Will working from home eventually work? Revisiting survey evidence with framing*

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October 2021

Abstract

Survey studies demonstrate that after Covid-19 pandemic the preference of workers to work from home (WFH) has risen. We test if these preferences are robust to simple framing and find that self-reported preference for working from home responds significantly to even mild framing.

JEL codes: J22

Key words: work from home, online survey, experiment

1 Introduction

Covid-19 pandemic outbreak made working from home (WFH) more prevalent than ever before (Bick et al. 2021). Barrero et al. (2021b) claim that this change will permanently affect the workers' preferences. Indeed, 40% of US workers who experienced WFH declare that they would look for another job if the employer required a full return (Barrero et al. 2021a). Yet, in non-pandemic circumstances, WFH was found to cause depression, exacerbate the already existing inequality between workers, despite neutral effects on productivity (Bloom et al. 2014).

In this study we study self-reported willingness to work remotely in the post-pandemic period. We utilize a large real-time social survey of the labor market in Poland.[1] We provide participants with true information about the effects of WFH on productivity, chances of promotion, and life satisfaction. We also include a control group, which did not receive any framing. We then ask participants about their preferred frequency of WFH, their attitude towards WFH as well as monetary compensation/loss associated with WFH.

We find that respondents react strongly to relatively mild framing. The treatment effects are statistically significant and economically large. Learning that WFH does not harm individual productivity raises willingness to work remotely. Prospects of promotion have no statistically significant effect on willingness to WFH.

*The authors are grateful to Michal Myck, Maros Servatka and Marek Weretka for insightful discussion on the design of the experiment. We also thank Erita Narhetali and Linas Tarasonis for their comments to earlier drafts of the paper. This project was supported by joint NCN-LMT DAINA initiative (grant #2017/27/L/HS4/03219). The experiment was pre-registered in the AEA RCT Registry (# AEARCTR-0007873). Ethical approval for this study was obtained from FAME|GRAPE Ethics Committee on 28.06.2021 (decision #2/2021).

[1] DIANOGZA.plus, the details of this survey are reported in an online Appendix A.

2 Literature

Working from home is a flexible working arrangements with relatively low prevalence — prior to the Covid-19 pandemic approximately 10% of US and European workers worked from home. Low adoption rates were related to employers' concerns about workers' productivity at home. Bloom et al. (2014), Angelici and Profeta (2020) show in experimental settings that these concerns do not need to be justified. However, WFH can reduce life satisfaction and work-life balance. Bloom et al. (2014) highlight the lower promotion rate among those working from home (conditional on performance) as well as higher depression rates and more prevalent sense of social isolation. Mas and Pallais (2017) point out that home based workers experience more stress and difficulties in combining work and family spheres.

During the pandemic, being exposed to the stress of in-person contacts could reduce productivity *in situ*, hence the analyzing the effects of WFH lacks a clear counterfactual. While still early, results suggests that self-reported productivity was in decline, though effects were heterogeneous across job titles and previous experience with WFH (Kitagawa et al. 2021, Felstead and Reuschke 2020, Etheridge et al. 2020, Morikawa 2020, report evidence on UK and Japan). Even during the pandemic, only in some jobs it was possible to WFH, which was reflected in asymmetric labor demand adjustments (Mueller-Langera and Gomez-Herrera 2021).

3 The sample and the experimental design

We rely on a sample from large real-time labor survey in Poland, DIAGNOZA.plus. This survey is implemented online, participants are attracted via media, social media and snow ball sampling. To account for the non-representative sample design, we utilize weights derived from covariate balancing propensity scores (see Imai and Ratkovic 2013, Smyk et al. 2021) and rely on 2020 Polish Labor Force Survey (PLFS) as a benchmark sample. DIagnoza.plus has a longitudinal and a cross-sectional dimension (see online Appendix A.). The data used in this analysis were collected in the seventh wave (July 2021).

Having completed the core questionnaire, the DIAGNOZA.plus participants were informed that this wave has questions related to WFH. After questions related to own experience of WFH, participants were randomly assigned to one of four treatment conditions: the control treatment and three experimental treatments. The participants in the control group received no information about WFH. The participants in the experimental treatments received true information about the implications of WFH, based on Bloom et al. (2014). The participants were informed that this information draws from causal scientific research and that results were obtained before the Covid-19 pandemic.

There were three treatment conditions. Each treatment had the same opening ("*Before the pandemic, for cases where WFH was an option, research has causally demonstrated (see an exemplary study here*[2]*) that ...* "). The three treatment conditions provided the following information to the participants:

- "... there were no differences in productivity between workers working from the office and those working from home." [*treatment: productivity*]
- "... working from home on average lowers life satisfaction and increases feeling of loneliness." [*treatment: satisfaction*]
- "... workers working from home had a much smaller chances for promotion than colleagues working on site." [*treatment: career*]

We ask three outcome questions. First, we ask self-reported preference for the number of days to WFH (stylized after Barrero et al. 2021b, for comparative purposes). We also ask whether the respondent has a positive, a negative or a neutral view of WFH. We use this variable as control in all specifications.

[2]The participants were provided with a link to the Bloom et al. (2014) study. We did not monitor the number of clicks on this link.

Second, respondents who reported a positive (negative) attitude were asked what percentage of their wage they would be willing to give up (additional compensation would require) to work from home twice a week. Third, we ask if their individual productivity increased/remained unchanged/decreased during WFH (asked only to individuals who could have worked remotely). The descriptive statistics are reported in Table A2. The distributions of answers to the first two questions are similar to US answers (Barrero et al. 2021b).

Table 1: Descriptive statistics

	Full sample	t:Control	t:Satisfaction	t:Productivity	t:Career
How often would you like to work remotely? (shares)					
Not at all	0.36	0.42	0.33	0.31	0.40
Once or twice a month	0.08	0.09	0.10	0.06	0.07
Once a week	0.10	0.10	0.12	0.07	0.10
Twice a week	0.12	0.09	0.12	0.12	0.16
Thrice a week	0.12	0.12	0.11	0.13	0.10
Four or more days a week	0.22	0.18	0.22	0.31	0.18
Attitude towards remote work (shares)					
Positive	0.52	0.46	0.55	0.58	0.47
Neutral	0.29	0.33	0.27	0.22	0.32
Negative	0.20	0.21	0.18	0.19	0.21
How has your productivity changed? (self-reported)					
Higher productivity (share)	0.41	0.35	0.40	0.42	0.47
Changes in wages (in percent of wage)					
Wage cut willing to accept	1.57	1.56	1.62	1.94	1.03
Wage increase required to accept	10.44	11.25	11.44	8.48	10.47
Observations	3720	952	943	921	904

Notes: The sample is restricted to individuals aged between 18 and 65 years old, who are not full time students. The sample is reweighed to reflect the population structure of a representative sample (Polish Labor Force Survey for 2020 is the reference sample).

We transform WFH preference into a binary variable taking on the value of one for willigness to work remotely at least once a week and zero otherwise (similar to Angelici and Profeta 2020). Similarly, we collapse the neutral and negative attitudes into a single category, thus we create a binary variable.

4 Results

We estimate the following models:

$$outcome_i = \alpha + \beta T_i + \gamma X_i + \delta Job_i + \epsilon_i$$

where $outcome_i$ indicates the three outcome variables (willingness to WFH, requested wage compensation and placebo of past productivity); T_i identifies the treatment assigned to individual i, the reference level is the control group. The remaining terms represent sets of control variables: X_i includes personal and household characteristics such as gender, age, education (three levels), urban status (two levels), presence of children under five years of age in the household, and household size. Likewise, Job_i covers firm size, the sector of economic activity, firms ownership status, and whether the position is full or part time. These variables are only available for respondents who had a job in the week prior to the survey. Finally, Job_i also includes self-reported share of tasks the individual is able to perform at home without detriment to productivity and the frequency of WFH during the pandemic.

The estimates of treatment effects in Table 2 take the control group as a base level. Table 2 reports

Table 2: Treatment effects – all individuals

	Want to WFH		Wage % change		Productivity (past)	
	(1)	(2)	(3)	(4)	(5)	(6)
t:Productivity	0.067***	0.030**	-0.41***	0.33	2.91**	2.91**
	(0.000)	(0.046)	(0.004)	(0.113)	(0.021)	(0.043)
t:Satisfaction	0.026***	-0.023***	0.039	1.05***	-0.59	0.34
	(0.001)	(0.004)	(0.303)	(0.001)	(0.310)	(0.613)
t:Career	0.039***	0.011	0.18***	0.48*	0.053	0.45
	(0.001)	(0.196)	(0.004)	(0.088)	(0.631)	(0.378)
Woman = 1	-0.0016	-0.011	0.16	1.15*	-1.75	-0.29
	(0.852)	(0.662)	(0.789)	(0.065)	(0.165)	(0.814)
Positive att to WFH = 1	0.65***	0.52***	-5.85***	-5.87***	7.35**	4.10*
	(0.000)	(0.000)	(0.000)	(0.001)	(0.015)	(0.056)
Job	No	Yes	No	Yes	No	Yes
WFH Exp	No	Yes	No	Yes	No	Yes
mean outcome	0.56	0.53	1.23	1.58	8.61	6.53
R-squared	0.53	0.67	0.15	0.19	0.080	0.16
# observations	3714	2292	3714	2292	1700	1390

Notes: standard errors clustered by treatment, linear probability models, $p - values$ reported in parentheses. Specifications in odd-numbered columns adjust for demographic and household characteristics. Specification in even-numbered columns also include control for job characteristics and WFH experience. Estimates in columns (1)-(2) refer to the outcome "Would you want to WFH at least once a week". Estimates in columns (3)-(4) portray WTP for WFH (wage change is non-negative for individuals who report positive attitude towards WFH and conversely, non-positive for individuals who report negative attitude towards WFH). Columns (5)-(6) report the results for a placebo question concerning *self-reported past change in productivity due to WFH* . *, **, *** indicate $p - values$ smaller than .10, .05 and .01, respectively.

mean outcome to facilitate gauging the magnitude of the treatment effects.[3] We find no clear gender patterns. We confirm that individuals with a positive attitude towards WFH report higher demand, greater productivity gains and a higher WTP for the ability to WFH. Against these intuitive results, we find really strong treatment effects. The *productivity* message raises willingness to WFH by 7-10% on a mean outcome of 56%, that is roughly 15-20%. The *satisfaction* and *career* messages have smaller effects, negative and insignificant, respectively. The treatment effects translate to WTP for the ability to WFH as reported in columns (3) and (4).

Columns (5) and (6) report the results of a placebo test: individuals were asked how their own productivity changed during WFH. Since this productivity materialized before we implemented the survey, one should expect no treatment effects. However, we find relatively large effects in all treatments in column (5), despite substantially smaller sample size. The significance is lost on *life satisfaction* treatment in column (6), which adjusts for job features.

5 Conclusions

The existing literature is brim with papers showing that self-reported views are easily affected by framing: from the original case of loss/gain framing by Tversky and Kahneman (1985) to a recent and powerful example on views about fracking by Bayer and Ovodenko (2019). We explored whether information

[3] Full results available upon request.

about the costs and benefits of WFH influences workers' stated preferences towards working remotely. Self-reported preference and attitude towards WFH appear to be easily affected by relatively mild framing intervention. Our subjects received just one sentence information about the consequences of WFH and we show statistically significant and economically large treatment effects. Stronger interventions such as perceived risk of loosing a job or reduced income may cause larger effects. We interpret our results as suggestion that as Covid-19 pandemic fades, the narratives about WFH may have important bearing on the actual prevalence of WFH.

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Online appendix

A DIAGNOZA.plus survey

DIAGNOZA.plus was established in May 2020 with the objective to collect timely and reliable data on labor market developments in Poland during the Covid-19 pandemic.[4] The project was a joint initiative of the University of Warsaw and independent research centers. The survey is implemented online and the study is both longitudinal (repeat participation) and cross-sectional (at any point, individuals may choose to participate in the survey, reporting their situation). Table A1 presents DIAGNOZA.plus when compared to other online surveys used in the literature during the Covid-19 pandemic.

The respondents are sourced through traditional media, social media (such as Facebook and Twitter) as well as through snow ball sampling (the respondents are repeatedly encouraged to spread the information about DIAGNOZA.plus in their network of family members, friends and professional colleagues). In addition, the participants were invited in the online participant panel ANSWEO (a Polish platform, similar to Qualtrics). Thanks to the cooperation with ANSWEO, the participants from this platform were subjected to the same rules and procedures as the other participants. The participants above retirement age cannot join the survey. The participants above 18 years of age, but whose primary activity is education, cannot join the survey.

Table A1: DIANOGZA.plus as source of survey data

Authors	Country coverage	Sample size	# of waves
Baert et al. (2020)	Flanders	$\sim$ 3 800	1
Belot et al. (2020)	CN, KR, JP,IT, US, UK	$\sim$ 1000 per cn	1
Adams-Prassl et al. (2020)	UK, DE, US	$\sim$ 4000 / 5000 per cn	2
Morikawa (2020)	JP	$\sim$ 5000	1
DIAGNOZA.plus	Poland	$\sim$ 5000 per wave	7

Once individuals join the panel, they are contacted for participation in subsequent waves. The questionnaire for repeat participants is shorter, as the household roaster and basic demographic information (age, gender, education) are not asked. Table A2 reports the sample sizes for each wave of DIAGNOZA.plus, splitting the sample to new entrants and repeat participants. Until October 2021, in total nearly 31 thousand individuals joined DIAGNOZA.plus. On average, the subsequent waves of this survey recorded between 4000 and 6500 respondents. Participation is rewarded via lotteries, where the expected value is between USD 0.30 and USD 3, depending on the wave.

The survey is conducted periodically every two months. In each wave of DIAGNOZA.plus, the questionnaire consists of two parts: a core questionnaire based on the labor force survey standard questionnaire and a wave-specific questionnaire with detailed issues. Each survey asks if an individual has worked from home in the week preceding the survey. The seventh wave of the survey featured additional questions about working from home.

In each wave of the study separately, the sample of participants is reweighed to reflect the demographics of a representative sample from the Polish Labor Force Survey. A unique feature of DIAGNOZA.plus is that the respondents are asked about their labor market status from 12 months before and this variable is used in the reweighing algorithm, along with age, gender, size of residence, region of the country and the educational level. For individuals who worked in 12 months prior to participating in DIAGNOZA.plus,

[4] With the outbreak of pandemic, timely data about economic and social developments were missing. Around the world, the academic community engaged in gathering data online; the examples include Bick and Blandin (2021) for the US (the Real-Time Population Survey, RTPS), Adams-Prassl et al. (2020) for a comparative study of the UK, US and Germany, Belot et al. (2020) for China, South Korea, Japan, Italy, the UK and the four largest states in the US. These and other studies typically relied on online panels (such as Qualtrics) and recruitment of participants via social media.

Table A2: Participation in DIAGNOZA.plus: number of participants

	Enter the sample	Repeat participants	Total
May 2020	5020	0	5020
Jun/Jul 2020	4257	2039	6296
Aug/Sep 2020	3213	2011	5224
Oct/Nov 2020	1059	2448	3507
Dec 2020/Feb 2021	3664	2725	6389
Mar/May 2021	2321	2675	4996
Jun/Jul 2021	2079	2478	4557
Total	21613	14376	35989

Notes: The table displays individuals with completed surveys. The sample is restricted to individuals aged between 18 and 65 years old, who are not full time students. The sample is reweighed to reflect the population structure of a representative sample (Polish Labor Force Survey for 2020 is the reference sample).

we also ask about the industry of employment and utilize this variable in the reweighing procedure.

We follow covariate-balancing propensity score matching to obtain weights. This method obtains the propensity score via Generalized Method of Moments, and thus secures that the reweighed sample and the reference sample are exactly matched (Imai and Ratkovic 2013). Comparing large international online survey to nationally representative samples for 17 countries, Smyk et al. (2021) show that this method is indeed effective in balancing the online samples on observable characteristics.