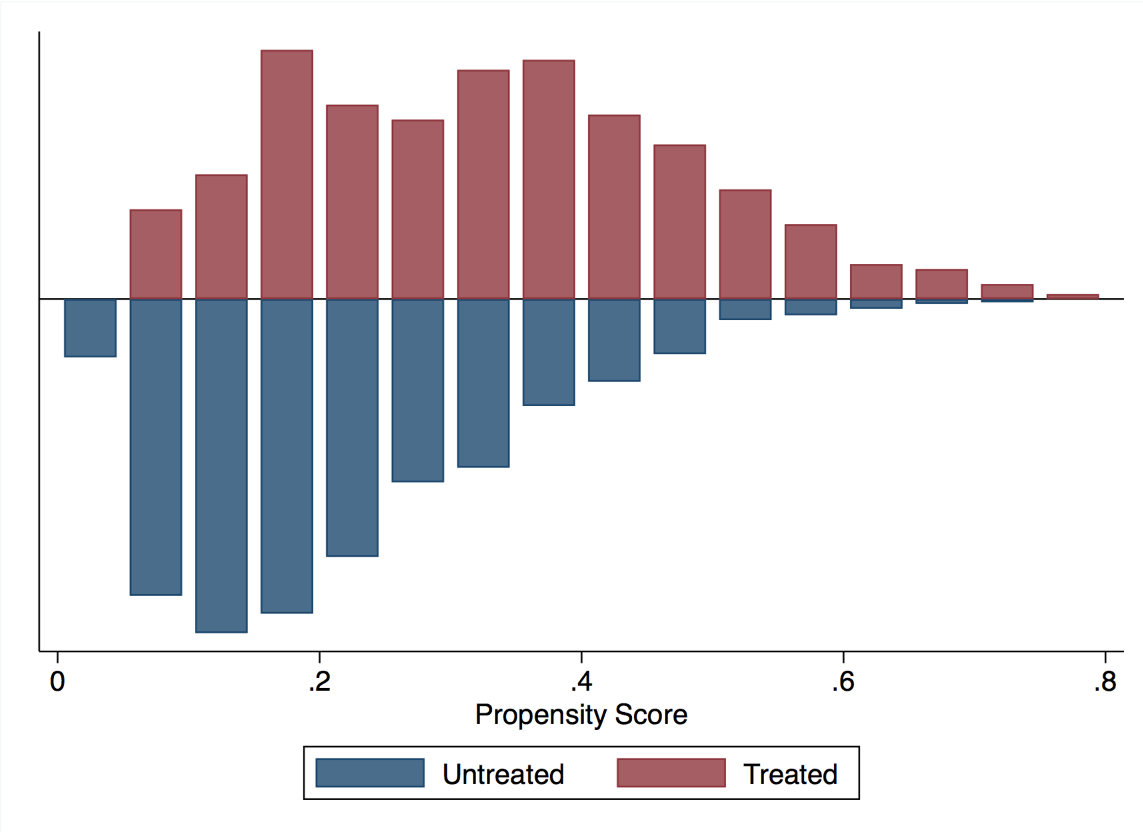


Figure A3: Who was mainly responsible for the housework

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
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

A.3 Additional Results

Table A3: 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								
Full Controls								
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
Full + COVID-Related Controls								
0.082	0.096	0.060	0.096	0.060	0.086	0.096	0.096	1364
(0.057)	(0.069)	(0.068)	(0.069)	(0.069)	(0.069)	(0.068)	(0.068)	1364
Panel B: IPWRA								
Full Controls								
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
Full + COVID-Related Controls								
0.091*	0.108	0.054	0.117*	0.070	0.104	0.094	0.110	1364
(0.055)	(0.066)	(0.068)	(0.065)	(0.066)	(0.067)	(0.068)	(0.067)	1364

Note: This table reports the estimated average treatment on the treated effect (ATT) of work from home. Each column denotes dependent variable used in each regression. 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. For linear regressions, two different specifications of control variables are reported. *Full Controls:* 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. *Full + COVID-Related Controls:* All variables included in full controls and indicators of experiencing unpaid leave, late payment, decrease in household income due to COVID. Robust standard errors are reported in parentheses. ***, **, and * indicate significance of the coefficients at the 1%, 5%, and 10% levels respectively.

Table A4: By Gender: 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: Male									
Kernel Matching									
Full Controls	0.028	0.038	-0.033	0.075	0.011	0.021	0.050	0.041	934
	(0.072)	(0.087)	(0.089)	(0.087)	(0.086)	(0.085)	(0.084)	(0.084)	934
Full + COVID-Related Controls	0.004	0.009	-0.042	0.021	-0.014	-0.003	0.037	0.028	832
	(0.077)	(0.093)	(0.093)	(0.093)	(0.092)	(0.090)	(0.089)	(0.090)	832
IPWRA									
Full Controls	0.043	0.055	-0.016	0.094	0.021	0.045	0.057	0.059	934
	(0.072)	(0.086)	(0.091)	(0.085)	(0.084)	(0.086)	(0.083)	(0.083)	934
Full + COVID-Related Controls	0.014	0.019	-0.039	0.066	-0.008	0.014	0.020	0.030	832
	(0.075)	(0.091)	(0.093)	(0.089)	(0.089)	(0.092)	(0.088)	(0.088)	832
Panel B: Female									
Kernel Matching									
Full Controls	0.169**	0.195*	0.184*	0.200**	0.147	0.190*	0.155	0.139	621
	(0.083)	(0.101)	(0.097)	(0.100)	(0.101)	(0.104)	(0.106)	(0.106)	621
Full + COVID-Related Controls	0.126	0.144	0.173*	0.105	0.133	0.125	0.114	0.110	532
	(0.085)	(0.104)	(0.102)	(0.102)	(0.105)	(0.108)	(0.110)	(0.111)	532
IPWRA									
Full Controls	0.156**	0.179*	0.157*	0.184*	0.116	0.182*	0.157	0.138	621
	(0.078)	(0.095)	(0.093)	(0.095)	(0.094)	(0.097)	(0.101)	(0.101)	621
Full + COVID-Related Controls	0.120	0.139	0.146	0.113	0.111	0.156	0.109	0.088	532
	(0.080)	(0.098)	(0.096)	(0.099)	(0.097)	(0.099)	(0.111)	(0.110)	532

Note: This table reports the estimated average treatment on the treated effect (ATT) of work from home. Each column denotes dependent variable used in each regression. 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. For linear regressions, two different specifications of control variables are reported. *Full Controls:* indicators for age over 40, presence of children under age 18 in the household, marital status, education, firm size, earnings categories, industry, and area of residence. *Full + COVID-Related Controls:* All variables included in full controls and indicators of experiencing unpaid leave, late payment, decrease in household income due to COVID. Robust standard errors are reported in parentheses. ***, **, and * indicate significance of the coefficients at the 1%, 5%, and 10% levels respectively.

Table A5: By Kids: 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: No Kids									
Kernel Matching									
Full Controls	0.131	0.158	0.033	0.228*	0.089	0.087	0.173	0.177	609
	(0.097)	(0.117)	(0.119)	(0.117)	(0.117)	(0.114)	(0.119)	(0.115)	609
Full + COVID-Related Controls	0.101	0.127	0.002	0.148	0.120	0.074	0.109	0.152	518
	(0.102)	(0.123)	(0.126)	(0.123)	(0.126)	(0.122)	(0.124)	(0.123)	518
IPWRA									
Full Controls	0.172**	0.213**	0.050	0.284***	0.140	0.128	0.234**	0.197*	609
	(0.088)	(0.105)	(0.108)	(0.107)	(0.105)	(0.104)	(0.110)	(0.107)	609
Full + COVID-Related Controls	0.188**	0.231**	0.066	0.288**	0.213*	0.145	0.183	0.234**	518
	(0.090)	(0.108)	(0.116)	(0.112)	(0.109)	(0.105)	(0.114)	(0.113)	518
Panel B: Have Kids									
Kernel Matching									
Full Controls	0.057	0.067	0.054	0.073	0.031	0.099	0.055	0.032	946
	(0.069)	(0.084)	(0.082)	(0.083)	(0.083)	(0.085)	(0.081)	(0.082)	946
Full + COVID-Related Controls	0.038	0.041	0.054	0.029	-0.000	0.073	0.046	0.030	846
	(0.073)	(0.089)	(0.086)	(0.088)	(0.088)	(0.089)	(0.086)	(0.087)	846
IPWRA									
Full Controls	0.065	0.073	0.075	0.074	0.046	0.111	0.043	0.041	946
	(0.066)	(0.080)	(0.082)	(0.079)	(0.080)	(0.083)	(0.078)	(0.078)	946
Full + COVID-Related Controls	0.020	0.020	0.027	0.014	-0.015	0.065	0.021	0.006	846
	(0.069)	(0.084)	(0.085)	(0.082)	(0.084)	(0.087)	(0.085)	(0.086)	846

Note: This table reports the estimated average treatment on the treated effect (ATT) of work from home. Each column denotes dependent variable used in each regression. 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. For linear regressions, two different specifications of control variables are reported. *Full Controls:* 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. *Full + COVID-Related Controls:* All variables included in full controls and indicators of experiencing unpaid leave, late payment, decrease in household income due to COVID. Robust standard errors are reported in parentheses. ***, **, and * indicate significance of the coefficients at the 1%, 5%, and 10% levels respectively.

Table A6: By Housework: 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: Not Main Person Doing Housework									
Kernel Matching									
Full Controls	0.047	0.052	0.044	0.108	0.013	0.043	0.044	0.033	721
	(0.077)	(0.093)	(0.096)	(0.093)	(0.092)	(0.092)	(0.090)	(0.089)	721
Full + Covid-Related Controls	0.037	0.038	0.064	0.082	0.004	0.031	0.034	0.009	656
	(0.082)	(0.099)	(0.102)	(0.099)	(0.099)	(0.097)	(0.096)	(0.096)	656
IPWRA									
Full Controls	0.037	0.038	0.031	0.111	-0.003	0.034	0.017	0.030	721
	(0.075)	(0.089)	(0.101)	(0.092)	(0.088)	(0.091)	(0.086)	(0.086)	721
Full + Covid-Related Controls	0.026	0.020	0.062	0.085	-0.029	0.026	0.008	0.004	656
	(0.079)	(0.095)	(0.104)	(0.096)	(0.094)	(0.097)	(0.093)	(0.091)	656
Panel B: Main Person Doing Housework									
Kernel Matching									
Full Controls	0.223**	0.262**	0.173	0.183*	0.157	0.277**	0.286**	0.259**	581
	(0.093)	(0.113)	(0.108)	(0.111)	(0.111)	(0.115)	(0.116)	(0.117)	581
Full + Covid-Related Controls	0.130	0.142	0.154	0.080	0.061	0.171	0.145	0.170	498
	(0.095)	(0.116)	(0.110)	(0.113)	(0.115)	(0.118)	(0.117)	(0.120)	498
IPWRA									
Full Controls	0.213**	0.249**	0.150	0.183*	0.149	0.254**	0.262**	0.278**	603
	(0.089)	(0.107)	(0.103)	(0.104)	(0.105)	(0.111)	(0.107)	(0.108)	603
Full + Covid-Related Controls	0.158*	0.177	0.159	0.084	0.099	0.208*	0.179	0.221*	516
	(0.090)	(0.109)	(0.107)	(0.108)	(0.109)	(0.114)	(0.112)	(0.114)	516

Note: This table reports the estimated average treatment on the treated effect (ATT) of work from home. Each column denotes dependent variable used in each regression. 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. For linear regressions, two different specifications of control variables are reported. *Full Controls:* 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. *Full + COVID-Related Controls:* All variables included in full controls and indicators of experiencing unpaid leave, late payment, decrease in household income due to COVID. Robust standard errors are reported in parentheses. ***, **, and * indicate significance of the coefficients at the 1%, 5%, and 10% levels respectively.

Table A7: 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. Each column denotes dependent variable used in each regression. 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.