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ABSTRACT

We use two surveys to assess why work from home (WFH) varies so much across countries and people. A measure of cultural individualism accounts for about one-third of the cross-country variation in WFH rates. Australia, Canada, the UK, and the US score highly on individualism and WFH rates, whereas Asian countries score low on both. Other factors such as cumulative lockdown stringency, population density, industry mix, and GDP per capita also matter, but they account for less of the variation. When looking across individual workers in the United States, we find that industry mix, population density and lockdown severity help account for current WFH rates, as does the partisan leaning of the county in which the worker resides. We conclude that multiple factors influence WFH rates, and technological feasibility is only one of them.

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1. Introduction

A lasting shift to work from home (WFH) is one key legacy of the COVID-19 pandemic. The share of workdays worked at home in the US increased slowly in the decades before the outbreak of the COVID-19 pandemic, reaching 7 percent in 2019. When the economy locked down in 2020 it surged to almost 60 percent before dropping back down and stabilizing at around 28 percent in the US according to the Survey of Working Arrangements and Attitudes (Barrero et al. 2021, 2023). The pattern is similar in other countries. In Germany for example, roughly 5 percent of employees worked from home at least partially pre-pandemic. That share jumped to 34 percent in the early phases of the pandemic, fluctuated during the pandemic period, and has been almost flat at around 24-25 percent since early 2022 according to the ifo business survey (Alipour 2023). Online job vacancy postings, office occupancy statistics from Kastle Security Systems and evidence from national surveys point in the same direction of a new normal with stable WFH rates (Hansen et al., 2023, Alipour et al., 2021a, Adrjan et al., 2022, Bloom et al., 2023).

Yet, the number of full paid days worked at home during COVID-19 differs widely across countries. Based on the first two waves of our Global Survey of Working Arrangements (G-SWA), conducted in mid-2021 and early 2022, Aksoy et al. (2022) report an average of 1.5 paid full days worked from home in a sample of 27 countries. The highest levels are in English-speaking countries and the lowest in developed Asia. Özgüzel et al. (2023) also uncover differences in WFH intensity in 2021 across 30 European countries.[1]

Cross-country differences in WFH levels persist post-pandemic, as we document in Aksoy et al. (2023b) based on the third wave of our Global Survey of Working Arrangements, collected in April and May 2023. In a sample of 34 countries, WFH levels are highest at an average of 1.4 days per week in English-speaking countries, followed by Latin American countries and South Africa (0.9 days), and then European countries (0.8 days) and Asian countries (0.7 days). These patterns match Workplace Mobility data published by Google until October 2022, which track the frequency of workplace visits by country and month.

Why does work from home vary so much across countries? There are several possible reasons. WFH intensity differs greatly across industries and occupations because some tasks and

[1] A large body of studies examined the extent and incidence of WFH during COVID-19 and outcomes associated with WFH. See, for example, Adams-Prassl et al. (2020), Althoff et al. (2022), Alipour et al. (2021b), Bartik et al. (2020), Bick et al. (2023), Brynjolfsson et al. (2020), and Deole et al. (2023), among others.

therefore some jobs cannot be done at home (Dingel and Neiman 2020, Alipour et al. 2023), so differences in the industry or occupation mix could lead to different amounts of WFH across countries. Additionally, differences in workplace cultures, managerial styles, and perceptions of the productivity of remote work could lead some organizations to adopt work-from-home arrangements but not others (Hansen et al. 2023).[2] Urban areas with higher population density also have high WFH rates (see, e.g., Barrero et al. 2023), but much of that is because cities are more likely to host knowledge jobs and industries that are well-suited to remote work (Althoff et al., 2022, Özgüzel et al. 2023). The pandemic experience, especially cumulative lockdown stringency that pushed workers and firms to adapt more fully to remote work, also predicts persistent WFH (Adrjan et al. 2023, Aksoy et al., 2022).

Our paper tests whether and how much each of these factors can account for differences in WFH intensity across countries. We regress the average number of full paid days WFH by country as of April and May 2023 in the third wave of our G-SWA against several predictors of WFH. The list includes GDP per capita (to capture overall labor productivity and the share of the workforce with tertiary education), cumulative lockdown stringency, population-weighted density, and the share of jobs that can be done remotely based on Dingel and Neiman (2020). We also test whether measures of individualism predict WFH independently from the other variables. Individualism is a key dimension of cultural differences across countries (see Heine 2008 and Triandis 1994, 1995, for instance). The review by Alesina and Giuliano (2015), Gorodnichenko and Roland (2017), and Tatliyer and Gur (2022), among others, establish individualism as an important cultural determinant of economic and institutional outcomes including labor market arrangements. A high individualism (score) indicates a culture where individuals value personal freedom, autonomy, and achievement, often promoting independence and self-reliance. Because the success of WFH often hinges on workers being able to deliver without direct monitoring from managers, we hypothesize that individualism might also affect remote work adoption. If more individualistic societies favor independent work environments, we should expect them to adopt WFH in greater numbers.

[2] The productivity effects of remote work seem to depend on how it is implemented (fully remote or hybrid, with or without coordination), and whether it's a matter of choice (post-pandemic) or a necessity (during lockdowns). See, for example, Angelici and Profeta (2023), Battiston et al. (2021), Bloom et al. (2015, 2023), Brucks and Levav (2022), Choudhury et al. (2021, 2024), Emanuel and Harrington (2023), Emanuel et al. (2023), Gibbs et al. (2023), Künn et al. (2020), and Yang et al. (2022), among others.

Indeed, individualism is the top factor accounting for cross-country variation in WFH. It explains (in an R-squared sense) about one third of the variance of WFH across the 34 countries we consider, and more when we focus on college graduates. The associated regression coefficient implies large differences in WFH associated with individualism. If we rank the countries in our sample by their individualism score and compare those at 10^{th} and 90^{th} percentiles (respectively, China and the Netherlands), our regression implies 0.54 more full paid days WFH per week in the latter. That difference is 63 percent as large as the average number of full paid days WFH per week in the full sample.

Lockdown stringency, population density, the industry mix, and GDP per capita all have some predictive power for cross-country WFH differences, but how much depends on the sample and specification. Collectively those four variables explain (again, in an R-squared sense) less of the cross-country variation in work from home than individualism alone does.

To complement the cross-country evidence, we run a similar set of exercises that study WFH intensity within the US using individual-level data from our Survey of Working Arrangements and Attitudes (SWAA). We regress each worker's number of full paid days WFH in 2023 on state-level lockdown stringency and average wages, county-level population density, and WFH propensity by industry. Lacking a good measure of individualism across US regions or demographic groups, we instead use county-level voting patterns in the 2020 presidential election (i.e., the share of votes for Joe Biden) to measure cultural-political differences. We find WFH levels across US workers rise with their industry's affinity with WFH, and with the population density and share of Biden voters where they live and work. Industry accounts for the largest share of the variation in this case, but population density becomes more important when we restrict our attention to college graduates. The latter group tend to have remote-friendly jobs, leaving more room for other factors.

WFH has a reputation for being a rich-country phenomenon. But measures of income like GDP per capita and average state wages are not robust predictors of WFH levels in either our cross-country or within-US regressions. Higher-income countries and states do have a higher prevalence of WFH in the raw data, but that relationship owes largely to other observable factors we consider, such as the industry mix. That leaves little variation to explain with residual income differences across countries and states.

The remainder of the paper is structure as follows. Section 2 describes the survey methodology. Section 3 presents our results. Section 4 concludes.

2. Survey Methodology and Empirical Analysis

2.1 Global Survey of Working Arrangements (G-SWA)

The G-SWA is an annual survey of individual workers around the world. Its third wave was fielded in 34 countries in April and May 2023 and covered full-time workers aged 20-64 who completed secondary or tertiary education.[3] The samples are broadly representative with respect to age, gender, and education because we used country-specific quotas for those key demographics. Table A.1 in Appendix A compares our country-level G-SWA samples to summary statistics retrieved from Gallup data for 2020-22 and OECD statistics (OECD 2022). In France, Germany, Italy, the UK, and the US, our samples include just over 2,500 respondents. In all other countries, our samples include roughly 1,000 full-time workers (see Appendix Table A.2).[4]

In addition to basic questions on demographics, employment status, earnings, industry, occupation, marital status and living arrangements, the survey asks about current, planned and desired WFH levels, and more. We design the G-SWA instrument, adapting questions from the U.S. SWAA developed by Barrero et al. (2021) and enlist professionals to translate our English-language questionnaire into the major languages of each country. To ensure high-quality translations, we also enlist independent third parties with knowledge of the survey to review the translations and revise as needed.

To field the G-SWA, we contract with Bilendi (a professional survey firm), which implements the survey directly and in cooperation with external partners. The survey effort taps pre-recruited panels of people who previously expressed a willingness to take part in research.[5] Recruitment into these panels happens via partner affiliate networks, multiple advertising channels (including Facebook, Google Adwords, and other websites), address databases, and referrals. New

[3] Aksoy et al. (2022, 2023a) report results from the previous two waves that were conducted in July and August 2021 (1st wave) and January and February 2022 (2nd wave). Descriptive statistics from the third wave conducted in April-May 2023 can be found in Aksoy et al. (2023b).
[4] The sample size in New Zealand is somewhat smaller and amounts to 733 respondents.
[5] Bilendi and its external partners do not engage in "river sampling," whereby people are invited to take a survey while engaging in another online activity. Relative to river sampling, the use of pre-recruited panels affords greater control over sample composition and selection. Respondents take the survey on a computer, smart-phone, iPad or similar device, so we miss persons who don't use such devices. See also Stancheva (2022).

recruits are added to the panel on a regular basis. When it is time to field a survey, Bilendi or its partner issues email messages that invite panel members to participate. The message contains information about compensation and estimated completion time but not about the survey topic. Clicking on the link in the invitation message takes the recipient to the online questionnaire. Respondents who complete the survey receive cash, vouchers or award points, which they can also donate.[6]

Before proceeding to our analysis of the G-SWA data, we drop "speeders," defined as respondents in the bottom 5 percent of the completion-time distribution for each country. We also screen out respondents who fail an attention check question. One near the beginning of the survey asks, "*What is 3 + 4?*" and the only acceptable answer is "*7*". The second one midway through asks "*In how many big cities with more than 500.000 inhabitants have you lived? Irrespective of the truth, please insert the number 33 in order to continue with the survey*" and the only acceptable answer is "*33*".

The resulting sample contains 42,426 observations across the 34 countries in Wave 3. Appendix Table A.2 reports statistics on response time, observation counts and dates in the field for each country. We calculate the number of full paid days WFH using the question "For each day last week, did you work 6 or more hours, and if so where?" Respondents select one of three options for each day (Monday to Sunday) of the prior week, namely "Did not work 6 or more hours," "worked *from home*," or "worked at employer or client site". We count the number of days each employed respondent reports work from home, which results in a variable that ranges from 0 to 5. Then we compute the raw average by country for all respondents and for those who have at least a college degree.

2.2 Factors accounting for cross-country variation in WFH levels

We merge our G-SWA data with external data on real GDP per capita, population-weighted population density, lockdown stringency, and Hofstede's Individualism Index. We use average

[6] We do not contact respondents ourselves, do not collect personally identifiable information, and have no way to re-contact them.

population weighted density in 2020 from Edwards et al. (2021), using a 1km resolution, as our measure of population density,[7] and use 2019 PPP GDP per capita measured in 2010 US dollars.

Economists have become increasingly aware of the importance of culture on international performance (e.g. Guiso, Sapienza, and Zingales, 2006). Our main measure of cultural differences across countries comes from Hofstede's Cultural Dimensions framework (Hofstede 1980 and 2011). We focus on their Individualism Index which measures the extent to which individuals in a society prioritize their own ambitions and independence above the collective goals and unity of the group. The index is based on four survey questions that elicit preferences for various attributes of an ideal job, shown in Appendix B. A high Individualism score suggests a society emphasizes self-reliance and expects individuals to take care of their own needs. A low score suggests a society values tight-knit community ties, with a focus on collective wellbeing (Hofstede 2011). People from societies that score highly on Individualism could be more comfortable with settings where workers have the freedom to tailor their schedules, work environments, and practices to suit their individual needs and duties. That would predict a greater propensity for remote work in such societies. We also tried other cultural indicators, for example the trust measures used by Guiso, Sapienza and Zingales (2009) and Bloom, Sadun and Van Reenen (2012). This was also significant, but had less explanatory power than the individualism measure, and given our sample size of 34 observations we only included one cultural measure.

We follow Baker, Davis, and Levy (2022) and Aksoy et al. (2022) and build an index of cumulative lockdown stringency that combines the extent and duration of government restrictions on commercial and social activity. Drawing on the widely used Oxford data described by Hale et al. (2021), in a first step, we compute a monthly lockdown stringency index. For country c and month t, we define this lockdown stringency index as:

$$LS_{ct} = \max\left\{SIPO, \left(\frac{3}{4}\right)BCO + \left(\frac{1}{4}\right)SCO\right\}$$

where $SIPO = 1$ when a shelter-in-place order is in effect, zero otherwise; $BCO = 1$ when a broad-based business closure order is in effect; and $SCO = 1$ when schools are closed. These indicator variables take fractional values when the order is in effect for part of the month. In a second step,

[7] Population density measures are less accurate for the average resident when calculated over larger geographical areas like countries. Population-weighted density measures counteract that force by focusing on the density of areas where more of the population lives.

we cumulate these values from January 2020 to December 2022, which results in our measure of cumulative lockdown stringency.

Finally, we build a measure of industry mix at the country-level using Dingel and Neiman (2020) estimates of the share of jobs that can be done from home by 2-digit industry and G-SWA respondents' reported industry of work. We measure the remote friendliness of the industry mix in country c as

$$IndustryMix_c = \sum_i WFH\ Propensity_i \times s_{ic},$$

where s_{ic} is industry i's share of employment in country c in the G-SWA, and $WFH\ Propensity_i$ is the Dingel and Neiman (2020) estimate for the share of jobs in industry i that can be done remotely.

Table 1 displays summary statistics of our key variables; average full paid days WFH (all respondents and college graduates only), cumulative lockdown stringency, (log) real GDP per capita, population-weighted density, Individualism, and industry mix. Appendix Table A.3 reports country-specific means for each of these variables, and Appendix Table A.4 reports country-specific average full paid days WFH by gender (all respondents and college graduates only).

2.3 Survey of Working Arrangements and Attitudes (SWAA)

The SWAA is a monthly online survey of between 2,500 to 10,000 U.S. residents, aged 20 to 64. In addition to questions on demographics, employment, industry, occupation and earnings, the survey asks about working arrangements during and after the pandemic, as well as personal experiences, attitudes, and preferences towards WFH. After removing respondents who complete the survey at an implausible speed and who fail attention check questions, we re-weight the data to match the joint distribution of the 2010-2019 Current Population Survey (CPS) in age-sex-education-earnings cells.

To obtain a SWAA sample that is comparable to the one from the cross-country G-SWA, we focus on 2023 respondents who earned $10,000 or more in the previous year and who worked four total days or more in the survey reference week. Those restrictions yield a sample of 34,055 SWAA respondents who are closely attached to the labor market, worked a full-time schedule during the reference week, and took the survey in January to October 2023 (spanning the G-SWA's 2023 collection period).

2.4 Factors accounting for individual-level variation in WFH levels in the US

We combine the SWAA survey data with external data on industry WFH propensity, average wages at the state level, lockdown stringency at the state-level, population density in the zipcode of residence and work, and the share of votes for Joe Biden in the 2020 presidential election in the respondent's county of residence. Again, we use Dingel and Neiman (2020) 2-digit industry estimates of the share of jobs that can be done from home to measure WFH propensity. We retrieve estimates of the average state wage from the BLS Occupational Employment and Wage Statistics (OEWS) Survey. The 2020 election data come from the MIT Elections data lab. We build a state-level measure of lockdown stringency following the same approach as described previously for the cross-country analysis, using Hale et al. (2021) U.S. state-level measures. Table 2 displays summary statistics for the variables in the SWAA sample of US individuals.

3. Results

3.1 Accounting for cross-country variation in WFH levels

Figure 1 shows the average full paid days WFH per week by country for all G-SWA respondents. Full-time employees worked an average of 0.9 full paid days per week from home across the countries in our sample. In English-speaking countries, WFH levels are higher, as full-time employees worked an average of 1.4 full paid days per week from home. In comparison, WFH levels average 0.7 days per week in the Asian countries covered by the G-SWA, 0.8 in European countries, and 0.9 in Latin American countries and South Africa. Figure 2 shows a similar pattern for college graduates, where WFH levels are higher.

We regress average full paid days WFH per week in the 34 countries of our G-SWA sample on the set of regressors described in section 2.2. To ease interpretation, we standardize each of the regressors to have mean zero and unit standard deviation. Table 3 shows the regression estimates when we calculate country-level WFH intensity using the full sample of G-SWA respondents, whereas Table 4 focuses on WFH among college graduates in each country. Because college graduates work in jobs that are better suited to WFH, compared with jobs that require only secondary education,[8] focusing on them can help us trace out how lockdown stringency and culture

[8] Indeed, the average number of WFH days per week is 1.14 among college graduates, compared with 0.86 among all respondents in our 2023 G-SWA data.

(individualism) relate to WFH adoption when it is possible. Additionally, we believe our samples are more representative of the college-educated population in several of the countries we consider (see the discussion in Aksoy et al., 2022).

Columns 1-5 in Tables 3 and 4 show how individualism is the only explanatory variable that predicts cross-country WFH levels statistically significantly. A one standard deviation increase in individualism is associated with an increase in average full paid days WFH of 0.15 among all workers and 0.21 among college graduates. Figure 3 shows the bivariate relationship between individualism and WFH and provides a sense of the magnitude of our estimate. Moving from the country with the lowest Individualism score (Taiwan, whose score is 0.17) to the one with the highest (the US, whose score is: 0.91) is associated with 0.7 more full paid WFH days per week in the full sample and 1.1 among college graduates.

In column 6 of Tables 3 and 4, we estimate specifications that include all five regressors at the same time. The coefficient for individualism remains significant and rises by a third. Moving from the 10th (China) to the 90th (Netherlands) percentile country by Individualism score implies 0.54 more WFH days per week, 63 percent as large as the average number of full paid days WFH across countries (see Table 1).

Lockdown stringency and population-weighted density also have statistically significant coefficients in the full specification in column 6. Thus, countries with stricter and longer lockdowns during COVID-19 and with a higher population-weighted density tend to have higher WFH levels. But the magnitude is smaller than that predicted by countries' Individualism scores. Moving from the 10th (Sweden) to the 90th (Austria) percentile of our lockdown stringency index implies an increase of 0.22 WFH days per week. The increase is smaller at 0.15 days WFH per week moving from the 10th (Poland) to the 90th (Türkiye) percentile countries by population density. In contrast, we do not estimate significant coefficients for GDP per capita and industry mix, and the coefficients are also smaller in magnitude.

Female labor force participation and occupational choice differs across countries, so we test for differences across the average WFH rate of men and women across countries in Columns 7 and 8 of Tables 3 and 4. We calculate our country-level average level of WFH separately for each sex and re-run the specification with the full set of regressors. Individualism predicts higher levels of WFH for both men and women, but lockdown stringency and population-weighted density only yield statistically significant estimates for women.

In Figure 4, we show the WFH gap in terms of actual full paid days WFH in Panel A and desired full paid days WFH in Panel B between women and men and plot it against GDP per capita. Figure 4 appears to show that the WFH gap between women and men shrinks with GDP per capita. However, when we run formal tests (see Table A.8), the difference drops or disappears when we include other explanatory variables in the regression. So, the WFH gap between women and men shrinks in rich countries, but that is largely due to differences in the industry mix, population-weighted density, and Individualism across rich and poor countries. How much of the international variation in WFH levels can our explanatory variables account for, collectively and individually? Figure 5 plots the R-squared from columns 1-6 of Tables 3-4, respectively. Collectively, our regressors account for roughly 50 percent of the variation in WFH levels across our 34 countries (Panel A of Figure 5) and slightly more (56 percent) of the cross-country variation for college graduates (Panel B of Figure 5). Individualism has the largest explanatory power among our variables, with a univariate R-squared of 30 percent (Panel A) or 37 percent (Panel B). Other variables account for much less of the cross-country variation. Even combining (naïvely) the univariate R-squared of these other variables yields a lower number than we get from the univariate R-squared of Individualism.

How accurately does our estimated linear model predict the observed WFH levels in G-SWA data? Figure 6 compares and plots average WFH levels by country against the prediction implied by the linear model estimated in column 6 of Tables 3 and 4, respectively for all workers and college graduates. We also plot the 45-degree line to show which countries have higher or lower levels than our model predicts. The five English-speaking countries in our sample (US, UK, Canada, Australia, and New Zealand) all have higher WFH levels than the model predicts, whereas South Korea, Greece, Denmark, France, and Italy have lower levels. So, even after accounting for differences in culture, technology, and lockdown stringency, English-speaking countries seem unusually amenable to WFH whereas South Korea and several European countries seem too averse to it.

3.2 Accounting for individual-level variation in WFH levels within the US

We complement our cross-country analysis by investigating whether we see similar predictors of WFH across individual workers in the US. We measure the number of full paid days

WFH among workers who responded to the SWAA 2023 and regress it against measures of state-level income, lockdown stringency, local population density, and voting patterns as a measure of politics and culture. We weight observations to ensure the SWAA matches the Current Population Survey by age-sex-education-earnings cells, and we include month fixed effects in our regressions to account for variation in WFH rates across time. Table 5 reports the estimates in the full SWAA sample, whereas Table 6 focuses on college graduates (i.e., respondents who have at least a 4-year college degree). As with our cross-country analysis we standardize our explanatory variables to ease interpretation.

Again, we first consider regression specifications that include each regressor individually and find all variables to be statistically significant predictors of WFH (columns 1-5 in Tables 5-6). WFH propensity in the worker's industry has the largest coefficient among the set of regressors in Table 5, but population density ranks highest among college graduates in Table 6 and Joe Biden's vote share takes second place there. The relative ranking is similar when we include all five regressors jointly in column 6, but the Biden vote share is much more important in the full sample of Table 5 than the sample of college graduates in Table 6. In that group, lockdown stringency is relatively more important and suggests that longer and deeper lockdowns might have helped workers and their managers adapt to WFH more whole-heartedly.

As with our cross-country results, we find population density is a stronger predictor of WFH levels among women than among men, both in the full sample and among college graduates (see columns 7 and 8 of Tables 5 and 6), For men, the political-cultural environment is relatively more important, especially in the full sample, but this pattern contrasts with roughly equal explanatory power that Individualism has for men and women's WFH share in the cross-country analysis of Tables 3 and 4.

Our explanatory variables explain much less of the individual-level variation in US WFH rates than they do cross-country averages. (As we should expect given our aggregation to just 34 country-level observations.) Our preferred specification in column 6 of Table 5 has an R-squared of 5 percent, for instance. But that 5 percent compares highly to the contribution of demographics like sex, age, education, and children, which only raise the R-squared marginally to 6 percent, as we show in Table 7.

A comparison of which variables have the largest univariate R-squared is broadly consistent with our analysis of the regression coefficients. For the full sample (Figure 7 Panel A), industry explains over 3 percent of the individual-level variation, whereas for college graduates (Panel B) population density comes out at the top with just under 2 percent. The local Biden vote share completes the top three. That means cultural and political factors are still strong predictors of WFH across US individuals, even if they are not the top predictor as Individualism is when looking across countries.

3.3 Robustness checks

We consider alternative measures of industrial propensity for remote work in our international and in our US sample. Our baseline measure from Dingel and Neiman (2020) asks whether jobs can potentially be done from home based on occupational classification information, rather than using actual WFH adoption by industry. For robustness, we therefore compute the WFH propensity across industries and occupations in the SWAA (Barrero et al. 2023), and the share of job postings across industries and occupations that allow remote work (Hansen et al. 2023) and re-run our analysis with the resulting predictors. All our results, in particular the significant coefficient estimates for Individualism and for the Joe Biden vote share, are robust to the inclusion of these alternative measures of the industry mix as shown in Appendix Tables A.5-A.7.

4. Conclusion

We examine how work from home varies across countries and across US workers in search of variables that can make sense of that variation. Our key finding is that cultural factors – specifically Individualism – accounts for about one third of the differences across countries. In an R-squared sense, Individualism explains far more of the variation than industrial composition, population-weighted density, or lockdown stringency.

Across US workers, industry and population density are the two most important determinants. But here cultural factors are still statistically significant. Respondents who reside in counties that voted for Joe Biden in 2020 by a larger margin, WFH at higher rates even after accounting for industry, state-level wages, population density, and a battery of demographics.

As businesses and policymakers navigate the post-pandemic world, understanding why workers and firms opt for a given working arrangement is crucial. Future research should further explore the long-term implications of the preference heterogeneity with respect to WFH on productivity, work-life balance, and urban planning, considering the continuing evolution of work cultures and technological advancements. Such research should also test whether the relationships we uncover are causal and whether they reflect workers' demand for WFH or, instead employers' propensity to offer it.

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Table 1: Summary statistics of cross-country variables

Variable	N	Mean	SD	Min	p25	p50	p75	Max
Average Full Paid Days WFH (All respondents)	34	0.86	0.27	0.42	0.69	0.81	0.97	1.67
Average Full Paid Days WFH (college graduates)	34	1.14	0.34	0.49	0.92	1.18	1.24	1.98
Cumulative Lockdown Stringency (in months)	34	16.73	6.23	5.01	12.09	16.7	20.4	33.65
Log GDP Per Capita	34	10.18	0.7	8.73	9.53	10.37	10.75	11.25
Population Weighted Density (in thousands)	34	5.08	4.53	0.88	2.23	3.96	5.87	23.24
Culture: Individualism	34	0.54	0.24	0.17	0.3	0.56	0.74	0.91
Industry Mix	34	37.79	2.97	29.9	36.77	37.68	39.47	45.09

Note: Country averages of full paid days worked from home are calculated from 42,426 observations across the 34 countries in the third wave of the G-SWA. The question reads: "For each day last week, did you work 6 or more hours, and if so where?". Lockdown Stringency consists of the sum of monthly index capturing stay-at-home orders and mobility restrictions, from January 2020 to December 2022. GDP Per Capita consists of the log of GDP Per Capita in 2019, in 2010 USD constant. Population density consists of the average population-weighted density in 2020, using a 1km resolution. Culture: Individualisms consists of the Hofstede index for collectivism vs. Individualism. Industry Mix consists of the average share of jobs that can be done from home, using Dingel and Neiman (2020) 2-digits industry estimates and computing the average by country, based on respondents' industry.

Table 2: Summary statistics of US variables

Variable	N	Mean	SD	Min	p25	p50	p75	Max
Full Paid Days WFH (All respondents)	34,055	1.523	2.11	0	0	0	3	7
Full Paid Days WFH (college graduates)	20,330	1.889	2.09	0	0	1	3	7
Cumulative Lockdown Stringency (in months)	34,055	10.567	3.493	3.044	7.435	11.581	13.169	18.104
Log Average wage in state	34,055	11.012	0.135	10.718	10.933	10.968	11.153	11.246
Population Density, ZIP code of job (in log)	34,055	7.174	1.932	2.442	5.813	7.468	8.383	11.493
County – Joe Biden Vote	34,055	53.953	18.588	8.721	40.337	54.74	67.844	91.091
Industry WFH Propensity	34,055	0.39	0.28	0.035	0.186	0.253	0.762	0.826

Note: Full Paid Days worked from home based on responses to SWAA question: "For each day last week, did you work 6 or more hours, and if so where?", elicited in 2023 for those who earned $10,000 or more in the previous year and who have worked 4 total days or more in the survey reference week, and weighted to match CPS on {age x sex x education x earnings}. Lockdown Stringency consists of the sum of state-level monthly index capturing stay-at-home orders and mobility restrictions, from January 2020 to December 2022. Average wage in state consists of the (log) average wage in state in May 2022. Population density is the log of the population density of the ZIP code of current job business premises. Joe Biden Vote consists of the share of Joe Biden vote in the county of residence (as a fraction of all Biden + Trump votes). WFH Propensity in Industry refers to the share of jobs that can be done from home from Dingel and Neiman (2020), by industry.

Table 3: Regression Table of the Average Full Paid Days WFH, Cross-country Analysis, All Respondents (G-SWA)

	Average Full Paid Days WFH							
	All						Men	Women
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Lockdown Stringency	0.04					0.08**	0.06*	0.10**
	(0.04)					(0.04)	(0.04)	(0.04)
GDP Per Capita		0.08*				-0.01	0.01	-0.04
		(0.04)				(0.04)	(0.05)	(0.05)
Weighted Population Density			-0.05			0.08**	0.05	0.12***
			(0.04)			(0.03)	(0.03)	(0.04)
Individualism				0.15***		0.21***	0.19***	0.23***
				(0.05)		(0.06)	(0.06)	(0.06)
Industry Mix					0.10	0.07	0.08	0.06
					(0.06)	(0.05)	(0.05)	(0.05)
Observations	34	34	34	34	34	34	34	34
R2	0.02	0.09	0.03	0.30	0.12	0.50	0.53	0.44

Note: All regressors are standardized. Lockdown Stringency consists of the sum of monthly index capturing stay-at-home orders and mobility restrictions, from January 2020 to December 2022. GDP Per Capita consists of the log of GDP Per Capita in 2019, in 2010 USD constant. Population density consists of the average population-weighted density in 2020, using a 1km resolution. Culture: Individualisms consists of the Hofstede index for collectivism vs. individualism. Industry Mix consists of the average share of jobs that can be done from home, using Dingel and Neiman (2020) 2-digits industry estimates and computing the average by country, based on respondents' industry. Robust standard errors

Table 4: Regression Table of the Average Full Paid Days WFH, Cross-country Analysis, College Graduates (G-SWA)

	Average Full Paid Days WFH							
	All						Men	Women
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Lockdown Stringency	0.08					0.13***	0.07	0.17***
	(0.06)					(0.04)	(0.05)	(0.05)
GDP Per Capita		0.07				-0.02	-0.04	-0.01
		(0.06)				(0.05)	(0.06)	(0.06)
Weighted Population Density			-0.09			0.08*	0.03	0.14***
			(0.06)			(0.04)	(0.05)	(0.04)
Individualism				0.21***		0.29***	0.30***	0.29***
				(0.05)		(0.06)	(0.07)	(0.06)
Industry Mix					0.08	0.05	0.05	0.04
					(0.07)	(0.06)	(0.06)	(0.07)
Observations	34	34	34	34	34	34	34	34
R^2	0.05	0.05	0.06	0.37	0.05	0.55	0.52	0.54

Note: All regressors are standardized. Lockdown Stringency consists of the sum of monthly index capturing stay-at-home orders and mobility restrictions, from January 2020 to December 2022. GDP Per Capita consists of the log of GDP Per Capita in 2019, in 2010 USD constant. Population density consists of the average population-weighted density in 2020, using a 1km resolution. Culture: Individualisms consists of the Hofstede index for collectivism vs. individualism. Industry Mix consists of the average share of jobs that can be done from home, using Dingel and Neiman (2020) 2-digits industry estimates and computing the average by country, based on respondents' industry. Robust standard errors

Table 5: Regression Table of Full Paid Days WFH, Individual-level Analysis, All Respondents (SWAA)

	Average Full Paid Days WFH							
	All						Men	Women
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Lockdown Stringency	0.14***					0.06**	0.08**	0.04
	(0.04)					(0.03)	(0.03)	(0.04)
Average wage in state (in log)		0.19***				-0.02	-0.03	-0.02
		(0.03)				(0.03)	(0.03)	(0.05)
Population Density, ZIP code of job			0.28***			0.14***	0.09**	0.20***
			(0.03)			(0.03)	(0.04)	(0.05)
County Joe Biden Vote				0.28***		0.13***	0.19***	0.07*
				(0.04)		(0.04)	(0.05)	(0.04)
Industry WFH Propensity					0.40***	0.37***	0.42***	0.30***
					(0.03)	(0.04)	(0.07)	(0.03)
Observations	34055	34055	34055	34055	34055	34055	17758	16297
R^2	0.00	0.01	0.02	0.02	0.03	0.05	0.07	0.03

Note: All regressors are standardized. Lockdown Stringency consists of the sum of state-level monthly index capturing stay-at-home orders and mobility restrictions, from January 2020 to December 2022. Average wage in state consists of the (log) average wage in state in May 2022. Population density is the log of the population density of the ZIP code of current job business premises. Joe Biden Vote consists of the share of Joe Biden vote in the county of residence (as a fraction of all Biden + Trump votes). WFH Propensity in Industry refers to the share of jobs that can be done from home from Dingel and Neiman (2020), by industry. Errors clustered at the state level and weighted to match CPS on {age x sex x education x earnings}

Table 6: Regression Table of Full Paid Days WFH, Individual-level Analysis, College Graduates (SWAA)

	Average Full Paid Days WFH							
	All						Men	Women
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Lockdown Stringency	0.17***					0.10***	0.09**	0.11**
	(0.04)					(0.03)	(0.04)	(0.05)
Average wage in state (in log)		0.16***				-0.07	-0.06	-0.07
		(0.03)				(0.04)	(0.04)	(0.07)
Population Density, ZIP code of job			0.28***			0.25***	0.18***	0.31***
			(0.03)			(0.06)	(0.06)	(0.08)
County Joe Biden Vote				0.23***		0.05	0.10	0.02
				(0.03)		(0.04)	(0.07)	(0.05)
Industry WFH Propensity					0.17***	0.17***	0.20***	0.14***
					(0.04)	(0.04)	(0.07)	(0.03)
Observations	20330	20330	20330	20330	20330	20330	13088	7242
R^2	0.01	0.01	0.02	0.01	0.01	0.03	0.03	0.02

Note: All regressors are standardized. Lockdown Stringency consists of the sum of state-level monthly index capturing stay-at-home orders and mobility restrictions, from January 2020 to December 2022. Average wage in state consists of the (log) average wage in state in May 2022. Population density is the log of the population density of the ZIP code of current job business premises. Joe Biden Vote consists of the share of Joe Biden vote in the county of residence (as a fraction of all Biden + Trump votes). WFH Propensity in Industry refers to the share of jobs that can be done from home from Dingel and Neiman (2020), by industry. Errors clustered at the state level and weighted to match CPS on {age x sex x education x earnings}

Table 7: Regression Table of Full Paid Days WFH, Individual-level Analysis, All Respondents (SWAA), Including Individual-Level Control Variables

	Average Full Paid Days WFH					
	All					
	(1)	(2)	(3)	(4)	(5)	(6)
Lockdown Stringency	0.06**	0.06**	0.06**	0.06**	0.05	0.05
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
Average wage in state (in log)	-0.02	-0.02	-0.04	-0.04	-0.04	-0.04
	(0.03)	(0.03)	(0.03)	(0.03)	(0.04)	(0.04)
Population Density, ZIP code of job	0.14***	0.15***	0.13***	0.12***	0.11***	0.11***
	(0.03)	(0.03)	(0.03)	(0.03)	(0.04)	(0.04)
County Joe Biden Vote	0.13***	0.14***	0.11***	0.11***	0.10***	0.10***
	(0.04)	(0.04)	(0.03)	(0.03)	(0.04)	(0.04)
Industry WFH Propensity	0.37***	0.36***	0.31***	0.31***	0.31***	0.31***
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
Observations	34055	34055	34055	34055	21982	21982
R^2	0.0482	0.0489	0.0572	0.0592	0.0551	0.0555
Month F.E.	X	X	X	X	X	X
Gender F.E.		X	X	X	X	X
Education F.E.			X	X	X	X
5-year age bins F.E.				X	X	X
Children F.E.						X

Note: All regressors are standardized. Lockdown Stringency consists of the sum of state-level monthly index capturing stay-at-home orders and mobility restrictions, from January 2020 to December 2022. Average wage in state consists of the (log) average wage in state in May 2022. Population density is the log of the population density of the ZIP code of current job business premises. Joe Biden Vote consists of the share of Joe Biden vote in the county of residence (as a fraction of all Biden + Trump votes). WFH Propensity in Industry refers to the share of jobs that can be done from home from Dingel and Neiman (2020), by industry. Errors clustered at the state level and weighted to match CPS on {age x sex x education x earnings}**.**

Appendix A

Table A.1: Comparisons of G-SWA Data with Gallup World Poll Data and OECD Data for Full-Time Workers

	Share of women		Aged 20 to 33		Aged 34 to 46		Aged 47 to 64		Secondary education, percent		Tertiary or more, percent	
	Gallup	G-SWA	Gallup	G-SWA	Gallup	G-SWA	Gallup	G-SWA	OECD	G-SWA	OECD	G-SWA
Argentina	35.08	35.14	44.42	44.43	33.3	33.21	22.27	22.36	69.9	69.92	30.1	30.08
Australia	42.88	45.63	30.52	32.58	33.25	35.53	36.23	31.89	48.22	51.32	51.82	48.68
Austria	43.51	43.18	26.46	26.35	37.88	38.06	35.67	35.59	65	65.32	35	34.68
Brazil	33.91	34.13	45.03	44.93	34.92	35.24	20.05	19.83	71.33	71.4	28.69	28.6
Canada	45.29	45.3	29.63	29.7	33.25	33.03	37.12	37.27	36.92	36.9	63.08	63.1
Chile	39.08	39.03	35.72	35.72	33.48	33.52	30.8	30.76	65.3	65.56	34.7	34.44
China	42.1	41.9	44.3	44.19	32	31.93	23.7	23.88	77.15	77.22	22.82	22.78
Czech Rep.	42.34	42.4	21.49	21.38	39.54	39.58	38.97	39.04	73.45	73.52	26.55	26.48
Denmark	42.42	42.75	27.11	26.71	29.04	28.81	43.85	44.48	57.33	57.06	42.67	42.94
Finland	48.22	47.99	25.11	24.86	36.74	36.84	38.15	38.3	57.01	57.31	42.99	42.69
France	47.3	47.69	30.43	29.96	32.82	32.93	36.75	37.11	57.21	57.27	42.79	42.73
Germany	48.1	47.95	25.6	25.42	33.13	33.04	41.27	41.54	67.42	67.51	32.58	32.49
Greece	38.3	38.25	27.22	27.14	38.37	38.52	34.42	34.34	61.15	61.2	38.85	38.8
Hungary	39.83	40.02	26.77	26.8	41.02	40.93	32.21	32.27	70.42	70.65	29.58	29.35
Israel	47.65	47.18	35.67	35.79	31.72	31.6	32.61	32.6	47.16	47.36	52.84	52.64
Italy	37.69	37.69	21.77	21.47	45.79	45.76	32.44	32.77	78.91	79.52	21.09	20.48
Japan	36.72	37.4	26.75	25.66	33.11	33.46	40.14	40.88	44.44	44.73	55.56	55.27
Malaysia	38.38	38.7	51	50.78	30.33	31.02	18.66	18.21	73.6	73.38	26.4	26.62
Mexico	36.11	36.41	45.53	45.75	30.57	30.31	23.9	23.94	72.83	72.92	27.17	27.08
Netherlands	31.57	31.93	30.02	30.01	29.67	29.46	40.31	40.53	54.17	54.44	45.83	45.56
New Zealand	42.57	60.31	34.54	49.03	28.8	34.63	36.66	16.34	59.5	42.41	40.5	57.59
Norway	43.36	45.69	28.25	27.01	32.98	34.75	38.77	38.24	52.37	49.47	47.63	50.53
Poland	42.8	43.07	30.65	30.66	37.84	38.05	31.51	31.3	66.44	66.61	33.56	33.39
Portugal	47.04	46.71	34.07	34.28	35.54	35.56	30.38	30.16	60.23	60.33	39.77	39.67

Table A.1 (Continued): Comparisons of G-SWA Data with Gallup World Poll Data and OECD Data for Full-Time Workers

	Share of women		Aged 20 to 33		Aged 34 to 46		Aged 47 to 64		Secondary education, percent		Tertiary or more, percent	
	Gallup	G-SWA	Gallup	G-SWA	Gallup	G-SWA	Gallup	G-SWA	Gallup	G-SWA	Gallup	G-SWA
Romania	40.06	40.07	28.33	28.32	36.18	36.25	35.49	35.43	75.7	75.68	24.3	24.32
Singapore	41.79	45.36	34.29	29.23	37.34	40.73	28.38	30.04	52	46.67	48	53.33
South Africa	40.95	43.53	42.6	42.28	40.24	43.26	17.16	14.45	81.62	81.18	18.38	18.82
South Korea	37.72	36.52	23.26	17.29	36.62	41	40.12	41.71	46.58	39.47	53.42	60.53
Spain	44.77	45.06	28.38	27.79	41.96	42.32	29.66	29.89	56.09	55.39	43.91	44.61
Sweden	45.38	45.07	25.42	24.98	32.3	32.63	42.27	42.4	52.14	52.9	47.86	47.1
Taiwan	42.4	42.9	31.71	31.16	38.85	39.41	29.44	29.42	48.6	47.75	51.4	52.25
Türkiye	27	27.05	57.27	57.19	29.97	30.05	12.77	12.75	59.82	59.74	40.18	40.26
UK	46.75	47.02	26.77	25.86	36.99	37.25	36.24	36.88	49.77	49.12	50.23	50.88
USA	43.65	44.58	34.61	35.27	28.7	29.42	36.69	35.31	48.07	44.1	51.93	55.9

Source: G-SWA Wave 3, Gallup World Polls (2023), and OECD Education Data (2023).

Table A.2: Statistics on Response Time (in minutes), Sample Size, and Field Dates in 2023

Country	Mean	5%	Median	95%	N	Start date	End date
Argentina	17.76	7.71	13.98	42.17	1,033	April 24	May 23
Australia	12.59	4.77	9.51	29.94	970	April 24	May 22
Austria	14.75	5.81	10.55	32.97	1,039	April 24	May 10
Brazil	18.52	7.12	14.52	42.89	1,030	April 24	May 4
Canada	13.19	4.56	9.8	34.52	1,030	April 24	May 20
Chile	19.53	7.82	14.88	48.05	1,035	April 24	May 4
China	12.66	4.75	10.2	26.53	1,039	April 24	May 10
Czech Rep.	12.65	5.65	10.43	24.24	1,047	April 24	May 12
Denmark	12.44	5.45	9.96	24.3	1,043	April 24	May 23
Finland	11.93	5.53	9.52	24.46	1,040	April 24	May 7
France	13.67	5.22	10.16	31.69	2,588	April 24	May 10
Germany	12.78	4.8	9.5	30.31	2,594	April 24	May 10
Greece	11.79	5.49	10.01	21.17	1,044	April 24	May 12
Hungary	13.81	5.31	10.19	31.57	1,043	April 24	May 13
Israel	14.02	6.06	11.25	27.98	1,044	April 24	May 15
Italy	12.96	4.65	9.57	30.07	2,589	April 24	May 10
Japan	11.41	4.72	9.01	22.81	1,037	April 24	May 8
Malaysia	15.99	5.86	12.3	35.8	1,039	April 24	May 31
Mexico	20.08	8.05	14.75	49.76	1,028	April 24	May 5
Netherlands	12.02	4.35	8.95	25.95	1,039	April 24	May 11
New Zealand	13.56	5.81	10.56	28.56	733	April 24	May 22
Norway	12.79	5.32	10.04	27.24	982	April 24	May 23
Poland	13.13	5.33	9.96	31.56	1,042	April 24	May 10
Portugal	15.6	6.56	11.91	37.22	1,040	April 24	May 4
Romania	13.56	5.94	11.14	28.39	1,044	April 24	May 11
Singapore	14.27	4.84	10.53	37.13	943	April 24	June 2
South Africa	18.75	8.41	15.58	37.79	1,065	April 24	May 8
South Korea	12.61	4.25	8.59	34.82	934	April 24	June 2
Spain	12.61	4.98	9.63	26.74	1,040	April 24	May 16
Sweden	12.7	5	9.55	27.7	1,032	April 24	May 10
Taiwan	10.82	4.74	8.72	20.32	1,037	April 24	May 23
Türkiye	11.82	4.6	9.65	25.31	1,045	April 24	May 11
UK	12.77	4.41	9.1	35.31	2,587	April 24	May 16
USA	12.56	4.59	9.43	28.78	2,551	April 24	May 23
Full sample	13.86	5.01	10.44	32	42,426		

Source: G-SWA Wave 3.

Table A.3: Cross-country Variables

Country	Average Full Paid Days WFH		Lockdown Stringency	Log GDP Per Capita	Population Weighted Density	Individualism	Industry Mix
	All respondents	College graduates					
Argentina	0.867	1.186	18.444	9.451	4.373	0.46	35.644
Australia	1.266	1.66	16.67	10.983	2.307	0.9	41.539
Austria	0.833	1.192	23.897	10.75	2.027	0.55	38.281
Brazil	0.913	1.071	20.4	9.059	6.257	0.38	37.685
Canada	1.669	1.979	22.878	10.717	3.293	0.8	43.654
Chile	0.97	1.228	20.774	9.53	5.034	0.23	38.679
China	0.796	0.935	33.648	9.226	7.271	0.2	37.365
Czech Rep.	0.691	0.958	10.683	9.914	1.196	0.58	35.2
Denmark	0.64	0.797	14.644	10.954	2.938	0.74	36.782
Finland	0.973	1.429	9.714	10.739	0.948	0.63	35.42
France	0.561	0.863	15.817	10.567	3.554	0.71	36.773
Germany	1.037	1.542	17.971	10.676	1.642	0.67	37.673
Greece	0.519	0.602	19.264	9.853	5.874	0.35	37.234
Hungary	0.768	1.223	11.565	9.621	2.338	0.8	32.428
Israel	0.688	0.889	12.091	10.586	4.737	0.54	45.087
Italy	0.722	1.233	22.971	10.377	4.485	0.76	39.511
Japan	0.544	0.705	5.006	10.492	5.366	0.46	37.377
Malaysia	0.603	0.972	22.131	9.316	2.848	0.26	39.219
Mexico	0.823	1.249	20.318	9.212	15.441	0.3	34.999
Netherlands	1.03	1.223	16.195	10.788	2.227	0.8	38.982
New Zealand	1.014	1.222	6.594	10.615	2.103	0.79	40.139
Norway	0.722	0.924	11.102	11.248	0.881	0.69	36.834
Poland	0.742	1.098	16.059	9.619	1.609	0.6	35.564
Portugal	0.755	1.049	20.357	9.981	3.51	0.27	39.524
Romania	0.769	1.178	23.911	9.328	7.796	0.3	29.904
Singapore	0.906	1.136	14.138	11.025	23.239	0.2	39.466
South Africa	0.913	1.409	25.469	8.731	5.264	0.65 [b]	36.958
South Korea	0.424	0.49	15.334	10.362	9.134	0.18	39.643
Spain	0.882	1.237	17.502	10.243	5.043	0.51	38.934
Sweden	0.9	1.21	6.877	10.887	2.327	0.71	39.391
Taiwan	0.656	0.629	5.614	10.153 [a]	10.738	0.17	38.211
Türkiye	0.711	0.769	16.728	9.387	10.319	0.37	32.746
UK	1.53	1.806	16.287	10.768	4.363	0.89	41.288
USA	1.352	1.765	17.734	11.014	2.235	0.91	36.857

Note: [a] We impute Taiwan GDP as follows: $Real\ GDP_{Taiwan} = Nominal\ GDP_{Taiwan}\left(\frac{Real\ GDP_{South\ Korea}}{Nominal\ GDP_{South\ Korea}}\right)$. [b] We impute South Africa's Individualism with the index corresponding to white respondents in South Africa.

Table A.4: Average Full Paid Days WFH, by Gender and Education

Country	All respondents		College Graduates	
	Women	Men	Women	Men
Argentina	1.060	0.762	1.162	1.206
Australia	1.359	1.179	1.790	1.547
Austria	0.821	0.838	1.042	1.354
Brazil	0.972	0.883	0.992	1.131
Canada	1.636	1.690	2.086	1.902
Chile	1.068	0.907	1.163	1.283
China	0.900	0.720	1.026	0.643
Czech Rep.	0.705	0.681	0.821	1.208
Denmark	0.635	0.644	0.761	0.832
Finland	0.963	0.979	1.329	1.535
France	0.479	0.638	0.724	0.935
Germany	1.061	1.013	1.606	1.467
Greece	0.538	0.508	0.719	0.521
Hungary	0.801	0.746	1.102	1.297
Israel	0.650	0.724	0.953	0.843
Italy	0.700	0.736	1.290	1.215
Japan	0.453	0.601	0.625	0.755
Malaysia	0.637	0.579	0.986	0.957
Mexico	0.906	0.776	1.294	1.210
Netherlands	1.021	1.035	1.141	1.274
New Zealand	1.070	0.934	1.196	1.280
Norway	0.641	0.787	0.813	1.077
Poland	0.750	0.738	0.935	1.230
Portugal	0.748	0.764	0.958	1.140
Romania	0.967	0.634	1.446	0.906
Singapore	1.100	0.739	1.311	0.978
South Africa	1.097	0.768	1.357	1.477
South Korea	0.515	0.372	0.642	0.414
Spain	0.757	0.989	1.000	1.433
Sweden	0.864	0.932	1.041	1.380
Taiwan	0.592	0.707	0.531	0.739
Türkiye	0.882	0.646	0.993	0.656
UK	1.486	1.569	1.721	1.885
USA	1.374	1.340	1.597	1.950

Source: G-SWA Wave 3.

Table A.5: Robustness Check: Alternative Measures for Industry/Occupation Mix, Cross-country Analysis, All Respondents (G-SWA)

	Average Full Paid Days WFH								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Lockdown Stringency	0.08**	0.07*	0.07*	0.10**	0.07*	0.08*	0.07	0.06	0.06
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
GDP Per Capita	-0.01	-0.01	-0.01	0.04	0.00	0.01	0.01	-0.01	-0.01
	(0.04)	(0.04)	(0.05)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
Weighted Population Density	0.08**	0.07**	0.07**	0.08**	0.06**	0.06**	0.08***	0.07**	0.07**
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
Individualism	0.21***	0.19***	0.19***	0.20***	0.17***	0.15***	0.20***	0.19***	0.19***
	(0.06)	(0.06)	(0.06)	(0.07)	(0.05)	(0.06)	(0.05)	(0.06)	(0.06)
Industry Mix (Dingel and Neiman)	0.07		0.01						
	(0.05)		(0.07)						
Occupation Mix (Dingel and Neiman)		0.09**	0.09						
		(0.04)	(0.06)						
Industry Mix (wfhmap.com)				0.00		-0.05			
				(0.04)		(0.04)			
Occupation Mix (wfhmap.com)					0.11***	0.13***			
					(0.04)	(0.04)			
Industry Mix (SWAA)							0.06		0.02
							(0.04)		(0.05)
Occupation Mix (SWAA)								0.09**	0.08
								(0.04)	(0.05)
Observations	34	34	34	34	34	34	34	34	34
R2	0.50	0.54	0.54	0.44	0.58	0.60	0.49	0.53	0.54

Note: All regressors are standardized. Industry Mix consists of the average WFH propensity using 1) Dingel and Neiman (2020) industry estimates of the jobs that can be done from home; 2) Hansen et al. (2023) share of job postings for remote work (wfhmap.com); or 3) SWAA average share of work days from home. Using respondents' industry, we compute the average by country. Occupation mix is defined similarly, using occupation estimates instead. Robust standard errors in parenthesis.

Table A.6: Robustness Check: Alternative Measures for Industry/Occupation Mix, Cross-country Analysis, College Graduates (G-SWA)

	Average Full Paid Days WFH								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Lockdown Stringency	0.13***	0.12***	0.12***	0.14***	0.12***	0.13***	0.12***	0.12***	0.12**
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
GDP Per Capita	-0.02	-0.02	-0.03	0.01	-0.02	-0.01	-0.01	-0.02	-0.02
	(0.05)	(0.05)	(0.06)	(0.04)	(0.04)	(0.05)	(0.05)	(0.05)	(0.05)
Weighted Population Density	0.08*	0.08	0.08	0.08*	0.07	0.07	0.09*	0.08	0.08*
	(0.04)	(0.04)	(0.05)	(0.04)	(0.04)	(0.04)	(0.04)	(0.05)	(0.05)
Individualism	0.29***	0.28***	0.29***	0.28***	0.27***	0.25***	0.29***	0.28***	0.28***
	(0.06)	(0.06)	(0.07)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)
Industry Mix (Dingel and Neiman)	0.05		0.01						
	(0.06)		(0.08)						
Occupation Mix (Dingel and Neiman)		0.06	0.05						
		(0.05)	(0.07)						
Industry Mix (wfhmap.com)				-0.01		-0.05			
				(0.05)		(0.05)			
Occupation Mix (wfhmap.com)					0.08	0.10**			
					(0.05)	(0.05)			
Industry Mix (SWAA)							0.05		0.03
							(0.05)		(0.06)
Occupation Mix (SWAA)								0.05	0.03
								(0.04)	(0.05)
Observations	34	34	34	34	34	34	34	34	34
R2	0.55	0.56	0.56	0.54	0.58	0.60	0.56	0.56	0.56

Note: All regressors are standardized. Industry Mix consists of the average WFH propensity using 1) Dingel and Neiman (2020) industry estimates of the jobs that can be done from home; 2) Hansen et al. (2023) share of job postings for remote work (wfhmap.com); or 3) SWAA average share of work days from home. Using respondents' industry, we compute the average by country. Occupation mix is defined similarly, using occupation estimates instead. Robust standard errors in parenthesis.

Table A.7: Robustness Check: Alternative Measures for Industry/Occupation Mix, Individual-level Analysis, All Respondents (SWAA)

	Full Paid Days WFH								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Lockdown Stringency	0.06**	0.06**	0.07**	0.07**	0.06**	0.07**	0.05**	0.05*	0.05*
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.02)	(0.03)	(0.02)
Average wage in state (in log)	-0.02	-0.02	-0.03	-0.03	-0.02	-0.04	-0.03	-0.03	-0.04
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
Population Density, ZIP code of job	0.14***	0.14***	0.13***	0.13***	0.15***	0.13***	0.13***	0.14***	0.12***
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
County - Joe Biden Vote	0.13***	0.15***	0.13***	0.13***	0.15***	0.13***	0.11***	0.14***	0.11***
	(0.04)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.04)	(0.03)	(0.04)
WFH Propensity in Industry, Dingel and Neiman	0.37***		0.31***						
	(0.04)		(0.04)						
WFH Propensity in Occupation, Dingel and Neiman		0.30***	0.19***						
		(0.03)	(0.03)						
WFH Propensity in Industry, wfhmap.com				0.40***		0.36***			
				(0.04)		(0.04)			
WFH Propensity in Occupation, wfhmap.com					0.30***	0.22***			
					(0.03)	(0.03)			
WFH Propensity in Industry, SWAA							0.57***		0.51***
							(0.04)		(0.04)
WFH Propensity in Occupation, SWAA								0.32***	0.17***
								(0.02)	(0.02)
Observations	34055	33655	33655	32926	33951	32831	34055	34033	34033
R2	0.05	0.04	0.06	0.05	0.04	0.06	0.08	0.04	0.09

Note: All regressors are standardized. WFH Propensity in industry or occupation consists of the WFH propensity using either Dingel and Neiman (2020) industry or occupation estimates of the jobs that can be done from home, Hansen et al. (2023) share of job postings for remote work (wfhmap.com), or SWAA estimates of the average share of workdays from home. Errors clustered at the state level and weighted to match CPS on {age x sex x education x earnings}.

Table A.8: Regression Table of the Women-Men Gap WFH Levels and Preferences, Cross-country Analysis, All Respondents (G-SWA)

	Gap between Women and Men			
	Average Full Paid Days WFH		Desired Full Paid Days WFH	
	(1)	(2)	(3)	(4)
GDP Per Capita	-0.07***	-0.04	-0.05*	-0.06
	(0.02)	(0.03)	(0.03)	(0.04)
Lockdown Stringency		0.04		0.00
		(0.02)		(0.03)
Weighted Population Density		0.08**		0.06**
		(0.03)		(0.03)
Culture: Individualism		0.03		0.02
		(0.03)		(0.04)
Industry Mix		-0.03		0.02
		(0.02)		(0.02)
Constant	0.05**	0.05**	0.13***	0.13***
	(0.02)	(0.02)	(0.02)	(0.02)
Observations	34	34	34	34
R^2	0.23	0.45	0.14	0.30

Note: All regressors are standardized. The gap between women and men is computed as the difference in the average of the outcome in each country. Average Full Paid Days WFH are based on responses to the question "For each day last week, did you work 6 or more hours, and if so where?". Desired Full Paid Days WFH are based on responses to the question "As the pandemic ends, how often would you like to have paid workdays at home?". Lockdown Stringency consists of the sum of monthly index capturing stay-at-home orders and mobility restrictions, from January 2020 to December 2022. GDP Per Capita consists of the log of GDP Per Capita in 2019, in 2010 USD constant. Population density consists of the average population-weighted density in 2020, using a 1km resolution. Culture: Individualisms consists of the Hofstede index for collectivism vs. individualism. Industry Mix consists of the average share of jobs that can be done from home, using Dingel and Neiman (2020) 2-digits industry estimates and computing the average by country, based on respondents' industry. Robust standard errors.

Appendix B: The Individualism Index based on the Values Survey Module 2013 (Hofstede and Minkov 2013)

The Individualism Index (IDV) is based on the following index formula:

IDV = 35(m04 – m01) + 35(m09 – m06) + C(ic)

in which m01 is the mean score for question 01, etc. See the Values Survey Module 2013 Manual for details: https://geerthofstede.com/wp-content/uploads/2016/07/Manual-VSM-2013.pdf

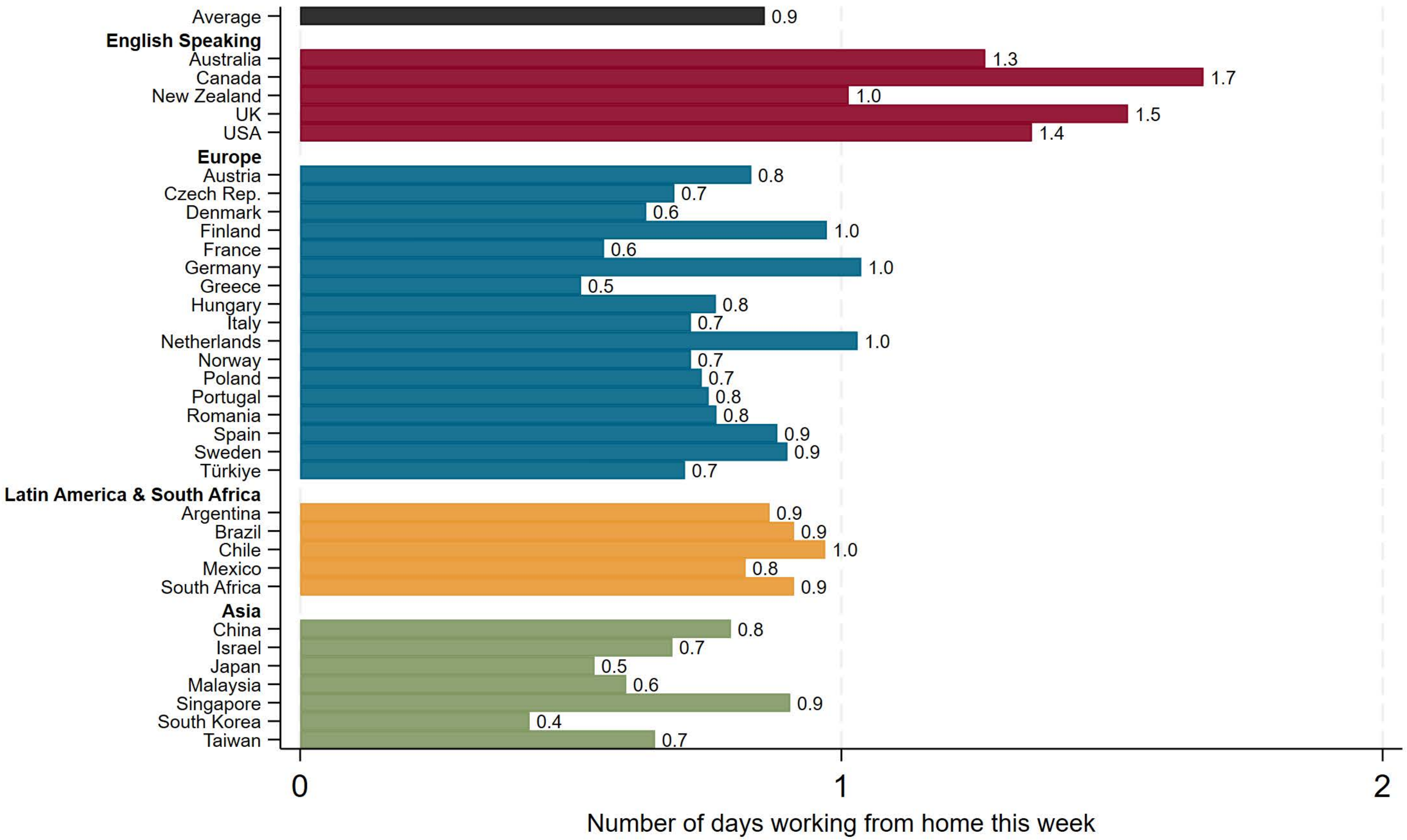
The survey items underlying the Individualism Index are the following:

Please think of an ideal job, disregarding your present job, if you have one. In choosing an ideal job, how important would it be to you to …
1 = of utmost importance
2 = very important
3 = of moderate importance
4 = of little importance
5 = of very little or no importance

01. have sufficient time for your personal or home life	*1*	*2*	*3*	*4*	*5*
04. have security of employment	*1*	*2*	*3*	*4*	*5*
06. do work that is interesting	*1*	*2*	*3*	*4*	*5*
09. have a job respected by your family and friends	*1*	*2*	*3*	*4*	*5*

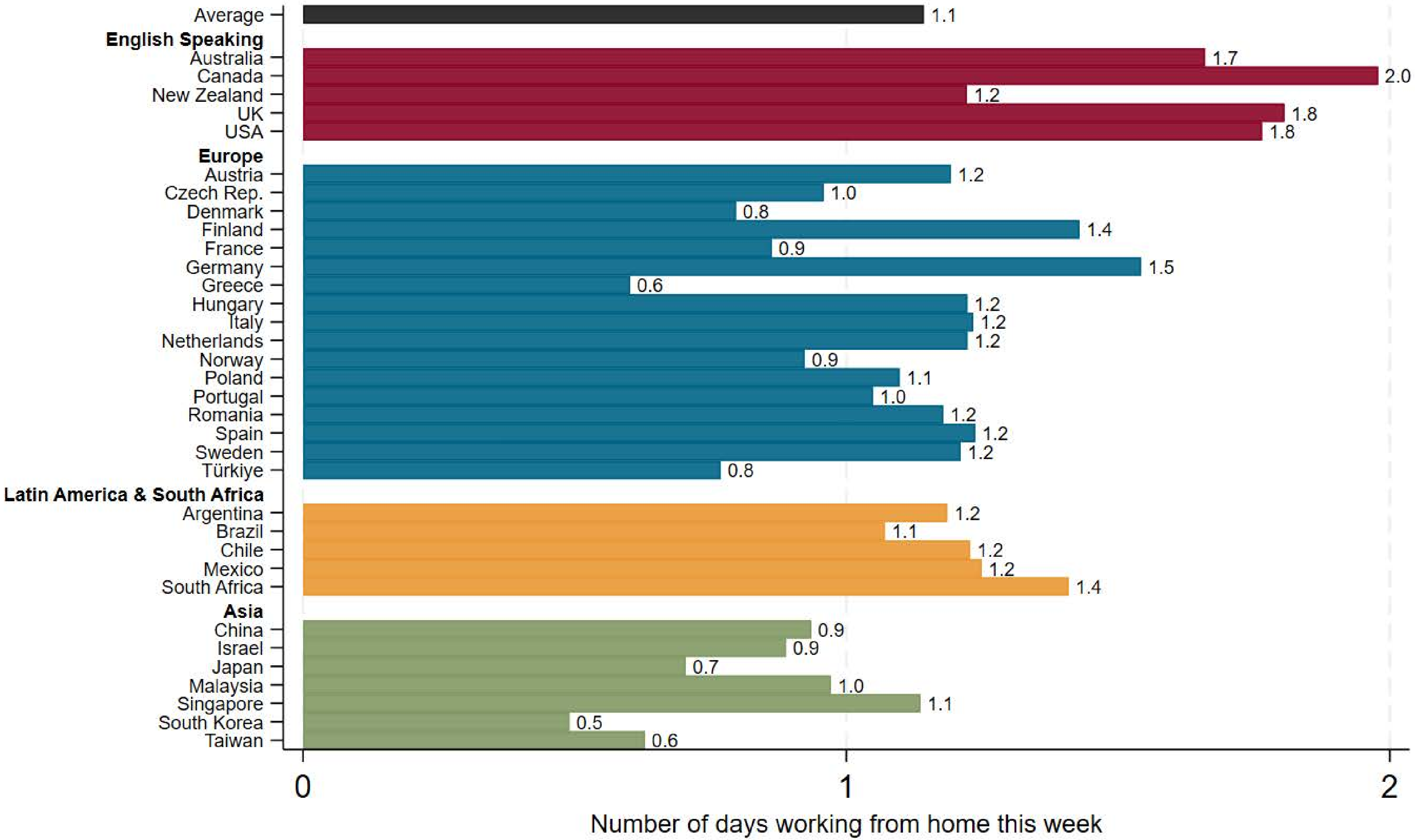
The questionnaire is available at https://geerthofstede.com/wp-content/uploads/2016/07/VSM-2013-English-2013-08-25.pdf

Figure 1: Average Paid Full Days Worked from Home per week



Note: Responses to the question "For each day last week, did you work 6 or more hours, and if so where?". Sample of N=42,426 respondents in the G-SWA from 34 countries surveyed in April-May 2023.

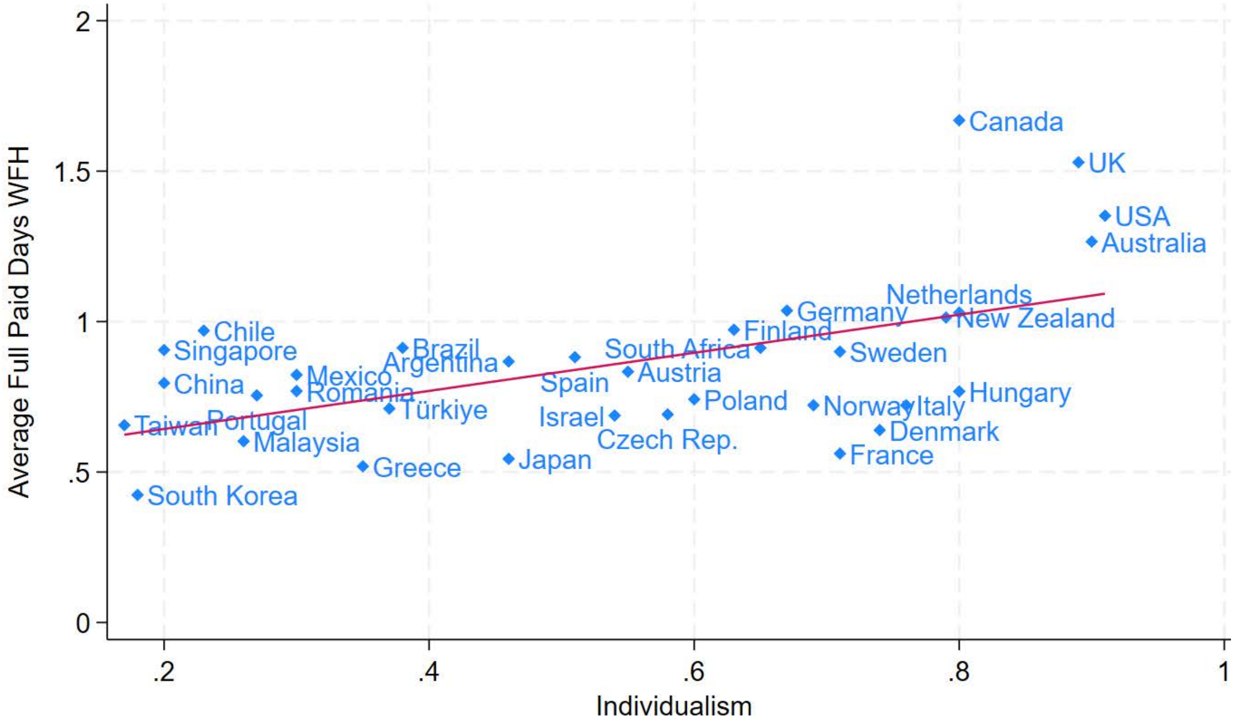
Figure 2: Average Paid Full Days Worked from Home per week, College Graduates



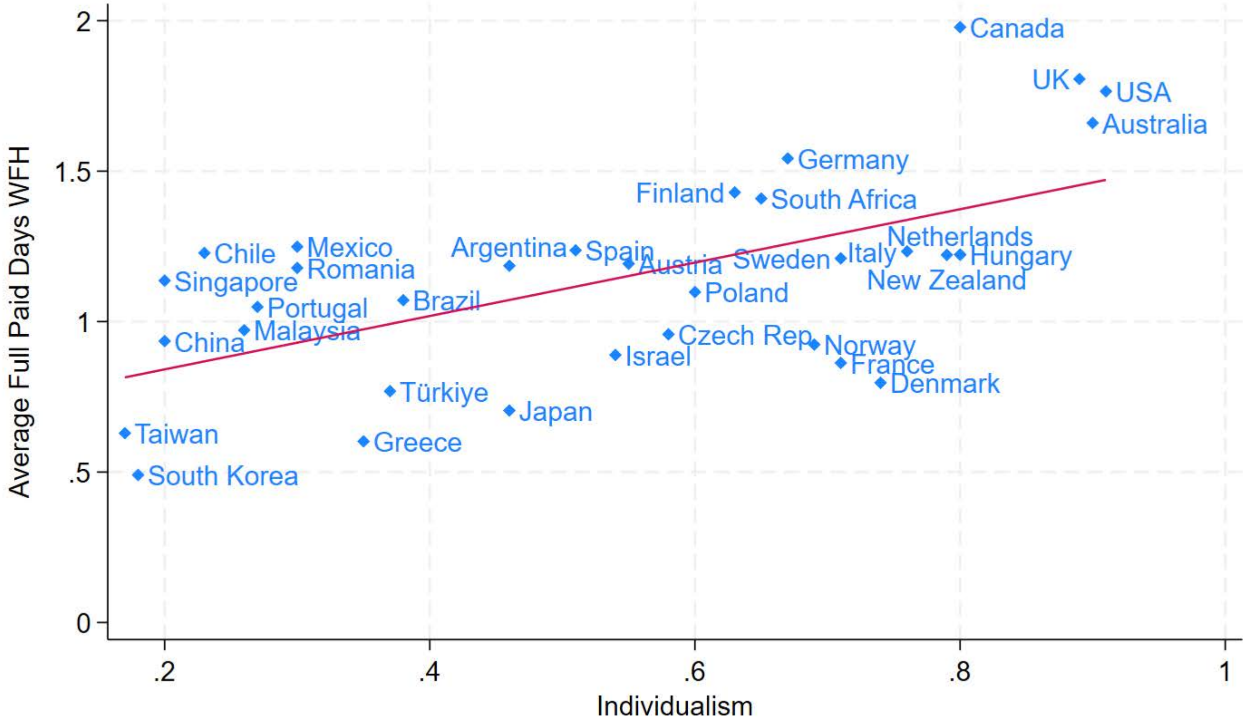
Note: Responses to the question “For each day last week, did you work 6 or more hours, and if so where?”. Sample of N=17,019 respondents with at least a college degree in the G-SWA from 34 countries surveyed in April-May 2023.

Figure 3: Individualism and WFH

Panel A: All respondents



Panel B: College graduates

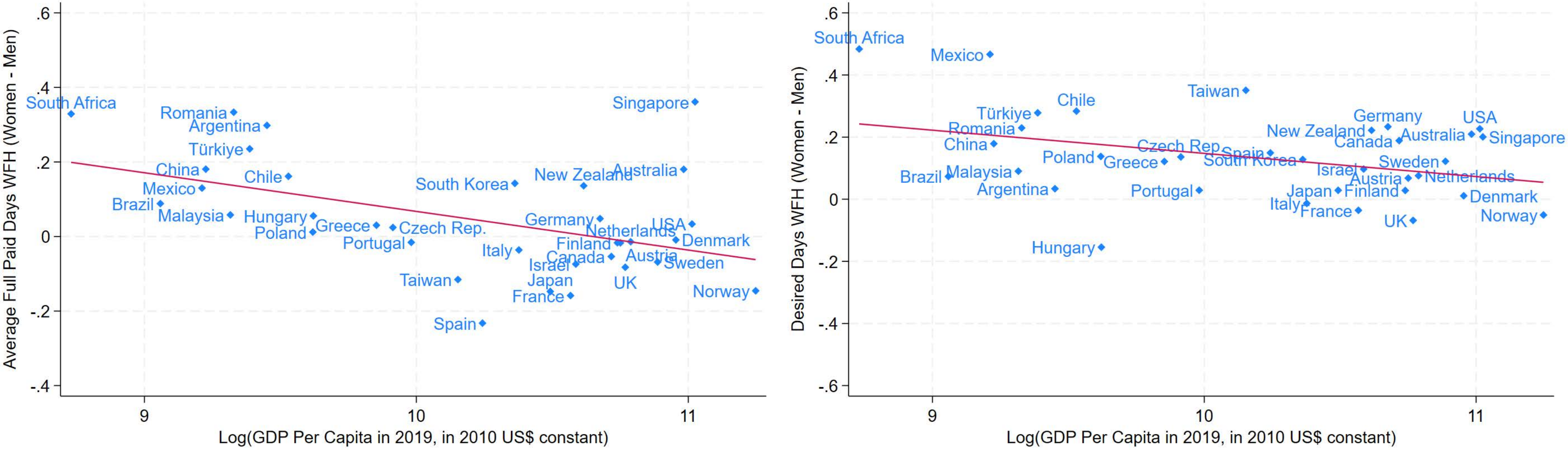


Note: The figure plots the Average Full Paid Days WFH and Hofstede's Individualism index. Panel A: Average Full Paid Days WFH calculated among all respondents in the G-SWA. Panel B: Average Full Paid Days WFH calculated among college graduates only.

Figure 4: GDP and Gender Gap in WFH levels and preferences

Panel A: Average Full Paid Days WFH

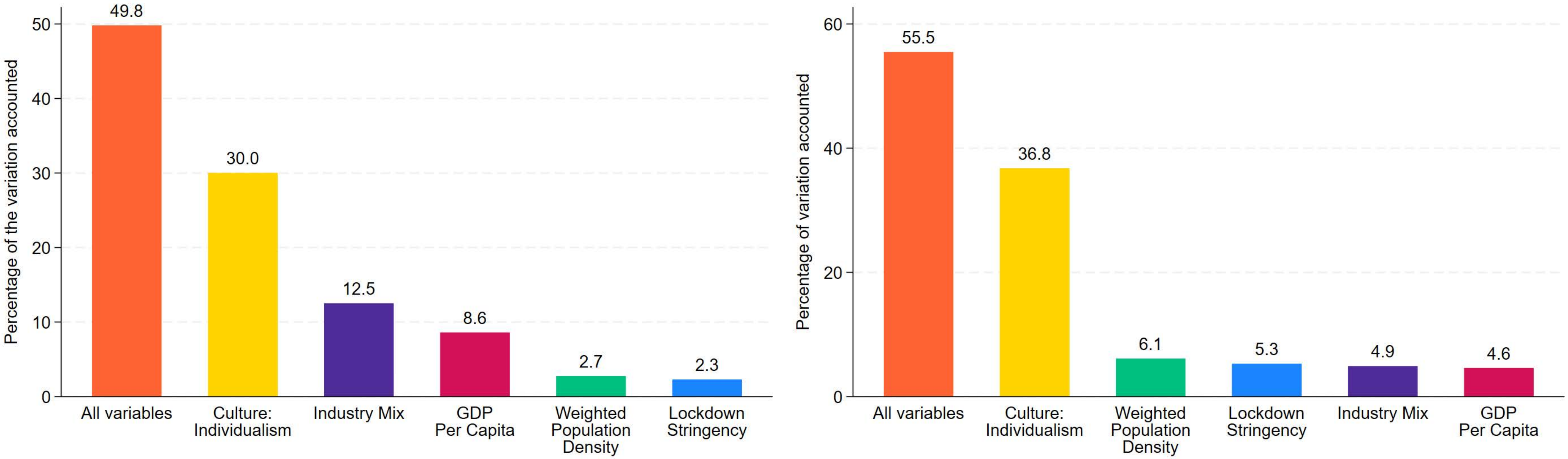
Panel B: Average Desired Full Paid Days WFH



Note: Among all respondents in the G-SWA. The figure plots the difference between the outcome for women and men by country, and the log of GDP Per capita in 2019, in 2010 USD constant. Panel A: Average Full Paid Days WFH, based on responses to the question “For each day last week, did you work 6 or more hours, and if so where?”. Panel B: Desired Full Paid Days WFH, based on responses to the question “As the pandemic ends, how often would you like to have paid workdays at home?”.

Figure 5: Percentage of cross-country variation accounted for by each variable

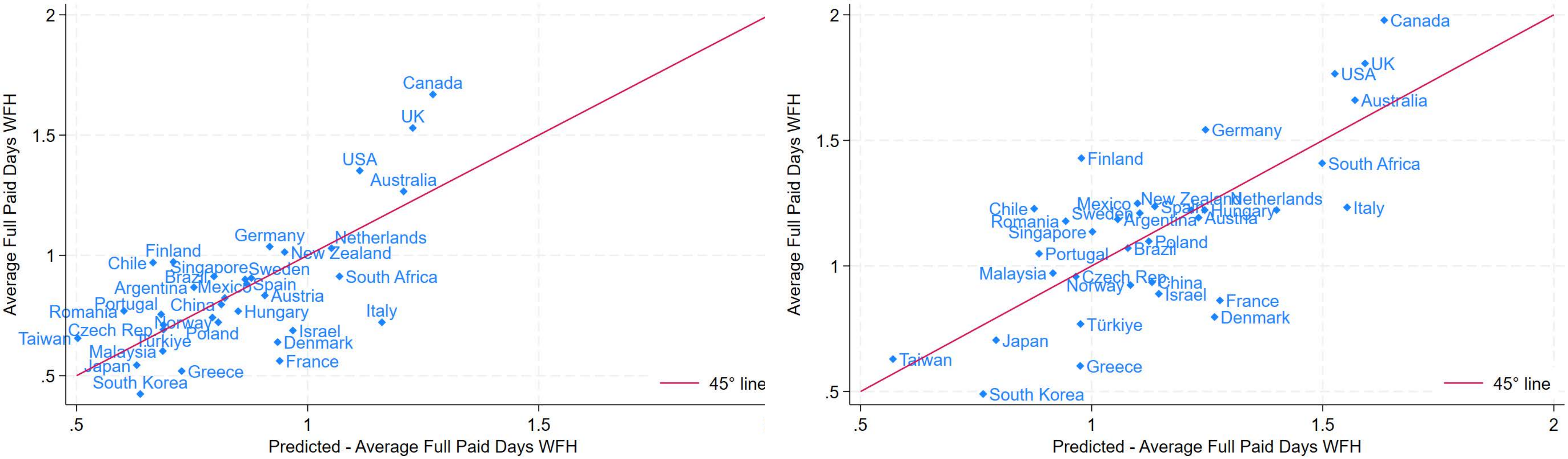
Panel A: All respondents **Panel B:** College graduates



Note: The figure plots the R^2 of the cross-country regression of the average Full Paid Days WFH on each individual variable. The first bar in each figure shows the R^2 of the cross-country regression including all five variables. Panel A: Average Full Paid Days WFH calculated among all respondents in the G-SWA. Panel B: Average Full Paid Days WFH calculated among college graduates only.

Figure 6: Predicted vs. observed values

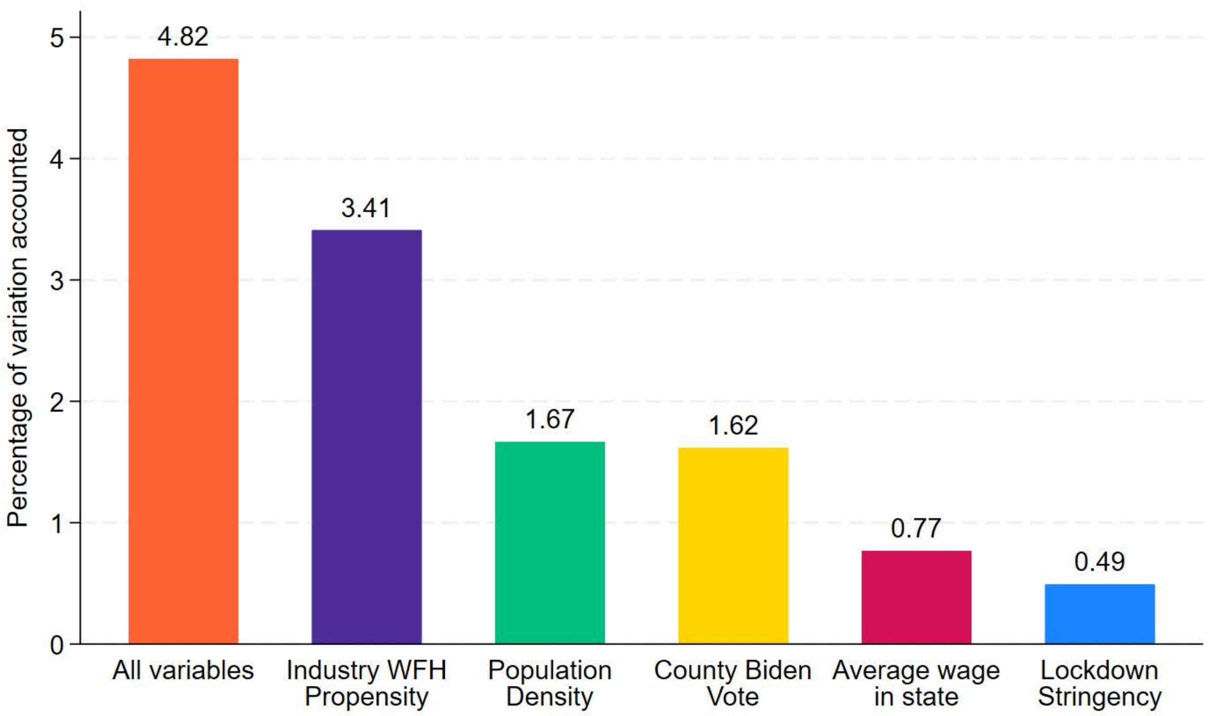
Panel A: All respondents **Panel B:** College graduates



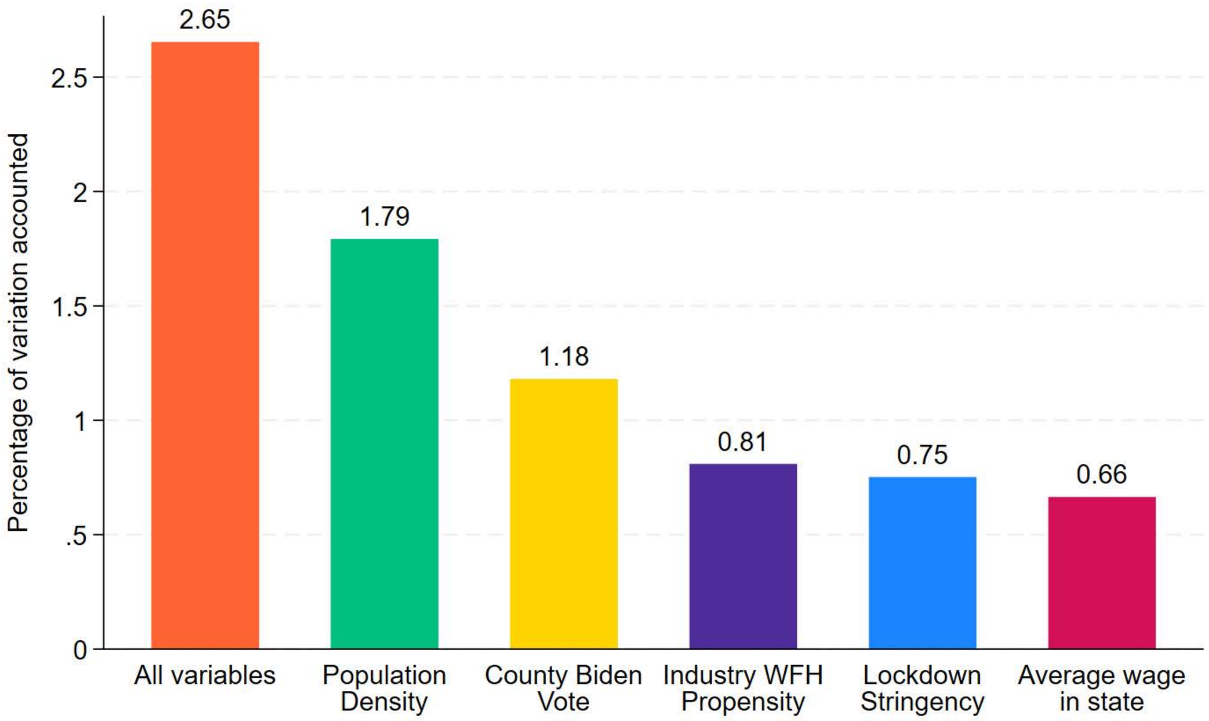
Note: The figure plots the observed Average Full Paid Days WFH and the predicted average from the specification shown in column 6 of Table 3 and 4. The model includes cumulative lockdown stringency, log GDP per capita, population-weighted density, individualism, industry mix and a constant. Panel A: Average Full Paid Days WFH calculated among all respondents in the G-SWA. Panel B: Average Full Paid Days WFH calculated among college graduates only.

Figure 7: Percentage of individual-level variation accounted for by each variable

Panel A: All respondents



Panel B: College graduates



Note: The figure plots the R^2 of the individual-level regression of Full Paid Days WFH on each individual variable. The first bar in each figure shows the R^2 of the individual-level regression including all five variables. Panel A: Average Full Paid Days WFH calculated among all respondents in the SWAA. Panel B: Average Full Paid Days WFH calculated among college graduates only.