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Will Working from Home Stick in Developing Economies?

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Papageorgiou

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Will Working from Home Stick in Developing Economies?
Prepared by Marina Conesa Martinez, Futoshi Narita, and Chris Papageorgiou*

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ABSTRACT: In developing economies, a shift to working from home during the COVID-19 pandemic varies substantially. An increase in teleworking days per week ranges from 0.7 to 17.6 percentage points across 10 developing countries covered by an online survey to about 500 respondents per country. An estimated income discount associated with telework disappeared temporarily at the onset of the pandemic. A calibrated model indicates that workers' preferences to telework may largely depend on their educational attainments. Whether telework will sustain in these countries could depend on obstacles to telework, particularly for workers with less education, and a degree of economy-wide externality.

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1. Introduction

The COVID-19 pandemic had changed the way we work globally, but a data gap exists on how significant it was in developing economies. A swift shift to working from home at the onset of the pandemic is well documented for many advanced economies, especially in the United States (e.g., Barrero, Bloom, Davis 2021a; Bick, Blandin, Mertens 2022; Jaumotte and others 2023). For developing economies, however, only limited data have been available regarding the extent to which people actually adjusted their work arrangements (except for contemporaneous research by Aksoy and others 2022).¹

To narrow this data gap, this paper presents evidence of how people adopted telework in 10 developing countries, covered by a new online survey dataset compiled by the IMF Research Department.² The survey dataset includes about 500 respondents from each of the following 10 countries: Argentina, Brazil, Ecuador, India, Indonesia, Pakistan, Peru, South Africa, Türkiye, and Vietnam. How many days the respondents worked per week without commuting was asked in early and late 2021 to gather retrospective information about before and after the onset of the pandemic, in addition to background characteristics of respondents.

The dataset shows a substantial cross-country difference in the degree of the shift to working from home. Several countries showed a larger increase than others in the share of telework days per week, ranging 11.7-17.6 percentage points (Argentina, Ecuador, Peru). Adjustment was very limited in other countries (Indonesia, Türkiye), ranging from 0.7 to 1.2 percentage points. In most cases, the overall telework level was much below the U.S. level, and parttime jobs were increased, likely as an alternative way to adjust to the pandemic situation. But some patterns are similar to those in the United States. For example, telework days increased more for workers with higher educational attainments.

The dataset also reveals that remote work was prevalent for low-income households before the pandemic in many of these countries (particularly Peru, Vietnam). For U.S. data, Oettinger (2011) finds that there was a sizable discount of 25-27 percent in wages associated with home-based work as of 1980, but it almost disappeared as of 2000. In the case of the 10 countries covered by the online survey dataset, an estimated income discount was sizable as of 2019, at 33 percent, but it almost disappeared at the onset of the pandemic and then partially reversed to -17 percent in late 2021. These estimated associations are consistent with the strong increase in the telework share by high-income households. But then, the question is whether it is because the pandemic-related concerns made people prefer to work remotely more or because the relative profitability of telework jobs increased upon the pandemic, compared to on-site jobs that were more exposed to COVID-19 infection risks or more subject to containment measures.

A simple model is developed to parsimoniously disentangle the telework choice into workers' preferences and jobs' relative profitability. The model is built on the idea of Bick, Blandin, and Mertens (2022) to use an equilibrium model to separate "telework adoption" and "telework substitution" from observed telework behaviors, respectively corresponding to a preference shift toward telework and a choice based on profitability

¹ Aksoy and others (2022) conduct an online survey on work from home in 27 countries including several developing countries. It covers three countries (Brazil, India, Türkiye) that are also covered in the survey dataset in this paper.

² This customized online survey was implemented by Nielsen, a global market research company. The work is financially supported by the U.K.'s Foreign, Commonwealth and Development Office (FCDO), the Government of Korea, and the partners in the IMF's COVID-19 Crisis Capacity Development Initiative (CCCDI)—Belgium, Canada, China, Germany, Japan, Korea, Spain, Singapore, and Switzerland.

(e.g., high on-site job costs due to social distancing). Unlike their model, our model assumes a search-matching friction in the labor market so that job profitability is tightly linked to workers' earnings, making the telework choice based on a simple comparison between profitability and workers' willingness to work remotely. Under some simplifying parametric assumptions, calibration can be easily done from an observed telework share, total employment share, and an estimated relative income from telework compared with on-site work.

The model also incorporates externality in profitability depending on the economy-wide share of the same work modality (on-site or remote). On the one hand, local agglomeration spillovers may increase the profitability of in-office jobs if more jobs are done in on-site office space, as modeled by Delventhal, Kwon, and Parkhomenko (2022). On the other hand, strategic complementarities among firms may exist because telework jobs may become more viable if their counterparty firms or clients have also adopted remote work arrangements, as discussed by Barrero, Bloom, and Davis (2021a).³ The model demonstrates that this coordination mechanism can induce diverse telework responses to small differences in fundamentals, suggesting that whether telework will sustain in the future or shrink back to pre-pandemic levels may depend on relatively small differences in observable features such as the level of access to internet or educational attainment.

These insights inform an ongoing debate on the future of remote work. The literature on working from home has strongly expanded since the onset of the COVID-19 pandemic. The literature has focused on advanced economies, in particular the United States.⁴ A key question is whether working from home will stick going forward, even after the pandemic situation ends (Barrero, Bloom, Davis 2021a). Working from home has implications on productivity, inequality, and resilience, as well as inflation pressures (Barrero, Bloom, Davis 2021b, Barrero and others 2022).⁵ The calibrated model analysis of this paper sheds light on a possible key mechanism, on which the sustainability of working from home depends.

This paper also contributes to the literature on development economics by narrowing the data gap on telework evidence in developing economies. Intensive efforts have been made to gather information on the pandemic situations in developing economies.⁶ But direct information on the actual telework behaviors has still been scarce (except for the recent study by Aksoy and others 2022). With the limited data availability many researchers impute the index of telework ability using the U.S. O*NET data, following an influential study by

³ Barrero, Bloom, and Davis (2021a, p.15) give an example that “[working from home] becomes more viable for law firms when more of their clients work remotely.” Strategic complementarity may generate a situation where equilibrium outcomes can differ even if fundamentals are similar (Cooper, John 1988). See also Mino (2017) for a survey of equilibrium indeterminacy, explaining strategic complementarity as a source of indeterminacy.

⁴ For the United States, in addition to several survey studies (e.g., Barrero, Bloom, Davis 2021; Bick, Blandin, Mertens 2022; Brynjolfsson and others 2020; Foote and others 2021; Ozimek 2020), the U.S. Census Bureau also publishes data on telework (Household Pulse Survey: <https://www.census.gov/programs-surveys/household-pulse-survey.html>), and the U.S. Bureau of Labor Statistics added five questions to the Current Population Survey (<https://www.bls.gov/cps/>) on telework in the pandemic context.

⁵ See also papers and articles available at the WFH Research's website (<https://wfhresearch.com/>).

⁶ For studies using the World Bank's High-frequency Phone Surveys (World Bank 2021), see also, for example, Josephson, Kilic, and Michler (2021), Kugler and others (2021), Khamis and others (2021), Kim and others (2021), Narayan and others (2022), and de Paz, Gaddis, and Muller (2021). Other surveys studies include PERC (2021), Kansime and others (2021), and Durizzo and others (2021) for sub-Saharan Africa; Bontan, Hoffmann, and Vera-Cossio (2020) and Arteaga-Garavito and others (2020) for Latin America and the Caribbean; Shinozaki and Rao (2020) for the Philippines; and Egger and others (2020) for nine developing countries. For India, Gupta, Malani, and Woda (2021) use monthly household survey by the Centre for Monitoring Indian Economy Pvt. Ltd. (CMIE). On remote learning (instead of working), Asanov and others (2021) provide evidence in Ecuador.

Dingel and Neiman (2020), to provide indirect evidence for many developing economies.⁷ The evidence provided by this paper complements those studies based on imputation from the U.S. evidence.

The rest of the paper is organized as follows. Section 2 documents evidence of telework behaviors in the 10 developing countries covered by the online survey. Section 3 considers a simple model to separate two factors behind telework behaviors—preferences or profitability. Section 4 concludes. Appendix A provides details of the new online survey, Appendix B presents regression results associated with telework and its implications during the pandemic, and Appendix C explains the details of the model.

2. Telework in developing economies during the pandemic

An online survey was conducted to better understand the impact of the pandemic in developing economies. The survey was designed by the IMF Research Department in collaboration with the Nielsen Company in 10 developing economies (Argentina, Brazil, Ecuador, India, Indonesia, Pakistan, Peru, South Africa, Türkiye, Vietnam). A total of 5,058 respondents—with an even distribution across the 10 countries—participated in the survey between October and November 2021. The questionnaire addressed various aspects, including demographic and household characteristics, employment status and work arrangements, pandemic-related incidents (e.g., illness, lack of food), perceptions of income and prices, and political support. The survey gathered yearly and quarterly data for pre-pandemic and pandemic periods, by asking retrospective questions based on the respondents' recollections. See Appendix A for details and descriptive statistics. The questionnaire is available online.

The survey asked the following questions to measure the frequency of telework before and after the onset of the pandemic. First, the survey asked (Q8a, Q8b, Q8c), “How many days per week did you usually work?” and then asked (Q9a, Q9b, Q9c), “How many days per week did you usually commute to work?” showing the following multiple-choice responses:⁸

- Zero or had never worked
- 1-2 days
- 3-4 days
- 5 days or more

The questions were asked for the following three periods, based on the WHO's declaration of a global pandemic on March 11, 2020, and one year after the declaration:

- Before end-March 2020 (i.e., before the onset of the pandemic)
- Between end-March 2020 and end-March 2021 (i.e., during the first year of the pandemic)
- After end-March 2021 (i.e., after one year of the pandemic)

⁷ See, for example, Brussevich, Dabla-Norris, and Khalid (2020), Gottlieb, Grobovsek, Poschke, and Saltiel (2021), Hasan, Rehman, and Zhang (2021), Hatayama, Viollaz, and Winkler (2020), and IMF (2020). Many researchers use the O*NET database (e.g., Boeri, Caiumi, Paccagnella 2020, Famiglietti, Leibovici, Santacreu 2020; Mongey, Pilossoph, Weinberg 2021). The American Time Use Survey is another data source in measuring telework ability (e.g., Alon and others 2020, Hensvik, Le Barbanchon, Rathelot 2020, Papanikolaou and Schmidt 2022).

⁸ The use of ranges (e.g., 1-2 days) was intended to reduce the fatigue of survey respondents, with an additional consideration that this survey asked retrospective questions based on respondents' recollections, which may be more burdensome. These questions follow those of the Real-time Population Survey (RPS) by Bick, Blandin, Mertens (2022), although the RPS asked for the exact number of days, instead of ranges. There is no distinction between whether people work from home as self-employed or not.

If the survey respondents were not the main income earner of the respondent's household (checked by Q18), then the same questions were repeated (Q25a-Q26c) to gather information about the main income earner's telework situation.⁹ We focus on the telework situation of main income earners because their working situations are more closely related to household-level income that we mainly analyze.¹⁰

The degree of teleworking is measured in two ways: (1) the share of telework days per week and (2) a categorical indicator of whether the person worked remotely all the time, part of the time, or none of the time. The first one is calculated as one minus the ratio of commute workdays over the total workdays per week, taking the mid-point of the range responses (e.g., 1.5 days if 1-2 days was selected). The second one is a classification variable that follows Bick, Blandin, and Mertens (2022). It is "Commute only" if the respondent did not telework during the week, "Work from home only" if she or he worked fully remotely, and "Work from home some days" for partial telework. The latter two categories are often combined as "some telework" in analysis.

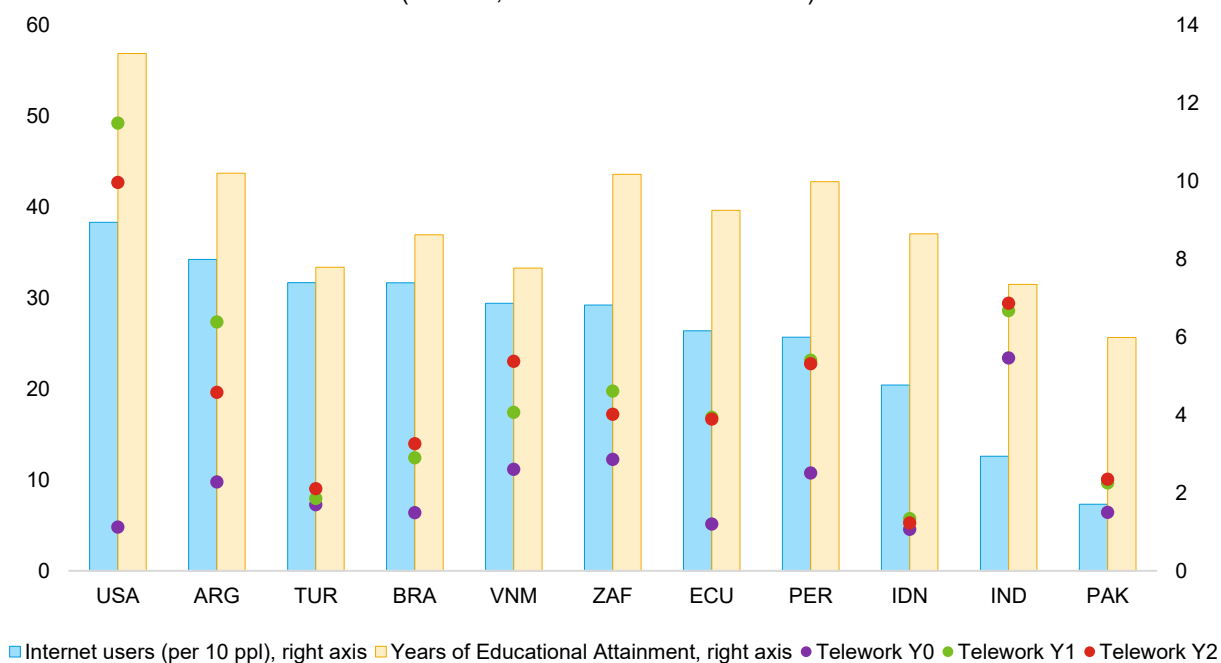
Looking at the data across countries reveals diverse telework experiences beyond the variations in features observed at the country level (Figure 1). An increase in telework was large and more than 10 percentage points for Argentina, Ecuador, and Peru, whereas it was very limited for Indonesia and Türkiye by just about one percentage point. There is almost zero correlation (0.08) between the pre-pandemic levels and the increases upon the pandemic. Although India may be an outlier, telework days per week both before and after the onset of the pandemic were generally positively correlated with the population share of internet users as of 2019 and the average year of total schooling for people of age 15-64 as of 2015 (see Appendix Table A3 for data details). When excluding India, the correlation coefficients are 0.46 and 0.70 for internet users and educational attainment, respectively. Even including India (still excluding the United States), the increase in telework days upon the pandemic positively correlated with these pre-pandemic fundamentals (with correlation coefficients of 0.41 and 0.69, respectively). But a simple multivariate regression on these two features and the logarithm of GDP per capita shows that about 70 percent (or 60 percent excluding India) of the cross-country variation in the telework share upon the pandemic is unexplained.

After one year from the onset of the pandemic, telework levels were mostly kept unchanged. The adjustments at this stage were minor for many countries. Argentina saw a reversal of its largest increase among the 10 countries by 8 percentage points, although maintaining the share of telework days at 20 percent. For India, even though the country saw a widespread infection of the Delta variant in April-June 2021, the level of telework did not change much. Vietnam saw a relatively large increase in the share of telework days to 23 percent. Variations unexplained by the fundamentals remain at about 70 percent (but reduce to about 40 percent if India is excluded).

⁹ Q18 asked "Who is the main income earner in your household? If there is more than one person who earns similar amounts, please pick one among them, for which you have the most information." with the following choice responses: "Yourself," "Someone else than yourself," or "No one". Less than 1 percent of respondents chose "No one" while choosing currently being "employed." We include these respondents in the sample of main earners.

¹⁰ Telework was generally more prevalent among respondents who are not main earners.

Figure 1. Cross-country difference in a shift to teleworking at the onset of the pandemic
(Percent, unless indicated otherwise)



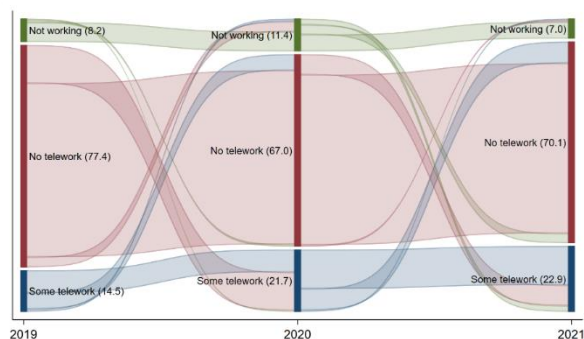
Sources. IMF COVID-19 Custom Tracker (2nd round), Barrero, Bloom, Davis (2021a), Barro and Lee (2013, updated in September 2021), and World Development Indicators (World Bank 2022a).

Notes. The dots show the country-level sample-weighted averages of telework days per week in percent of total workdays, based on the information on the main income earner of the respondent's household (Q25a-Q26c) if the respondent was not the main income earner (Q18), and otherwise, based on the information on respondents themselves (Q8a-Q9c). Label "Y0" corresponds to before March 2020, "Y1" corresponds to April 2020-March 2021, and "Y2" corresponds to April 2021-October/November 2021. See Appendix Table A3 for the underlying data.

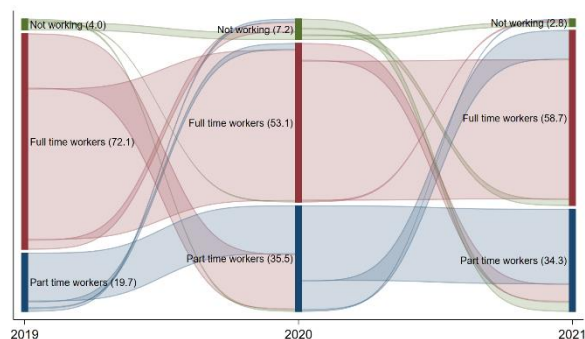
Following the transition of workers across different work arrangements shows that telework jobs increased at the onset of the pandemic but an increase in parttime jobs was also remarkable (Figure 2). Almost 20 percent of respondents who did not work from home before the pandemic shifted to a work arrangement where there was some telework. Although the proportion of workers that kept some type of telework arrangement remained at a similar level until late 2021, there were relatively sizable reshuffles between on-site and remote workers. In particular, almost half of the teleworkers in the pre-pandemic period shifted to fully on-site jobs at the onset of the pandemic. It is not clear whether new hires in 2021 did telework more or not. Many workers also shifted to parttime jobs, including those who worked remotely, and more than two thirds of parttime jobs were on-site (Appendix Figure A5). There are more workers who needed to adjust their work arrangements from fulltime to parttime jobs than those who adjusted to telework to preserve fulltime jobs. A potential explanation is that telework might have been different in essence prior to the pandemic in developing economies so that adjustments were still required due to the forced increase in social distancing.

Figure 2. Transition across work arrangements in developing economies during the pandemic
(Percent)

Panel A. Remote vs. on-site work



Panel B. Parttime vs. fulltime work

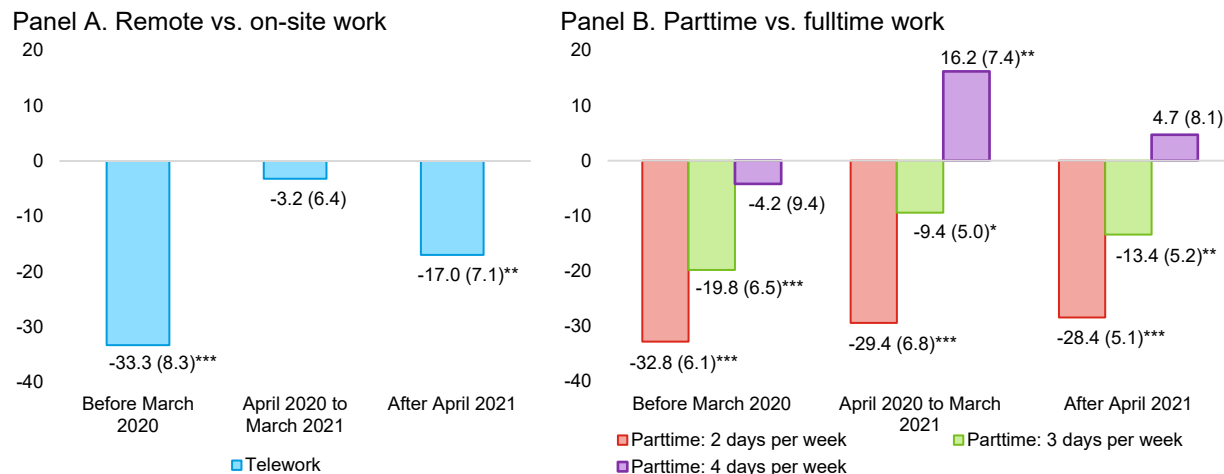


Source. IMF COVID-19 Custom Tracker (2nd round).

Notes. For ease of exposition, year label “2019” corresponds to before March 2020, “2020” corresponds to April 2020–March 2021, and “2021” corresponds to April 2021–October/November 2021. The numbers in parentheses indicate the shares to the total (with population weights). This type of chart is often called “Sankey plot,” produced by the Stata command `sankey_plot` (Rios-Avila 2022). See Appendix Figure A5 for the transition covering the intersection of remote and parttime work.

The characteristics of workers who tend to increase telework days more during the pandemic are found to be in line with existing studies. Those include workers with higher educational attainments, older workers, those living with elderly people (reflecting higher health risks from COVID-19 infection), and those worked on jobs that are easy to conduct from home (see regression results in Appendix B and charts in Appendix Figure A4). The workers in the industries considered to be essential to the economy or society tended to telework less. Male workers telework less than female workers (not statistically significantly). These patterns are consistent with the U.S. data (Barrero, Bloom, Davis 2021a, Bick, Blandin, Mertens 2022). Also, as observed in the United States (Oettinger 2011, Bick, Blandin, Mertens 2022), low-income people worked more in work arrangements without commuting before the pandemic (particularly Peru, Vietnam), although high-income households increased telework days more strongly since the onset of the pandemic.

There was a sizable income discount associated with working remotely before the pandemic, but it disappeared temporarily at the onset of the pandemic, until it partially reemerged afterward (Figure 3, Panel A). The estimated income discount associated with working remotely, approximately measured using annual household-level income, was as large as 33 percent before the pandemic in the 10 developing economies in the sample. This compares to 25–27 percent in 1980 in the United States (Oettinger 2011, Table 3). But it became almost zero (or just 3 percent, without statistical significance) at the onset of the pandemic before it widened again to 17 percent later in 2021. The income discount from telework is larger and more persistent for less educated workers (Appendix Table B3, Panels B, C, D). Considering two-way causality, the estimated income discount reflects both workers’ preferences (i.e., lower reservation wages if they prefer remote work) and the relative profitability of remote work jobs.

Figure 3. Estimated income differentials by work arrangement (percent)

Sources. IMF COVID-19 Custom Tracker (2nd round) and authors' estimation.

Notes. See Appendix Table 2 (table footnotes) for how household-level annual income is constructed. The estimation sample excludes those respondents who are in the top income bin of their countries. "Telework: all workdays" indicates the situation where the worker does not commute at all during workdays (regardless of fulltime or parttime jobs). "Parttime" indicates that the worker worked less than 5 days per week (regardless of remote or on-site work). Estimates are obtained by a linear regression model in Appendix Table B2, converting coefficients into percent changes by applying the exponential function (using the Stata command nlcom). In the case of parttime work, first, the coefficient on the workday share is multiplied by one minus the fraction of days considered (e.g., $1/5 = 1 - 4/5$ if 4 days per week), and then, the coefficient on the fulltime dummy is subtracted from it, to obtain the difference in incomes between parttime and fulltime work. The observations of all 10 countries are pooled, with region fixed effects (which absorb country fixed effects). Standard errors are clustered at the region level and are shown in parentheses. The number of regions is 93 across all 10 countries. See Appendix B for estimation details. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

In contrast, an estimated income discount associated with parttime jobs was not as large in the case of more than three workdays per week (Figure 3, Panel B). The income discount for parttime work (regardless of remote or on-site work) is estimated, considering both a linear increase in income by the number of workdays and a potential gap between fulltime work (i.e., 5 days or more in a week) and parttime work. The estimated income discount for two workdays per week was largely negative in most cases with statistical significance, but it was not as severe for parttime work for more than three days per week. In the case of four days per week, it turns positive since the pandemic. This may be a compositional effect because the forced social distancing due to the pandemic may have reduced workdays of fulltime workers and mechanically increased income associated with those working less than 5 days, especially if the feasibility of remote work is limited.

Adjustments to work arrangements may have helped avoid severe incidents due to the pandemic situation, but conversely, adjustments may have been needed when severe incidents happened. Telework is associated with a lower chance of job loss at the onset of the pandemic, but not with other incidents such as suffering from any kind of illness (not only COVID-19 but also other diseases), lack of food, and rent payment delinquencies (Appendix Table B4). The statistically insignificant results may stem from reverse causality, i.e., adjustments may be triggered by these severe incidents. In general, low (or high) income levels were associated with a higher (or lower) chance of these severe incidents, indicating that the pandemic may have disproportionately hit lower income households. Working parttime tends to be rather positively associated with the occurrence of these incidents, implying either that income effects may have exceeded the benefit of reducing workdays or that the causality is the opposite.

At the country level, a higher telework share is associated with a larger increase in workdays in a week when pandemic-related disruptions started to ease during 2021 (Appendix Figure A6). Although the association is not strong, it indicates the resilience of telework arrangements, supporting both employment and hours worked for those employed, in a situation still affected by the pandemic. Jaumotte and others (2023, Figure 14) find a similar pattern for advanced economies, looking at the deviations from the trend in labor force participation.

3. Preferences or profitability: A model of telework choice

To better understand observed telework experiences, we develop a simple model to parsimoniously separate the roles of workers' preferences and jobs' profitability across work arrangements. Observed telework shares are partly due to a reduced income discount for remote work upon the pandemic, but also due to an increase in the willingness for workers to work remotely, considering risks of COVID-19 infection and unrealized benefits from flexible work arrangements (Barrero, Bloom, Davis 2021a, Figure 7). A simple model can disentangle these underlying factors in a parsimonious way. In addition, the diverse cross-country experiences in adjusting work arrangements during the pandemic indicate a possible mechanism that might have amplified a small difference in the circumstances. The mechanism that we explore is a strategic complementarity that arises from local agglomeration spillovers among on-site jobs as well as efficiency gains in logistics among teleworking jobs if agreed with counterparties. The model developed in this paper accommodates this type of externality.

The model is built on a search-matching friction between representative firms and heterogeneous workers regarding their preferences among different work arrangements. There are two types of production technologies, denoted by F and R , requiring an on-site worker or a remote worker, respectively. After job matching, one of the two work arrangements is selected under Nash bargaining, jointly with the wage level, reflecting profitability and the worker's preferences between the two job types. The profitability of the two technologies can be different, represented by parameters a_F and a_R , respectively. We later assume externality in production such that on-site (or remote) work would be more profitable if more jobs are arranged on site (or remotely). The population of workers is normalized to be of measure one, and the distribution of workers with different preferences has two parameters β_F and β_R , but β_F is normalized as $\beta_F = 1$ such that β_R represents the willingness of working remotely relative to working on site. See Appendix C for the full model description.

In this simple model, the telework share increases if the relative profitability of telework jobs increases or workers' preference to work remotely increases. The profitability of jobs is defined to be very inclusive, covering more output given input (i.e., productivity), lower job setup cost, and lower degree of job search frictions. Profitability also potentially depends on the level of externality, when assumed, such that jobs are more profitable if the share of the same job type is higher. The observed telework share among workers can be attributed to either relative profitability (a_R/a_F) of telework jobs compared to on-site jobs or workers' preferences to telework (β_R).

Simplifying parametric assumptions lead to a tractable calibration strategy based on the observed telework shares, total employment share, and estimated income differentials. The model implies that a parameter for workers' preference to work remotely β_R can be calibrated to an income-adjusted odds ratio of choosing remote work relative to choosing on-site work. In other words, an excess level of telework shares that are not proportional to the income differential between remote and on-site work is fully attributed to "preferences" in this

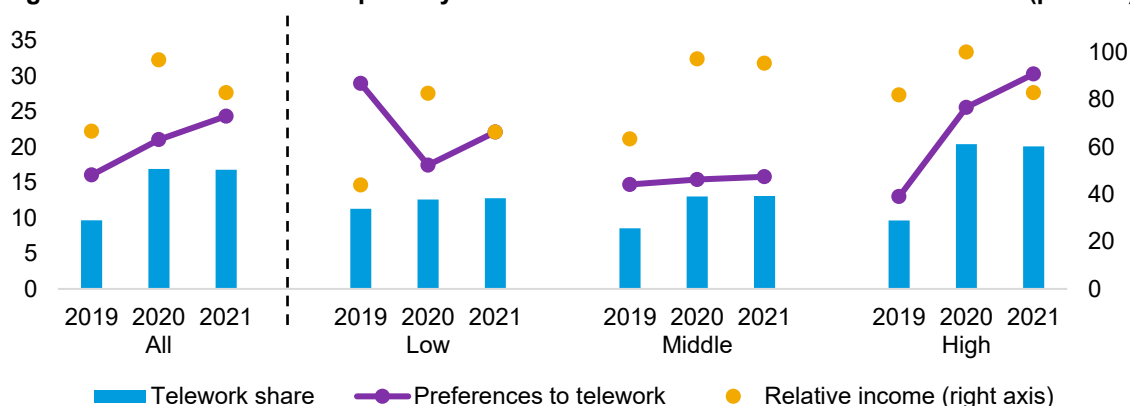
simple model. In this sense, β_R represents all the residual that is not captured by the model, such as regulatory requirements (particularly COVID-19 containment measures), skill mismatches, and the degree of access to telework technologies. Note that COVID-19 containment measures also affect relative profitability (a_R/a_F), and their effects may be shown as an increase in β_R or in a_R/a_F .

Looking through the lens of this model, observed telework experiences imply a shift in preferences toward teleworking (Figure 4). The increased telework share was more than the proportional level implied by the large reduction in estimated relative income for remote workers compared to on-site workers. The simple calibration of the model translates it as an upward shift in the willingness to work remotely at the onset of the pandemic.

However, there was an unintuitive downward shift in telework preferences among workers in the low education category, which rather suggests other driving factors than preferences. Workers in the low education category did not increase telework shares as much as implied by a substantial improvement in relative income from teleworking. This likely reflects other factors that are not captured by this model, such as limited access to telework technologies or skill mismatch. In contrast, higher education categories were associated with an increase in the willingness to work remotely, especially for the high education category.

Other evidence supports the conjecture that other driving factors are captured to be a “preference shift” as the residual, for the low education category. The online survey asked to those who changed their jobs after the onset of the pandemic whether their new jobs were exposed to less COVID-19 infection risks, compared to their previous jobs (Q7, Q24). The fraction of respondents who answered “less risks” is slightly higher for the low education category at 80 percent than in the other two categories at 72-74 percent. Also, those who answered “less risks” in the low education category took parttime jobs more frequently than telework jobs (Appendix Figure 7). These findings rather imply that, even though telework preferences for workers in the low education category may have increased, they had to take other options than teleworking due to other reasons than preferences, as described above.

Figure 4. Preference shifts implied by telework shares and estimated relative income (percent)

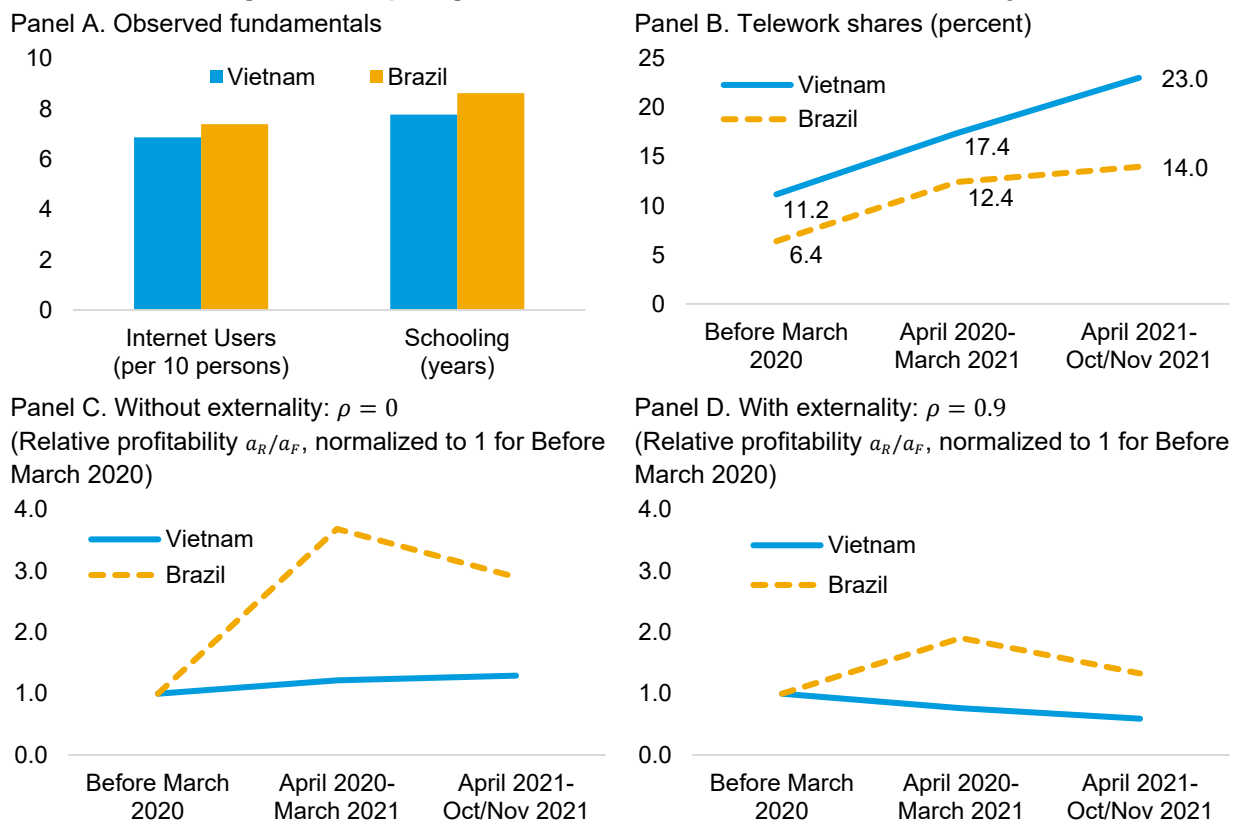


Sources. IMF COVID-19 Custom Tracker (2nd round) and authors' estimation.

Notes. Preferences to telework is parameter β_R in the model described in Appendix C, calibrated using observed telework shares and estimated relative income from remote work compared to on-site work (Appendix Table B3). Education attainment of main income earners (Q21, Q4) is categorized as “High” for university or above, “Low” for secondary or below, and “Middle” for those in between. The category “All” shows full sample results without education grouping. See Appendix B for details of the regression analysis. For ease of exposition, year label “2019” corresponds to before March 2020, “2020” corresponds to April 2020-March 2021, and “2021” corresponds to April 2021-October/November 2021.

Regarding the large cross-country differences in telework experience, economy-wide externality may have played a role to amplify relatively low variations in fundamental parameters. The 10 countries in the sample could be very different in terms of their fundamental economic structures, but some of them look similar based on observed characteristics related to telework. For example, the level of internet access and education attainments are similar in Brazil and Vietnam (Figure 5, Panel A). But the observed telework share is markedly higher in Vietnam than in Brazil (Figure 5, Panel B). The baseline calibration without assuming externality indicates a sizable difference in over-time changes in the implied relative profitability for remote work (Figure 5, Panel C). In the case of Brazil, the implied relative profitability increased by a factor of almost four at the onset of the pandemic, while it is only a 20 percent increase for Vietnam. If externality exists, however, the changes look closer between the two countries (Figure 5, Panel D). This result does not exclude other possible explanations, such as measurement error, social norms and cultures, and other fundamentals (e.g., transportation, population density, economic structure). But it indicates the potential role of externality, which may lead to very different outcomes stemming from relatively small differences in circumstances.

Figure 5. Comparing Brazil and Vietnam without or with externality



Sources. IMF COVID-19 Custom Tracker (2nd round), Barro and Lee (2013, updated in September 2021), and World Development Indicators (World Bank 2022a), and authors' calculations.

Notes. For Panels A and B, see Appendix Table A3 for the underlying data. For Panels C and D, to compare changes over time for each country, relative profitability a_R/a_F is normalized to the value calibrated for data before March 2020 for each country. See Appendix C for a full model description.

4. Conclusion

There is limited evidence on actual shifts to telework in developing economies during the pandemic. A new online survey conducted by an IMF team in collaboration with Nielsen narrows the information gap by providing evidence-backed insights. The survey highlights the diverse experiences across the 10 developing countries in the sample, regarding how people adopted teleworking at the onset of the pandemic and how they adjusted it over time. It also provides evidence on how income discounts across work arrangements change before and after the pandemic in developing economies, comparing remote and on-site jobs, as well as fulltime and parttime jobs, the latter of which was more prevalent at the onset of the pandemic in these countries.

A simple model developed in this paper helps analyze observed telework behaviors further. Calibrating this model is very simple, thanks to parsimonious assumptions that may fail in reality, but it is helpful by separating two factors behind telework choices—workers' preferences and relative profitability across work arrangements. The results indicate an increase in the preferences toward working remotely at least for highly educated workers very clearly, corroborating similar findings in advanced and emerging market economies (Aksoy and others 2022).

The results for workers in the low education category are mixed, likely reflecting some obstacles to working remotely that are not captured by the model. On the one hand, the model calibration indicates a decline in telework preferences, but on the other hand, another part of the survey indicates that the preference shift toward telework would have been even slightly higher for the low education category. The result may likely point to obstacles that these workers may face regarding teleworking, such as skill mismatch or limited access to telework technologies. For example, access to the internet was found to be essential to telework (e.g., Barrero, Bloom, Davis, 2021b; Taneja, Mizen, Bloom 2021). Mitigating these obstacles could be key to whether remote work will sustain in developing economies.¹¹

Economy-wide externality among the same work arrangements may also help understand diverse cross-country differences beyond the portion explained by observed fundamentals, such as internet access. If externality is key, there may be room for public policy intervention towards better outcomes based on social preferences regarding work arrangements. More research is needed to explore this possibility further.

The online survey dataset also contains useful information for future research on the distributional implications of the pandemic in developing economies. Beyond basic demographic statistics, the dataset includes survey responses to the questions related to whether they suffered from illness, lack of food, or difficulty in paying rent. It also includes variables on any public support as well as political sentiments. Analyzing these variables in this dataset has the potential to provide insights by filling information gaps in economic behaviors and responses in developing economies during the pandemic.

¹¹ Recent cross-country studies examine internet adoption during the pandemic, drivers of digital adoption, and costing of affordable universal broadband (Amaglobeli and others 2023; Kumer, Amaglobeli, Moszoro 2023; Oughton, Amaglobeli, Moszoro 2023). For India, there is an ongoing initiative to enhance digital infrastructure (see, e.g., Alonso and others 2023).

Appendix A. Online survey details

This Appendix explains how the online survey “IMF COVID-19 Custom Tracker” is conducted through a partnership between an IMF staff team and [ACNielsen Company of Canada](#) (Nielsen). The survey work is financially supported by the U.K.’s Foreign, Commonwealth and Development Office (FCDO), the Government of Korea, and the partners in the IMF’s COVID-19 Crisis Capacity Development Initiative (CCCDI)—Belgium, Canada, China, Germany, Japan, Korea, Spain, Singapore, and Switzerland.

To monitor economic conditions during the COVID-19 pandemic, a team in the IMF Research Department sought the services of Nielsen to conduct an online survey. Nielsen is a global market research company that produces survey data on consumer confidence and sentiment across the globe. Nielsen partners with global and local clients to execute projects in over 100 countries with diverse operational challenges for data collection, with more than 7,000 projects and over 8 million respondents. For this survey project, Nielsen also partnered with Dynata (<https://www.dynata.com/>), a global online market research firm that has expertise in survey fieldwork in various markets.

There were two rounds of online surveys, covering 10 developing countries. The first round was conducted in April and May 2021, asking retrospective questions to respondents to collect yearly and quarterly information during both pre-pandemic and pandemic periods, based on their recollections. For the second round conducted in October and November 2021, respondents in the first round were invited to the second round again because the questionnaire was refined, although the return rate was 13 percent (635 respondents). For each round, the number of respondents per country is about 500. The 10 countries are Argentina, Brazil, Ecuador, India, Indonesia, Pakistan, Peru, South Africa, Türkiye, and Vietnam. The target respondents were citizens or residents of the respective countries aged between 18 and 65 years old in Nielsen’s online network of surveyed people. The respondents received monetized compensation.

The dataset from the second round of the survey is used as a baseline. Although using both rounds could increase the number of observations for the period before end-March 2021 (excluding the overlaps for 635 respondents who participated in both 1st and 2nd rounds), it would be subject to compositional effects when the results are compared before and after April 2021. Therefore, the second round is taken as a baseline, and the dataset combining both rounds is examined for robustness. Appendix Tables A1, A2, and A3 show summary statistics for the second round of the survey.

The survey questionnaire prepared by the IMF team contains 37 multiple-choice questions.¹² The questions are about respondents’ demographics, employment status, household characteristics, health and economic impacts during the pandemic period, and political sentiment. The questionnaire also contains country-specific questions used for socio-economic classification by Nielsen. The survey design broadly follows existing studies that use online or phone surveys (Bick, Blandin, Mertens 2022; Bottan, Hoffmann, Vera-Cossio 2020; Coibion, Gorodnichenko, Weber 2020a 2020b; PERC 2021; World Bank 2021), as well as Nielsen’s New Normal Tracker. The survey response duration is about 15 minutes. The survey questionnaire is composed in English, but it is translated into regional languages when necessary to increase survey responses.

¹² There is a guideline for online survey research, produced by ESOMAR and the Global Research Business Network (<https://esomar.org/code-and-guidelines/guideline-for-researchers-and-clients-involved-in-primary-data-collection>).

A caveat of this type of online survey is selection bias, caused by the need for respondents to have internet access. Online modality requires respondents to use a smartphone or a computer, potentially generating selection bias towards the workers who may work remotely more often. Also, online surveys tend to reach those living in larger cities, younger people, and relatively higher-income groups.

To mitigate the selection bias, Nielsen implemented “soft” quotas, in addition to producing population weights. The survey system monitors demographic questions (e.g., age, region, gender, income levels) that were asked at the beginning of the questionnaire, and if necessary, the system will terminate the survey in the middle if the respondent falls in an overrepresented group. Although this is only loosely applied (as named as “soft” quotas), this procedure makes the sample population closer to the country’s population, at the expense of waiting longer to reach the target number of respondents (i.e., 500). The standard population weights were also produced. Nielsen uses the Rake Weights procedure of the SPSS (<https://community.ibm.com/HigherLogic/System/DownloadDocumentFile.ashx?DocumentFileKey=17fd2f0b-7555-6ccd-c00c-5388b082161b&forceDialog=0>). The use of “soft quota” leads to relatively similar results with or without applying the population weights, because the sample is already filtered by “soft quota” to be close to the population census of each country.

Appendix Table A1. Demographics summary—2nd round only
(Percent, shares in total, with population weights, unless otherwise specified)

Country	Sample count with no weights	Respondents				Main earner of the household ¹				Live in urban area ⁴
		Female ²	University graduates	Age 18-34	Service sector worker ³	Female ²	University graduates	Age 18-34	Service sector worker ³	
Argentina	512	50.4	46.8	37.8	80.1	36.2	42.7	26.6	79.5	69.0
Brazil	500	51.2	34.1	39.0	71.3	36.9	32.9	34.3	73.4	81.4
Ecuador	510	50.8	72.9	44.7	78.0	39.4	67.2	33.6	84.2	51.8
India	500	48.6	72.4	42.5	75.8	37.6	67.3	35.0	78.4	96.0
Indonesia	510	50.0	45.8	39.0	64.1	28.5	46.4	32.5	69.1	79.2
Pakistan	515	49.2	69.7	50.4	76.2	17.6	59.5	29.9	77.3	90.2
Peru	501	51.8	57.5	43.7	75.8	35.6	56.1	32.6	73.2	67.8
South Africa	500	50.6	36.3	49.8	61.3	42.7	38.6	39.1	66.8	73.6
Türkiye	500	49.6	46.7	38.7	49.8	32.7	34.5	24.4	54.1	76.4
Vietnam	510	50.2	79.9	40.0	66.5	45.2	77.6	34.7	66.3	58.5
Total	5,058	50.2	56.2	42.6	69.9	35.2	52.3	32.3	72.2	74.4

Source: IMF COVID-19 Custom Tracker (2nd round)

¹ The survey asked whether the respondent is the main income earner of the respondent’s household (Q18). If not, the survey further asked characteristics of the main income earner (Q19-Q29).

² The share calculation excludes those who responded “Prefer not to answer” in Q3 for the respondent or Q20 for the main earner.

³ The industry classification (Q12, Q29) follows the ISIC rev.4 (United Nations 2008). The share is relative to the total number of respondents (with population weights), including those who were unemployed or out of the labor force at the time of this survey.

⁴ The “urban” area is defined as a city in which more than 300,000 people live, in line with the definition by United Nations (2018).

Appendix Table A2. Income summary—2nd round only

Country	Median per-capita before-tax annual income (In the 2017 international dollars) ^{1,2}				World Bank's Poverty and Inequality Platform (PIP) data (Latest observed year) ⁴	Share of respondents with per capita before-tax annual income of less than 1,000 international dollars ^{1,2} (Weighted population share)			Share of respondents who report income levels numerically ¹ (Weighted population share)		
	2019	2020	2021 ³			2019	2020	2021 ³	2019	2020	2021 ³
Argentina	8,078	6,446	6,388	4,444 (2020) ^{5,6}	3.4	5.0	4.4	53.6	54.8	58.3	
Brazil	2,198	2,420	2,503	4,924 (2020)	38.2	34.6	32.3	62.6	62.0	63.4	
Ecuador	3,755	3,425	5,099	3,342 (2020)	10.4	12.3	6.7	56.0	54.2	58.7	
India	1,935	1,664	1,913	1,520 (2011) ^{6,7}	32.5	34.8	33.6	59.1	62.0	63.8	
Indonesia	2,910	2,706	3,526	2,319 (2021) ^{6,7}	20.2	22.2	17.5	57.3	58.6	58.3	
Pakistan	1,941	1,769	2,068	1,487 (2018) ⁷	18.9	21.7	19.0	58.3	59.1	61.1	
Peru	2,645	2,295	3,229	2,896 (2020)	18.0	18.9	11.8	44.0	43.4	44.5	
South Africa	4,742	4,282	7,018	1,736 (2014) ⁷	17.9	19.2	14.5	48.7	51.0	54.3	
Türkiye	7,613	7,265	7,088	5,907 (2019) ⁷	4.7	4.3	5.3	77.7	78.8	79.3	
Vietnam	3,610	3,264	3,503	3,987 (2018) ⁷	6.9	8.6	10.7	82.8	83.8	84.2	
Total	3,648	3,364	4,159	N/A	17.1	18.1	15.6	60.0	60.7	62.6	

Sources: IMF COVID-19 Custom Tracker (2nd round); International Financial Statistics (IFS, IMF 2022); 2017 International Comparison Program (ICP, World Bank 2020); and Poverty and Inequality Platform (PIP, World Bank 2022b).

¹ The survey first asked income ranges with preset bins (Q16a, Q17a, Q18a) and then asked income levels numerically (Q16b, Q17b, Q18b) with an option “Prefer not to answer” because of sensitivity considerations. Nominal annual household income before tax was asked in local currencies, including before-tax incomes of all earning members in the household living with the respondent. For those who reported income ranges only, the mid-point of the specified range is used, except for those with the top income bin, to whom the income level is set at the threshold value of the top bin plus the width of the second top income bin.

² The 2017 international dollar is equivalent to the U.S. dollar in United States in 2017 in terms of purchasing power, based on the ICP's purchasing-power-parity conversion factors for “9100000: Households and NPISHS final consumption expenditure”, as well as period-average CPI inflation of the listed 10 countries from the IFS database (IMF 2022). Per capita income is calculated by simply dividing income by the number of household members (Q13), following the PIP (see <https://worldbank.github.io/PIP-Methodology/welfareaggregate.html#equivalence-scale>).

³ Expected annual income for the year 2021 was asked in October and November 2021 (Q18a, Q18b).

⁴ The data from the PIP database are not exactly comparable with this survey's income data, as explained in other footnotes. Data are collected by the Stata command “pip” (forthcoming), a renewed version of “povcalnet” (Castañeda Aguilar and others, 2019).

⁵ For Argentina, the unit is in the 2011 international dollars, instead of 2017.

⁶ For Argentina, India, and Indonesia, the median for the urban area is used, instead of the national level median.

⁷ The PIP provides the median household consumption expenditure, instead of income, for Indonesia, India, Pakistan, Türkiye, Vietnam, and South Africa.

Appendix Table A3. Telework and pre-pandemic fundamentals—2nd round only
(Percent, with population weights, unless otherwise specified)

Country	Shares of telework days per week ¹					Internet users in 2019 ³ (Population share)	Average total schooling for people of age 15-64 in 2015 ⁴ (Number of years)	GDP per capita in 2019 ³ (In the 2017 international dollars)
	Level	Change		Level	Change			
	Before March 2020	April 2020-March 2021	After 2021 ²	April 2020-March 2021	After 2021 ²			
Argentina	9.8	27.4	19.6	17.6	-7.8	79.9	10.2	22,066
Brazil	6.4	12.4	14.0	6.0	1.5	73.9	8.6	14,736
Ecuador	5.1	16.9	16.7	11.7	-0.2	61.6	9.3	11,371
India	23.4	28.6	29.4	5.2	0.8	29.4	7.4	6,689
Indonesia	4.6	5.7	5.3	1.2	-0.5	47.7	8.6	11,812
Pakistan	6.4	9.7	10.1	3.2	0.4	17.1	6.0	5,318
Peru	10.8	23.2	22.8	12.4	-0.4	60.0	10.0	12,858
South Africa	12.3	19.8	17.2	7.5	-2.6	68.2	10.2	13,710
Türkiye	7.3	8.0	9.0	0.7	1.1	74.0	7.8	28,197
Vietnam	11.2	17.4	23.0	6.3	5.6	68.7	7.8	10,134
Total	9.7	16.9	16.8	7.2	-0.1	58.0	8.6	13,689
Memo: United States ⁵	4.8	49.3	42.7	44.5	-6.5	89.4	13.3	62,459

Sources. IMF COVID-19 Custom Tracker (2nd round), Barrero, Bloom, Davis (2021a), Barro and Lee (2013, updated in September 2021), and World Development Indicators (World Bank 2022a).

¹ The share of telework days per week is calculated as one minus the share of commute workdays (Q9a, Q9b, Q9c) in the total workdays (Q8a, Q8b, Q8c), using the mid-points of the response ranges (e.g., 1.5 if 1-2 days was selected). The table shows the results for the main income earner of the respondent's household (Q18). If the respondent self is not the main earner, the same questions asked for the main income earner (Q25a-Q26c) are used.

² The 2nd round survey was conducted in October and November of 2021, and therefore "After 2021" means until either of these months. When we compare with other datasets, we treat "After 2021" as either April 2021-November 2021 or simply the year 2021.

³ Data are taken from the World Development Indicators (World Bank 2022a) Data series codes are IT.NET.USER.ZS for internet users and NY.GDP.PCAP.PP.KD for GNI per capita in the constant 2017 international dollars. The "Total" line shows the simple cross-country averages.

⁴ Data are taken from the Barro-Lee database (Barro and Lee 2013), which was updated in September 2021.

⁵ The U.S. estimates are taken from the aggregate time series of the Survey of Working Arrangements and Attitudes (SWAA) by Barrero, Bloom, and Davis (2021a). The pre-pandemic value is the one based on the 2017-2018 American Time Use Survey. For the other periods, the simple period averages are shown for April 2020-March 2021 and April 2021-November 2021, respectively.

Appendix Figure A1. Background information on main income earners—2nd round only
(Percent, shares in total, with population weights)



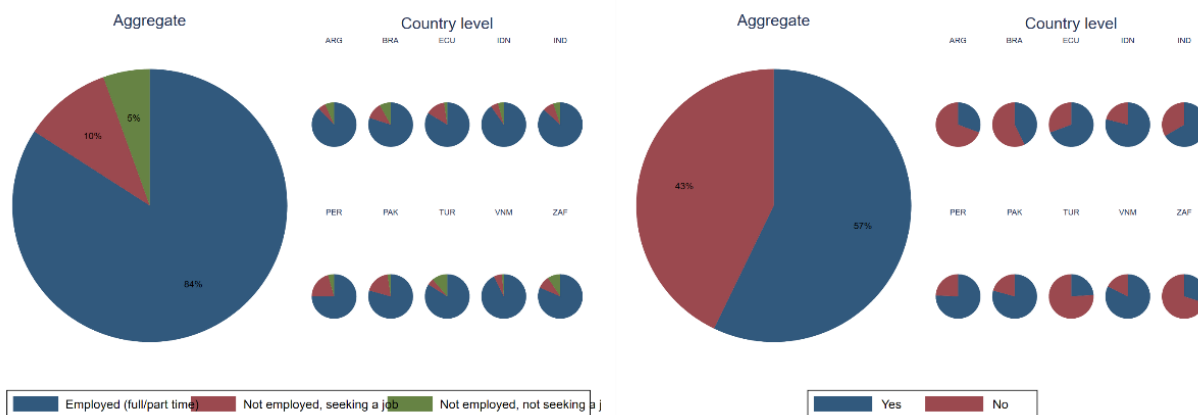
Sources. IMF COVID-19 Custom Tracker (2nd round).

Notes: The Figure shows the characteristics of the main income earner of the respondent's household (Q19, Q20, Q21, Q28, Q29) if the respondent was not the main income earner (Q18), and otherwise, the respondents' characteristics are shown (Q2, Q3, Q4, Q11, Q12). The occupation classification (Q11, Q28) follows 10 major groups of the ISCO-08 (International Labour Organization, ILO, 2012). The industry classification (Q12, Q29) follows the 21 sections of the ISIC, rev.4 (United Nations 2008), and Panel F shows its three-sector aggregation. The "urban" area is defined as a city in which more than 300,000 people live, in line with the definition by United Nations (2018).

Appendix Figure A2. Employment status of main income earners—2nd round only
(Percent, shares in total, with population weights)

Panel A: Employment Status

Panel B: Unemployed and not seeking a job: Is it due to COVID-19?



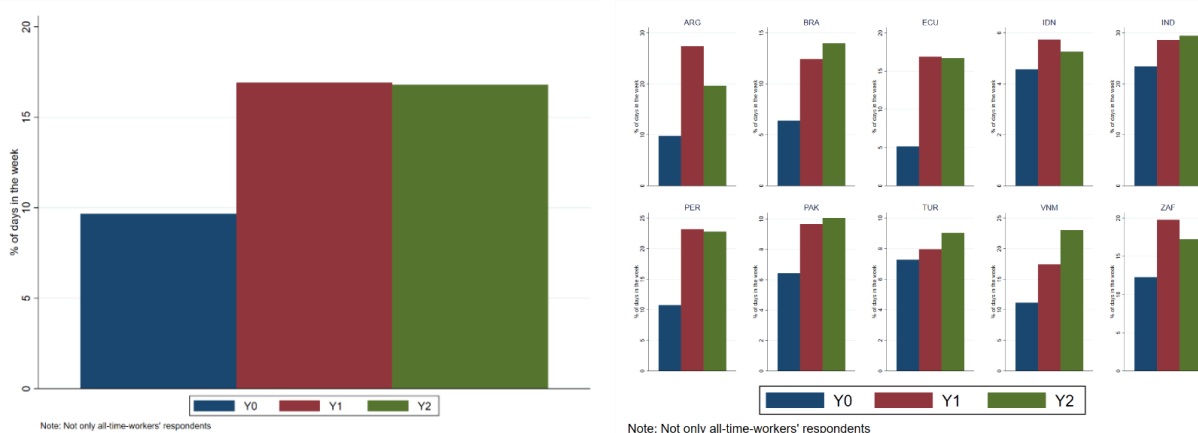
Sources. IMF COVID-19 Custom Tracker (2nd round).

Notes: The Figure shows the employment status and a related question for the main income earner of the respondent's household (Q22, Q23) if the respondent was not the main income earner (Q18), and otherwise, it shows the respondents' responses (Q5, Q6).

Appendix Figure A3. Telework situations in developing countries—2nd round only
(Percent, shares in total, with population weights)

Panel A: Aggregate

Panel B: Country level

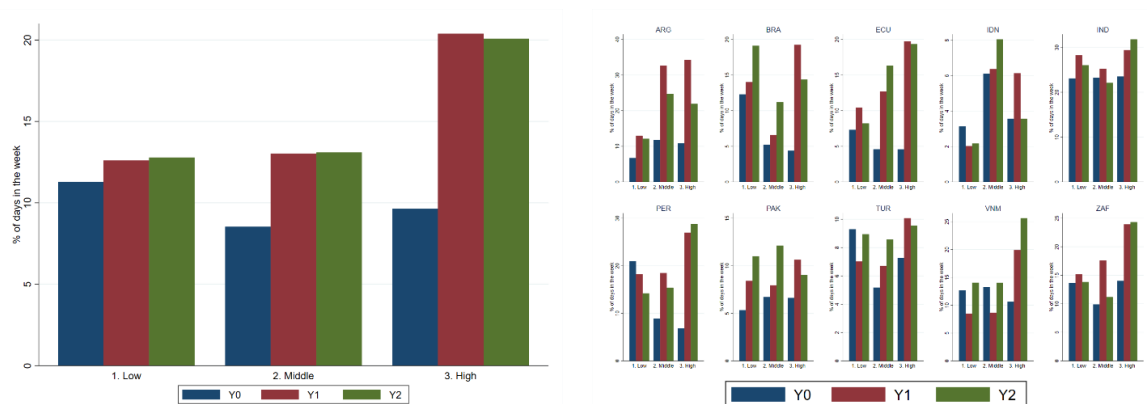


Sources. IMF COVID-19 Custom Tracker (2nd round).

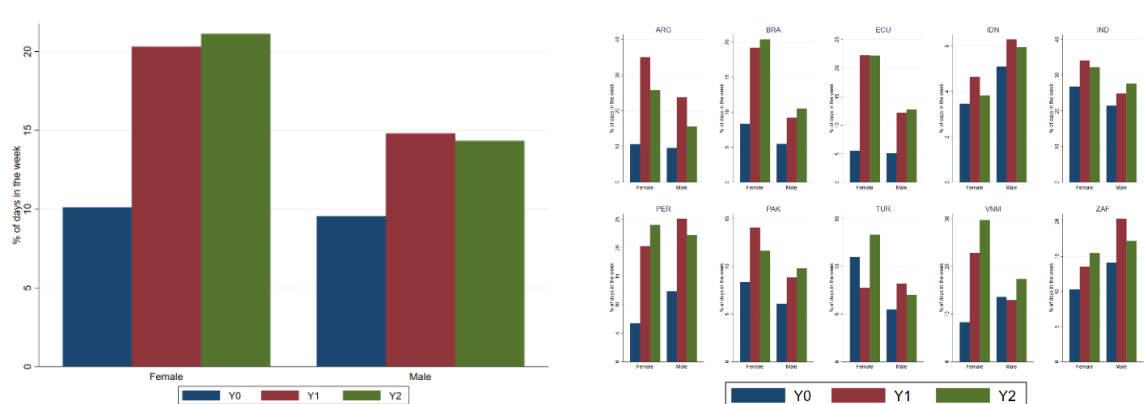
Notes: The Figure shows the telework situations for the main income earner of the respondent's household (Q25a-Q26c) if the respondent was not the main income earner (Q18), and otherwise, the respondents' situations are shown (Q8a-Q9c). Label "Y0" corresponds to before March 2020, "Y1" corresponds to April 2020-March 2021, and "Y2" corresponds to April 2021-October/November 2021.

Appendix Figure A4. Telework situations by worker/household characteristics—2nd round only
(Percent, shares in total, with population weights)

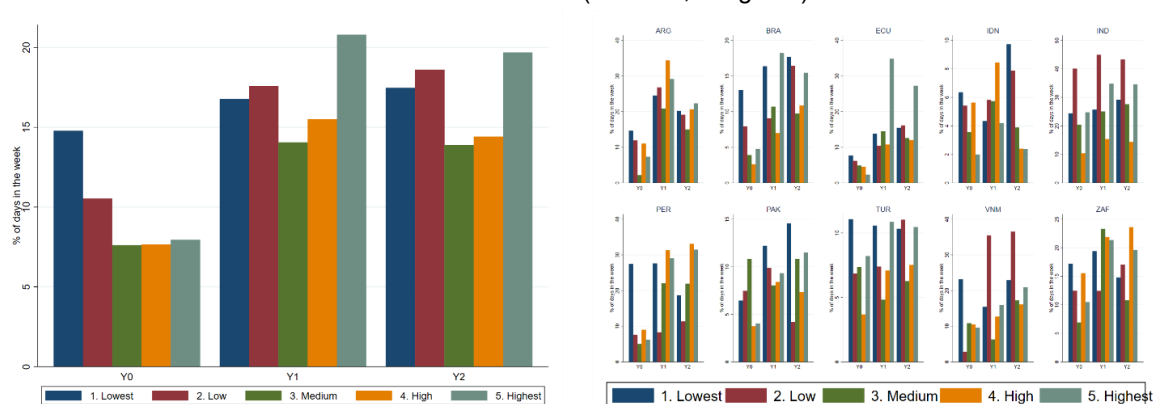
Panel A: Education



Panel B: Gender



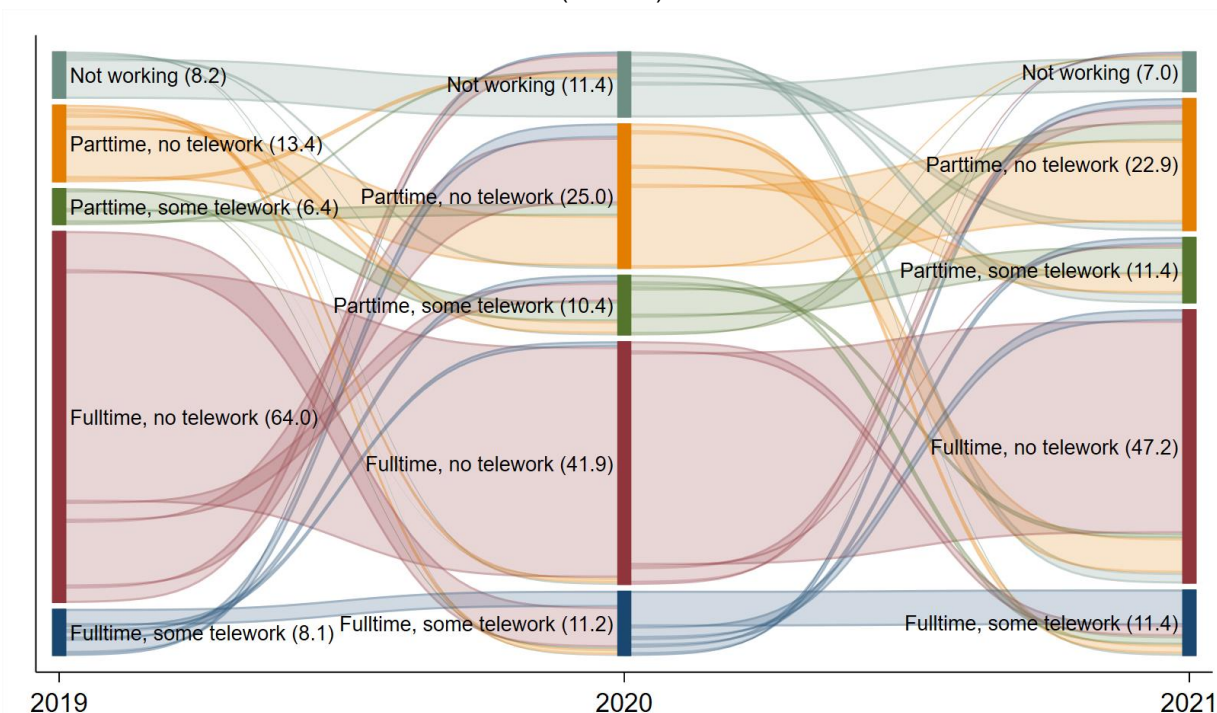
Panel C: Income bin (1 lowest, 5 highest)



Sources. IMF COVID-19 Custom Tracker (2nd round).

Notes: The Figure shows the telework situations for the main income earner of the respondent's household (Q25a-Q26c) if the respondent was not the main income earner (Q18), and otherwise, the respondents' situations are shown (Q8a-Q9c). Education and gender characteristics are also based on the ones for the main earner (Q21, Q20) or the respondent self (Q4, Q3), accordingly. Label "Y0" corresponds to before March 2020, "Y1" corresponds to April 2020-March 2021, and "Y2" corresponds to April 2021-October/November 2021. Income bins are based on approximated quintiles using before-tax annual household income for 2019, 2020, and 2021 (expected as of October/November 2021), including all before-tax earnings by household members (Q16a, Q16b, Q17a, Q17b, Q18a, Q18b).

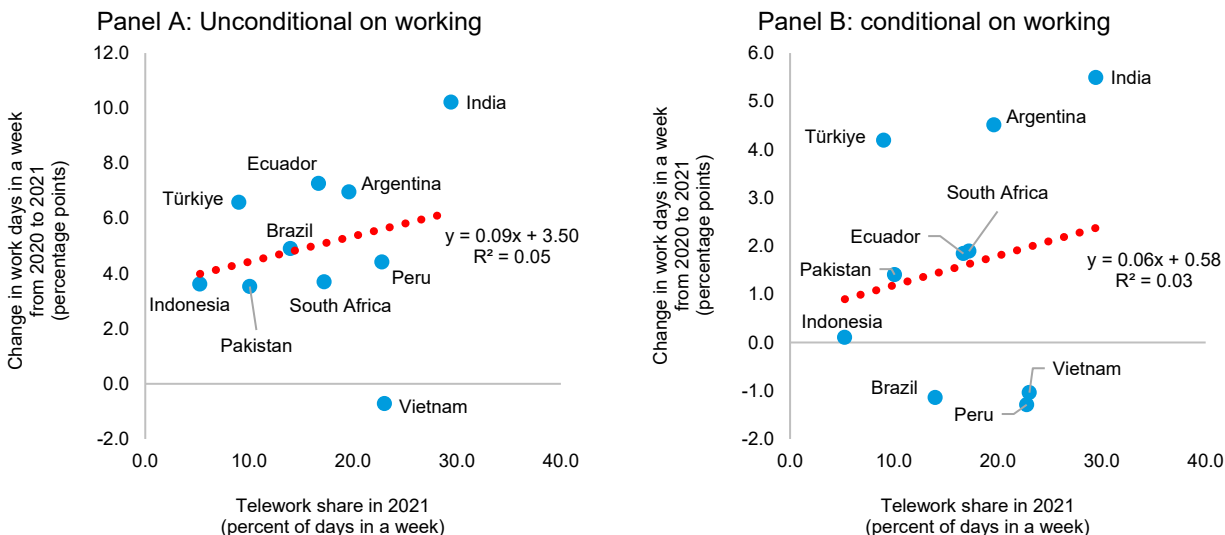
Appendix Figure A5. Not only telework but also parttime jobs increased during the pandemic
(Percent)



Source. IMF COVID-19 Custom Tracker (2nd round).

Notes: For ease of exposition, year label “2019” corresponds to before March 2020, “2020” corresponds to April 2020-March 2021, and “2021” corresponds to April 2021-October/November 2021. The numbers in parentheses indicate the shares to the total in percent (with population weights). This type of chart is often called “Sankey plot,” produced by the Stata command `sankey_plot` (Rios-Avila 2022).

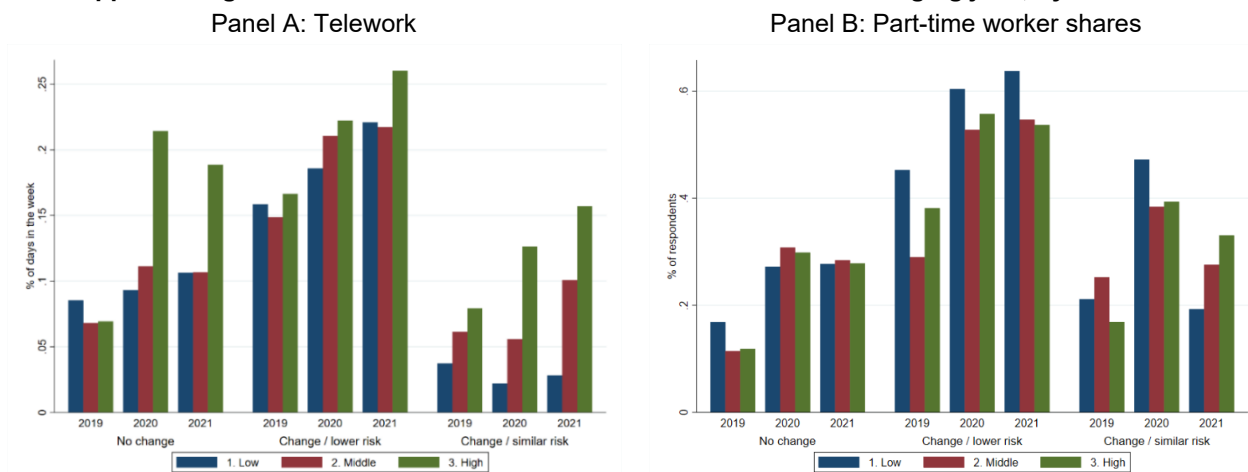
Appendix Figure A6. Telework share and recovery in workdays from the pandemic-related shocks



Sources. IMF COVID-19 Custom Tracker (2nd round).

Notes: The vertical axis shows changes in the country-level weighted average of workdays in a week from “2020” (April 2020-March 2021) to “2021” (April 2021-October/November 2021) for the main income earner of the respondent’s household (Q25b-Q25c) if the respondent was not the main income earner (Q18), and otherwise, for the respondents (Q8b-Q8c). The horizontal axis is the level of telework shares in “2021” (April 2021-October/November 2021), correspondingly compiled from Q26c and Q9c. Panel A is based on the full sample, including those that did not work during these periods, to capture both extensive and intensive margins. Panel B is based on the sample restricted to those who worked at least one day during these periods, to focus on the intensive margin only.

Appendix Figure A7. Reflection of COVID-19 infection risk when changing jobs, by education



Sources. IMF COVID-19 Custom Tracker (2nd round).

Notes: The charts show the work arrangements for the main income earner of the respondent’s household (Q25a-Q26c) if the respondent was not the main income earner (Q18), and otherwise, the respondents’ work arrangements are shown (Q8a-Q9c). Whether they changed their job, and if so, whether the new job is associated with a lower or similar risk of COVID-19 infection, as well as education attainments, are based on the ones for the main earner (Q24, Q21) or the respondent self (Q7, Q4), accordingly. For ease of exposition, year label “2019” corresponds to before March 2020, “2020” corresponds to April 2020-March 2021, and “2021” corresponds to April 2021-October/November 2021.

Appendix B. Characteristics associated with telework

This Appendix explores characteristics of workers associated with telework, income levels, and severe incidents related to the pandemic, using linear regressions with region-level fixed effects. Most variables are taken from the online survey, but some variables are taken from external sources. A dummy for “urban” regions is based on whether the habitants are over 300,000 or not (United Nations 2018). The indexes of “essential sector”, “physical proximity”, and “hard to work from home” are based on the dataset by Mongey, Pilossoph, and Weinberg (2021), through industry-occupation matches from NAICS to ISIC rev 4. and from OES and ISCO-08.

Results using the telework share in days of a week broadly confirm the findings in other studies (Appendix Table B1). Before the pandemic, there were no significant disparities among education, sector, and occupation types (essentiality for the economy, difficulty to work from home). After the pandemic, telework adoption differed across these characteristics in the expected directions as discussed in the literature (e.g., more for high education, female, older workers, occupations/industries not essential and easier to work from home). Those living with very young children below age 3 tended to telework more prior to the pandemic, but this tendency was reversed although without statistical significance. Those who live with school aged children (age 4-17) tended to telework less, and the tendency became statistically significant during the pandemic periods. Those who live with senior people (above age 66) tended to telework less before but telework more after the onset of the pandemic, likely reflecting greater health risks from COVID-19 for older people. In terms of household-level income, demographic characteristics are also broadly in line with priors (Appendix Table B2).

The estimates of income discounts are obtained as linear combinations of the corresponding regression coefficients. The ones without education categories are based on the regression estimates of equation (A) as follows (whose estimates are shown in Appendix Table B2):

$$y_{it} = \alpha_0 + \alpha_1 T_{it} + \alpha_2 W_{it} + \alpha_3 1_{\{W_{it}=1\}} + \alpha_4' X_{it} + \varepsilon_{Ait}, \quad (A)$$

where y_{it} is the natural log of annual household-level income for respondent i in period t ; $T_{it} \in [0,1]$ is the telework days in the share of workdays of the main earner of the household of respondent i ; $W_{it} \in [0,1]$ is the workdays as a share of five weekdays (i.e., $W_{it} = 1$ implies a fulltime worker); X_{it} is a vector of all other control variables that are included in the estimation of Appendix Table B2, including region dummies; ε_{Ait} is the residual, and all $\alpha_0, \dots, \alpha_4$ are corresponding coefficients (noting that α_4 is a vector conformable with X_{it}). The telework income discount is calculated as $\exp(\alpha_1)$, considering the case of full telework (i.e., $T_{it} = 1$). The parttime income discount for τ workdays per week is calculated as: $\exp(\tau\alpha_2 - \{\alpha_2 + \alpha_3\})$. All income discounts are presented in percent as a deviation from 100 (e.g., -33.3 percent if the estimates indicate $\exp(-0.405) \approx 0.667$). For standard errors, the Stata command nlcom is used. The estimated income discount associated with telework was large in the pre-pandemic period, but it disappeared at the onset of the pandemic and did not fully reverse to pre-pandemic levels yet in late 2021 (Appendix Table 3, Panel A).

Estimates by education attainments show that a sharper income discount was associated with remote work for workers with less education attainments (Appendix Table 3, Panels B, C, D). Education attainment of main income earners (Q21, Q4) is categorized as “High” for university or above, “Low” for secondary or below, and

“Middle” for those in between. Workers in the “low” education category faced an income discount by half if fully worked remotely. The income discount shrinks and loses statistical significance as the education level increases to “middle” and further to “high”. The pattern continues after the onset of the pandemic, while those in the “middle” education category saw a more persistent reduction in the income discount from telework, even compared with those in the “high” education category.

These estimates by education category are based on the regression estimates of equation (B) as follows:

$$y_{it} = \gamma_0 + \gamma_1 T_{it} + \sum_j \gamma_{2j} 1_{\{E_{it}=j\}} + \gamma_3 W_{it} + \gamma_4 1_{\{W_{it}=1\}} + \sum_j 1_{\{E_{it}=j\}} \{ \gamma_{5j} T_{it} + \gamma_{6j} W_{it} + \gamma_{7j} 1_{\{W_{it}=1\}} \} + \gamma_8' X_{it} + \varepsilon_{Bit}, \quad (B)$$

where $E_{it} \in \{\text{low, middle, high}\}$ is the education category of the main earner; ε_{Bit} is the residual, and all $\gamma_0, \dots, \gamma_8$ are corresponding (conformable) coefficients. The telework income discount for education category j is calculated as $\exp(\gamma_1 + \gamma_{5j})$, considering the case of full telework (i.e., $T_{it} = 1$). The parttime income discount for education category j for τ workdays per week is calculated as:

$$\exp(\tau\{\gamma_3 + \gamma_{6j}\} - \{\gamma_3 + \gamma_{6j} + \gamma_4 + \gamma_{7j}\}).$$

Appendix Table B4 presents the regression results regarding severe incidents related to the pandemic. Telework is negatively associated only with job loss during the first year of the pandemic. It did not have a significant association with the rest of the incidents. Respondents in the lowest Income bins more frequently suffered from these incidents. Respondents in the highest income bins were more able to cope with these incidents, except for falling ill (including other diseases than COVID-19 too), potentially reflecting a higher frequency of in-person interactions.

All results broadly remain under alternative estimation setups, examined for robustness check. Those alternative setups include the ones using country fixed effects (instead of region fixed effects that absorb country fixed effects), the ones with standard errors clustered at the city level (although in many cases, only one respondent is observed in a city, making this clustering close to simple “robust” standard errors), or the ones using a dummy variable for telework where 0 is fully commute and 1 is some type of work from home. The estimation sample excludes those respondents who are in the top income bin of their countries (10 percent of the sample) to reduce the influence of outliers because the top income bin does not have a ceiling. But the main results broadly remain the same, even if respondents in the income bin are included in the estimation sample, only with minor changes in the statistical significance of some coefficients to a marginal extent. Data from both 1st and 2nd rounds can be used for the regressions before end-March 2021, and the results are not markedly different, although data from 1st round tend to show less teleworking in general.

Appendix Table B1. Telework shares and workers' characteristics

VARIABLES	<i>Telework days in the week, main earner</i>		
	Before March 2020	April 2020 to March 2021	After April 2021
Education (main earner) = Low	-0.27 (1.53)	-2.27 (2.08)	-2.47 (2.07)
Education (main earner) = High	0.06 (1.13)	5.01*** (1.71)	0.83 (1.61)
Gender (main earner) = Male	0.63 (1.35)	-2.14 (1.69)	-2.19 (1.73)
Age (main earner) = Young (<29)	2.05* (1.07)	0.37 (1.59)	3.08 (1.89)
Age (main earner) = Older (>50)	1.03 (1.56)	6.07** (2.33)	7.04*** (2.24)
Urban (United Nations measure over 300k hab)	-0.71 (1.68)	1.78 (1.49)	-0.19 (1.62)
Initial Income Bin (1 lowest, 5 highest) = 1	5.70*** (1.56)	5.57*** (1.74)	4.58** (2.02)
Initial Income Bin (1 lowest, 5 highest) = 2	2.27 (1.99)	4.47* (2.55)	3.07 (2.34)
Initial Income Bin (1 lowest, 5 highest) = 4	0.28 (1.34)	0.41 (1.92)	-0.95 (1.97)
Initial Income Bin (1 lowest, 5 highest) = 5	-0.79 (1.39)	4.78** (2.17)	2.22 (2.16)
Sector (main earner) = Industry	-0.67 (2.30)	3.27 (2.51)	2.32 (3.36)
Sector (main earner) = Services	-0.28 (2.32)	2.10 (2.37)	2.74 (3.29)
More than one income earner	0.69 (1.34)	-2.64* (1.55)	-3.45** (1.57)
Full time worker (main earner)	-6.96 (4.98)	-7.50** (3.09)	-11.35*** (3.26)
Workdays in the week (From 0 to 1 main earner)	-14.75 (13.54)	2.26 (7.90)	-0.99 (7.41)
Need of care of support by respondent or household member	-0.90 (0.87)	-2.98* (1.55)	-2.94** (1.40)
Live with household member(s) below age 3	2.60** (1.24)	-0.42 (1.63)	-0.83 (1.88)
Live with household member(s) between age 4 to age 17	-1.31 (1.26)	-5.23*** (1.45)	-5.60*** (1.68)
Live with household member(s) above age 66	-9.09*** (2.73)	23.06** (11.14)	22.82** (11.27)
Essential sector	0.89 (1.63)	-5.19** (2.20)	-2.00 (2.11)
Physical proximity	1.84 (2.38)	0.93 (2.71)	-2.39 (3.05)
Hard to work from home	-0.44 (0.31)	-0.74** (0.31)	-0.92*** (0.34)
Received economic support after March 2020		1.70 (1.46)	-3.16** (1.52)
Number of Respondents (observations)	3,889	3,771	3,534
Average Dep. Var.	0.10	0.16	0.16
Within R squared (overall R-squared)	0.06 (0.16)	0.05 (0.16)	0.07 (0.19)

Sources. IMF COVID-19 Custom Tracker (2nd round), Mongey, Pilossoph, and Weinberg (2021), ILO (2012), United Nations (2008), and authors' estimation.

Notes. "Initial Income Bin" is an approximated household income quintile as of the year 2019, and the third quintile is taken as the base. The observations of all 10 countries are pooled, with region fixed effects (which absorb country fixed effects). Standard errors are clustered at the region level. The number of regions is 93 across all 10 countries. *** p<0.01, ** p<0.05, * p<0.1.

Appendix Table B2. Income levels and workers' characteristics

VARIABLES	Annual Household Income level (Natural logarithm)		
	Before March 2020	April 2020 to March 2021	After April 2021
Telework days in the week (From 0 to 1 main earner)	-0.41*** (0.12)	-0.03 (0.07)	-0.19** (0.09)
Education (main earner) = Low	-0.46*** (0.08)	-0.42*** (0.09)	-0.45*** (0.08)
Education (main earner) = High	0.27*** (0.08)	0.31*** (0.07)	0.24*** (0.08)
Gender (main earner) = Male	-0.02 (0.06)	0.00 (0.08)	-0.01 (0.06)
Age (main earner) = Young (<29)	-0.31*** (0.07)	-0.35*** (0.08)	-0.39*** (0.08)
Age (main earner) = Older (>50)	0.07 (0.08)	0.05 (0.09)	0.14** (0.07)
Urban (United Nations measure over 300k hab)	0.10 (0.07)	0.14** (0.06)	0.09 (0.08)
Sector (main earner) = Industry	0.46*** (0.17)	0.30* (0.16)	0.38** (0.19)
Sector (main earner) = Services	0.37** (0.17)	0.25 (0.16)	0.30 (0.18)
More than one income earner	0.46*** (0.07)	0.46*** (0.07)	0.44*** (0.08)
Full time workers (main earner)	-0.14 (0.13)	-0.40*** (0.11)	-0.24** (0.11)
Workdays in the week (From 0 to 1 main earner)	0.89*** (0.25)	1.25*** (0.30)	0.95*** (0.22)
Need of care of support by respondent or household member	-0.08 (0.06)	-0.12* (0.07)	-0.03 (0.05)
Essential sector	0.22*** (0.08)	0.31*** (0.09)	0.21** (0.09)
Physical proximity	-0.16** (0.08)	-0.12 (0.08)	-0.10 (0.08)
Hard to work from home	-0.06*** (0.01)	-0.05*** (0.01)	-0.04*** (0.01)
Received economic support after March 2020		-0.19*** (0.07)	0.00 (0.07)
Number of Respondents (observations)	3,888	3,771	3,533
Average Dep. Var.	12.74	12.75	12.91
R-squared	0.915	0.903	0.910
Within R squared	0.176	0.158	0.145

Sources. IMF COVID-19 Custom Tracker (2nd round), Mongey, Pilossoph, and Weinberg (2021), ILO (2012), United Nations (2008), and authors' estimation.

Notes. See Appendix Table 2 (table footnotes) for how household-level annual income is constructed. The estimation sample excludes those respondents who are in the top income bin of their countries. The observations of all 10 countries are pooled, with region fixed effects (which absorb country fixed effects). Standard errors are clustered at the region level. The number of regions is 93 across all 10 countries. *** p<0.01, ** p<0.05, * p<0.1.

Appendix Table B3. Estimated income differentials by work arrangement and education

	Before March 2020	April 2020 to March 2021	After April 2021
Panel A. Full sample			
Telework: all workdays	-33.33*** (8.30)	-3.22 (6.35)	-17.04** (7.12)
Parttime: 4 days per week	-4.16 (9.44)	16.19** (7.38)	4.74 (8.14)
Parttime: 3 days per week	-19.76*** (6.47)	-9.42* (4.97)	-13.40** (5.20)
Parttime: 2 days per week	-32.83*** (6.14)	-29.39*** (6.80)	-28.39*** (5.10)
Panel B. Education: low			
Telework: all workdays	-56.06*** (11.31)	-17.30 (13.91)	-33.69* (14.98)
Parttime: 4 days per week	15.34 (23.81)	1.75 (13.35)	-2.58 (14.33)
Parttime: 3 days per week	-12.68 (10.24)	-10.09 (11.69)	-25.65 (7.30)
Parttime: 2 days per week	-33.90** (14.53)	-20.56 (18.85)	-43.26*** (8.96)
Panel C. Education: middle			
Telework: all workdays	-36.58* (16.74)	-2.78 (13.61)	-4.62 (13.76)
Parttime: 4 days per week	-20.30* (11.31)	37.37** (18.06)	9.03 (13.35)
Parttime: 3 days per week	-28.19** (9.17)	-5.62 (11.72)	-6.88 (9.77)
Parttime: 2 days per week	-35.30*** (13.06)	-35.15** (17.87)	-20.47 (13.57)
Panel D. Education: high			
Telework: all workdays	-18.02* (10.66)	0.12 (10.24)	-17.04* (9.23)
Parttime: 4 days per week	-4.20 (14.49)	12.38 (9.57)	5.44 (10.63)
Parttime: 3 days per week	-19.66** (8.54)	-11.38** (5.23)	-11.82* (6.70)
Parttime: 2 days per week	-32.63*** (5.98)	-30.12*** (6.24)	-26.25*** (5.69)

Sources. IMF COVID-19 Custom Tracker (2nd round), Mongey, Pilossoph, and Weinberg (2021), ILO (2012), United Nations (2008), and authors' estimation.

Notes. See Appendix Table 2 (table footnotes) for how household-level annual income is constructed. The estimation sample excludes those respondents who are in the top income bin of their countries. "Telework: all workdays" indicates the situation where the worker does not commute at all during workdays (regardless of fulltime or parttime jobs). "Parttime" indicates that the worker worked less than 5 days per week (regardless of remote or on-site work). Estimates are obtained by a linear regression model in Appendix Table B2 in the case of "Full sample" (equation A in Appendix B). Coefficients are converted into percent changes by applying the exponential function (using the Stata command nlcom). For estimates by education attainment, the model is extended to include the interaction terms between education categories and the telework share as well as a fulltime worker dummy and the workday share (equation B in Appendix B). In the case of telework, the coefficient on the telework share and its interaction with the education category is used. In the case of parttime work, first, the coefficient on the workday share is multiplied by one minus the fraction of days considered (e.g., $1/5 = 1 - 4/5$ if 4 days per week), and then, the coefficient on the fulltime dummy is subtracted from it, to obtain the difference in incomes between parttime and fulltime work. Education attainment (Q4, Q21) is categorized as "high" for "University" or above, "low" for "secondary" or below, and "middle" for those in between. The observations of all 10 countries are pooled, with region fixed effects (which absorb country fixed effects). Standard errors are clustered at the region level. The number of regions is 93 across all 10 countries. See Appendix B for estimation details. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Appendix Table B4. Severe incidents related to the pandemic and respondent's characteristics

	<i>Lost job</i>		<i>Felt ill</i>		<i>Lack of food</i>		<i>Rent payment delinquencies</i>	
	April 2020 to March 2021	After April 2021	April 2020 to March 2021	After April 2021	April 2020 to March 2021	After April 2021	April 2020 to March 2021	After April 2021
Initial Income Bin = 1	11.10*** (3.57)	0.48 (2.42)	-0.46 (3.37)	-2.61 (3.45)	9.73*** (3.63)	3.19 (2.23)	7.52** (3.37)	-3.43 (3.04)
Initial Income Bin = 2	-1.72 (2.11)	4.14** (2.00)	2.21 (2.69)	3.04 (4.29)	2.70 (2.22)	-0.17 (1.90)	3.40 (2.54)	-3.85 (2.39)
Initial Income Bin = 4	-3.06 (2.67)	2.45 (2.08)	3.78 (4.21)	4.08 (3.06)	-1.85 (2.69)	1.21 (1.60)	-2.94 (2.63)	-2.05 (2.20)
Initial Income Bin = 5	-6.15** (2.58)	3.22 (2.49)	-1.42 (2.94)	6.45** (3.04)	-6.74*** (2.52)	1.63 (2.75)	-3.17 (3.09)	-5.66** (2.37)
Estimated total effects								
Telework:	-4.73*	-2.20	0.05	3.29	0.04	0.89	0.72	-0.25
all workdays	(2.80)	(2.34)	(3.30)	(3.60)	(2.56)	(2.06)	(2.93)	(3.24)
Parttime:	0.05	-0.46	-0.84	-0.83	-0.07	3.81	4.69*	3.55
4 days per week	(2.30)	(2.50)	(2.62)	(3.14)	(2.22)	(2.57)	(2.58)	(3.12)
Parttime:	0.84	2.57	1.20	1.05	1.14	6.17***	2.71	6.42**
3 days per week	(1.76)	(1.64)	(2.19)	(2.22)	(1.78)	(1.70)	(2.09)	(2.75)
Parttime:	1.63	5.59***	3.24	2.93	2.35	8.53***	0.72	9.29***
2 days per week	(2.21)	(2.02)	(2.60)	(2.52)	(2.07)	(2.27)	(2.42)	(3.28)
No. Obs.	3771	3534	3558	3323	3771	3534	3771	3534
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Average Dep. Var.	0.22	0.15	0.28	0.26	0.24	0.14	0.27	0.22
R-squared	0.16	0.12	0.16	0.09	0.30	0.17	0.23	0.14
Within R squared	0.09	0.05	0.06	0.03	0.17	0.08	0.14	0.06

Sources. IMF COVID-19 Custom Tracker (2nd round), Mongey, Pilossoph, and Weinberg (2021), ILO (2012), United Nations (2008), and authors' estimation.

Notes. The dependent variables are dummies for any incident during the respective periods. The same independent variables as in Appendix Table B1 are used, except for the inclusion of the telework share. "Initial Income Bin" is an approximated household income quintile as of the year 2019, and the third quintile is taken as the base. The observations of all 10 countries are pooled, with region fixed effects (which absorb country fixed effects). Standard errors are clustered at the region levels. The number of regions is 93 across all 10 countries. *** p<0.01, ** p<0.05, * p<0.1.

Appendix C. Model details

This Appendix presents a detailed explanation of the model. Section C.1 provides a full description of the model structure. Section C.2 explains how the model is calibrated. Section C.3 shows how these results are derived.

C.1 Model

Environment

Time is discrete, and the time horizon is infinite (although the decision making is static). The notation of time is suppressed unless it is necessary. The economy is closed, and the public sector is abstracted. There is a continuum of heterogeneous households, of measure one in total. There is a representative firm that operates a continuum of jobs to produce consumption goods.

Production technology

There are two types of production technology, denoted by subscript $k \in \{F, R\}$. Each technology produces the same consumption goods. The first technology F requires an on-site worker (F for “field”) and the second one R requires a remote worker. There is externality in production efficiency, depending on the economy-wide shares of on-site or telework arrangements (generating strategic complementarities).

Specifically, each unit of production type k produces y_k amount of consumption goods as follows:

$$y_k \stackrel{\text{def}}{=} a_k h_k, \quad h_k \stackrel{\text{def}}{=} \left(\frac{L_k}{L_F + L_R} \right)^\rho, \quad k \in \{F, R\}, \quad \rho \in [0,1]$$

where $L_k \geq 0$ denotes the economy-wide total number of jobs using technology $k \in \{F, R\}$, satisfying $\sum_k L_k \leq 1$; a_F and a_R are parameters for production efficiency; and $h_k \in [0,1]$ denotes a proportional cost of economy-wide coordination among production units with different work modalities, as a fraction of a ‘potential’ production level (i.e., a_k), with ρ being the elasticity of this cost to the labor allocation.¹³ Larger ρ implies that economy-wide coordination is more costly between on-site and remote working production units. There is no externality if $\rho = 0$. The range of $\rho \in [0,1]$ is to ensure higher a_k to lead to a higher share of L_k , as shown later, and to exclude $\rho = 1$ where either a continuum of equilibria or no equilibrium exists.

Aggregate output Y is the unit output multiplied by the number of units so that we have:

$$\begin{aligned} Y &\stackrel{\text{def}}{=} y_F L_F + y_R L_R = a_F h_F L_F + a_R h_R L_R \\ &= (a_F L_F + a_R L_R) - \left[a_F L_F \left(1 - \left(\frac{L_F}{L_F + L_R} \right)^\rho \right) + a_R L_R \left(1 - \left(\frac{L_R}{L_F + L_R} \right)^\rho \right) \right], \end{aligned}$$

showing that Y is in general smaller than the potential output level without coordination costs (i.e., when $\rho = 0$), denoted by $Y_0 \stackrel{\text{def}}{=} a_F L_F + a_R L_R$, because $\left(\frac{L_k}{L_F + L_R} \right)^\rho$ ranges between 0 and 1 for $k \in \{F, R\}$.

¹³ It is easy to extend the model to have different degrees of externality by technology (i.e., ρ_k for $k \in \{F, R\}$). We use one value of ρ for the ease of exposition and to reduce the degree of freedom of the model. If ρ_k is set differently for $k = F$ and $k = R$, what tends to matter is the value of ρ_R because $\frac{L_F}{L_F + L_R}$ is closer to one in most cases, and thus, $\left(\frac{L_F}{L_F + L_R} \right)^{\rho_F}$ is less sensitive to the value of ρ_F .

Preferences

Households work to earn income to consume, and their preferences are very parsimoniously assumed to be a multiple of linear utility from consumption c and idiosyncratic utility x_k from working, depending on job type k . Households receive different levels of utility from working, whose joint distribution is denoted by $G(x_F, x_R)$ with its joint density $g(x_F, x_R)$. Each x_k independently follows a Fréchet distribution with parameter θ as follows:¹⁴

$$G(x_F, x_R) \stackrel{\text{def}}{=} e^{-\beta_F x_F^{-\theta}} e^{-\beta_R x_R^{-\theta}}.$$

All jobs last only for one period so that households need to apply for a job in each period. In addition, saving is abstracted so that the utility maximization has no dynamic trade-off and can be done period by period as follows (i.e., the decision making is static):

$$\max \{W(x_F, x_R), u\},$$

where $W(x_F, x_R)$ is the value of applying for a job and u is the value of being unemployed. For ease of computation, we make a simplifying assumption that $u = 0$ holds so that every household applies for a job.

Labor market with frictions

There is a job-search friction where the number of matches $\mu(n, N)$ depends on the number of job vacancies n and applicants N , which is assumed to be of the Cobb-Douglas form with elasticity b :

$$\mu(n, N) \stackrel{\text{def}}{=} (q_0 n)^b N^{1-b},$$

where q_0 is a parameter to control the number of matches to be less than n and N in the analysis. The probability for job searchers to be hired is denoted by q as below, and the probability for posted jobs to be filled is $q \frac{N}{n}$, as follows:

$$q \stackrel{\text{def}}{=} \frac{\mu(n, N)}{N} = \left(\frac{q_0 n}{N}\right)^b, \quad \frac{\mu(n, N)}{n} = \frac{\mu(n, N)}{N} \frac{N}{n} = q \frac{N}{n}.$$

After matching, work modality $k \in \{F, R\}$ and its associated real wage w_k are jointly negotiated through the asymmetric Nash bargaining with b being the firm's bargaining power (and the worker's bargaining power is $1 - b$), following the so-called Hosios condition (Hosios 1990; see also Wright and others 2021, p.96). There is no gain from having a job in a previous period because all jobs last for only one period by assumption.

The asymmetric Nash bargaining leads to a solution that maximizes the generalized Nash product as follows:

$$\max_{\substack{k \in \{F, R\}, \\ w_k \in [0, y_k]}} [y_k - w_k]^b [x_k w_k - u]^{1-b}.$$

¹⁴ An alternative is a logit specification where each x_k independently follows a Gumbel distribution $\exp(-\exp(-x_k))$ so that $\Delta x_{kj} \stackrel{\text{def}}{=} x_k - x_j$ follows a logistic distribution $1/(1 + \exp(-\Delta x_{kj}))$, assuming the utility to be linear in consumption c and preference shock x_k . This logit specification allows for $u > 0$, although the value of u has no direct implication to the choice over work modality $k \in \{F, R\}$ because u is a common disagreement point in the Nash bargaining. Calibrating the model in this logit setup requires to solve a simple but nonlinear equation, whereas it does not in our preferred Fréchet specification with $u = 0$.

The set of feasible outcomes in this Nash bargaining may not be always convex, although it is convex conditional on job type k is always convex given the values of y_k and x_k . Correspondingly, the Nash product is not concave in its arguments (i.e., $k \in \{F, R\}$ and $\{w_k\} \in [0, y_k]$), but once job type k is fixed, the conditional Nash product is concave in real wage w_k . Nonconvexity of the feasible set (or a nonconcave Nash product) can lead to multiple Nash solutions, but in our application, it happens only with probability zero, as shown later. See Xu and Yoshihara (2020) for a survey on nonconvex Nash bargaining problems.

The Nash product conditional on job type k (which is concave) is uniquely maximized at the wage level that shares a match surplus in proportional to bargaining powers, as follows:

$$w_k = (1 - b)y_k + \frac{bu}{x_k}.$$

Assuming $u = 0$, real wage w_k is independent of idiosyncratic utility x_k from working in a job of type k .

Based on this negotiated wage level, one job type is chosen to maximize the Nash product. It turns out that type k^* will be chosen if k^* solely maximizes $y_k^{\frac{1}{1-b}}x_k$ (see section C.3). In the case of a tie, one of the two types is assumed to be randomly chosen with probability $\frac{1}{2}$. But this random choice has no implication to the results because a tie happens with probability zero.

A matched job will be of type k with probability p_k as follows:

$$p_k \stackrel{\text{def}}{=} \text{P}[\text{Type } k \text{ job is chosen in Nash bargaining}] = \frac{\beta_k y_k^{\frac{\theta}{1-b}}}{\sum_{j \in \{F, R\}} \left\{ \beta_j y_j^{\frac{\theta}{1-b}} \right\}},$$

which holds under the assumed simple environment, such as $u = 0$ and x_k following a Fréchet distribution.

Posting a job requires an ex-ante cost η in unit of final consumption goods, whereas a job application is costless. Free entry for job vacancies is assumed, and ex-ante expected profit by posting a job vacancy is zero as follows:

$$q \frac{N}{n} \sum_{k \in \{F, R\}} p_k \{y_k - w_k\} = \eta.$$

Equilibrium

Definition. An equilibrium is a sequence of wages $(w_F, w_R) > 0$ and associated allocations that satisfy (1) household optimization; (2) free entry for job vacancies; (3) job-match rate consistency; (4) Nash bargaining over wage levels and work modalities; and (5) market clearing, as follows:

- (1) Household optimization. All households apply for a job given $u = 0$, leading to $N = 1$, where their consumption levels are either $c = w_k$ if employed at a job of type k or $c = u = 0$ if unemployed, with the value for applying a job satisfying the following, almost surely:

$$W(x_F, x_R) = qw_{k^*}x_{k^*} > 0 = u,$$

where k^* denotes the type of job that will be chosen in the Nash bargaining when matched.

(2) Free entry for job vacancies:

$$q \frac{N}{n} \sum_{k \in \{F, R\}} p_k \{y_k - w_k\} = \eta,$$

with normalization of $\eta = b$ (as explained later).

(3) Job-match rate consistency: $q = \left(\frac{q_0 n}{N}\right)^b \leq 1$.

(4) Nash bargaining over wage levels and work modalities: for each $k \in \{F, R\}$, assuming $u = 0$,

$$w_k = (1 - b)y_k, \quad p_k = \frac{\beta_k y_k^{\frac{\theta}{1-b}}}{\sum_{j \in \{F, R\}} \beta_j y_j^{\frac{\theta}{1-b}}}, \quad k^* = \begin{cases} F & \text{if } y_R^{\frac{1}{1-b}} x_R < y_F^{\frac{1}{1-b}} x_F \\ F \text{ or } R \text{ with prob. } 0.5 & \text{if } y_R^{\frac{1}{1-b}} x_R = y_F^{\frac{1}{1-b}} x_F \\ R & \text{if } y_R^{\frac{1}{1-b}} x_R > y_F^{\frac{1}{1-b}} x_F \end{cases}$$

where x_k independently follows a Fréchet distribution $e^{-\beta_k x_k^{-\theta}}$ with normalization of $\theta = 1 - b$ (as explained later), and k^* denotes the type of job that will be chosen.

(5) Market clearing:

$$L_k = qNp_k \text{ for each } k \in \{F, R\}, \quad \sum_{k \in \{F, R\}} w_k L_k + (1 - q)Nu + \eta \sum_{k \in \{F, R\}} L_k = Y,$$

$$Y \stackrel{\text{def}}{=} \sum_{k \in \{F, R\}} y_k L_k = a_F h_F L_F + a_R h_R L_R,$$

with $y_k \stackrel{\text{def}}{=} a_k h_k$ for $k \in \{F, R\}$ and proportional coordination cost functions $\{h_k\}$ as follows:

$$h_k \stackrel{\text{def}}{=} \left(\frac{L_k}{L_F + L_R} \right)^\rho, \quad \rho \in [0, 1).$$

Parameter normalization

Some parameters lead to observatory equivalent equilibria, and therefore, we made some assumptions on those parameters, for ease of exposition, at the expense of losing identification of some underlying structural factors.

- The scale of (a_F, a_R) , η , and q_0 all relate to the level of overall employment qN . Therefore, we set η at a value that simplify the free entry condition (i.e., $\eta = b$), as well as setting $q_0 = 1$, and let the scale of (a_F, a_R) absorb any underlying changes in these structural parameters. Consequently, by these assumptions, the interpretation of an increase in the scale of (a_F, a_R) will include not only an increase in productivity but also a decrease in entry cost η or in the degree of search friction q_0 .
- Any change in the elasticity parameter θ of the Fréchet distributions for preference shocks $\{x_k\}$ can be fully offset by the corresponding changes in the scale of (a_F, a_R) and q_0 . For example, even when θ shrinks by 1 percent (i.e., new θ becomes 0.99 times the old value), the equilibrium can still be kept unchanged, by changing a_F to $a_F^{1/0.99}$ while keeping the ratio of (a_F, a_R) the same, together with dividing q_0 by the proportional increase in a_F . This can be done because of a degree of freedom in the unit of idiosyncratic preference shocks, relative to consumption goods. Therefore, we set $\theta = 1 - b$ to simplify the determining equations of the work-modality choice probabilities $\{p_k\}$ as follows:

$$p_k = \frac{\beta_k y_k}{\beta_F y_F + \beta_R y_R}.$$

- Any pair of parameters (β_F, β_R) of the Fréchet distributions for preference shocks $\{x_k\}$ leads to the same equilibrium if the ratio of the two are the same, because what matters is a relative preference between work modalities. Therefore, we normalize $\beta_F = 1$.

With these assumptions on parameters, the equilibrium conditions reduce to the following equations:

$$p_k = \frac{\beta_k a_k h_k}{\beta_F a_F h_F + \beta_R a_R h_R} = \frac{\beta_k a_k p_k^\rho}{\beta_F a_F p_F^\rho + \beta_R a_R p_R^\rho}, \quad q = (a_F h_F p_F + a_R h_R p_R)^{\frac{b}{1-b}} = (a_F p_F^{1+\rho} + a_R p_R^{1+\rho})^{\frac{b}{1-b}}.$$

Solving these equations leads to a unique equilibrium if normalized parameters satisfy an inequality for q to be a proper probability (i.e., the solved q satisfies $q \in [0,1]$). The unique equilibrium can be derived by:

$$p_F = \frac{1}{\left\{ \frac{\beta_F a_F}{\beta_R a_R} \right\}^{\frac{1}{\rho-1}} + 1}, \quad p_R = 1 - p_F, \quad q = (a_F p_F^{1+\rho} + a_R p_R^{1+\rho})^{\frac{b}{1-b}}, \quad n = Y = q \sum_k a_k p_k^{1+\rho}$$

and associated endogenous variables are determined as follows:

$$L_k = q p_k, \quad h_k = p_k^\rho, \quad y_k = a_k p_k^\rho, \quad w_k = (1-b) a_k p_k^\rho,$$

for $k \in \{F, R\}$, together with $N = 1$ under the assumption of $u = 0$. See section C.3 for all the derivations.

C.2 Calibration

For the entire analysis, we maintain $u = 0$ and $b = 0.3$ (i.e., labor share is 0.7), as well as all the normalization assumptions described in section C.1 (i.e., $q_0 = 1$, $\eta = b$, $\theta = 1 - b$, $\beta_F = 1$). Changing u to be a nonzero value will lose the benefit of simple computations. Changing b only affects the overall employment level, keeping the choice probability between job types unchanged. Since our focus is the job type choice, we keep $b = 0.3$.

The rest of the parameters (except for ρ) are calibrated to make equilibrium outcomes equal to observed data points related to the telework situation. Data points to calibrate parameters are (1) the average number of days when people work in a week, (2) the average number of commuting days among the days when people in a week, (3) the average number of telework days among the days when people in a week, and (4) estimated relative income of remote workers relative to on-site workers, corresponding to $(q, p_F, p_R, \frac{w_R}{w_F})$ in the model, respectively. Although there are four values, the degree of freedom is only three, because of $p_F + p_R = 1$. The number of remaining free parameters is still four (i.e., a_F , a_R , β_R , ρ) so that we set either $\rho = 0$ or $\rho = 0.9$ for illustrative purposes. Then, β_R and a_R/a_F will be calibrated by the following equilibrium conditions:

$$\frac{w_R}{w_F} = \frac{y_R}{y_F} = \frac{a_R p_R^\rho}{a_F p_F^\rho} = \frac{p_R \beta_F}{p_F \beta_R} \Rightarrow \beta_R = \left(\frac{w_R}{w_F} \right)^{-1} \frac{p_R}{p_F}, \quad \frac{a_R}{a_F} = \left(\frac{w_R}{w_F} \right) \left(\frac{p_R}{p_F} \right)^{-\rho},$$

noting that β_F is normalized to one. Lastly, the level of a_F (and a_R at once) will be determined by the following equilibrium condition:

$$q = (a_F p_F^{1+\rho} + a_R p_R^{1+\rho})^{\frac{b}{1-b}} \Rightarrow q^{\frac{1-b}{b}} = a_F \left[p_F^{1+\rho} + \frac{a_R}{a_F} p_R^{1+\rho} \right] \Rightarrow a_F = \left[p_F^{1+\rho} + \left(\frac{W_R}{W_F} \right) \left(\frac{p_R}{p_F} \right)^{-\rho} p_R^{1+\rho} \right]^{-1} q^{\frac{1-b}{b}}.$$

This calibration strategy leads to simple relationships between data points and calibrated parameters. First, β_R can be interpreted as an earning-adjusted odds ratio for remote work relative to on-site work. In other words, if workers choose remote work more often than justified by relative earnings, then it is attributed to preferences. The simple proportional property stems from parsimonious assumptions, at the expense of specification error. Second, the calibrated value of β_R does not depend on the value of ρ . Third, relative profitability a_R/a_F is simply equal to relative earnings w_R/w_F if $\rho = 0$.

Note that the telework preference β_R and relative profitability a_R/a_F have the same implication for the choice over job types in equilibrium. An increase in either β_R or a_R/a_F will increase p_R . Putting differently, changing β_R and a_R/a_F at once, while keeping their multiple $\beta_R \left(\frac{a_R}{a_F} \right)$ unchanged, does not change the equilibrium level of (p_F, p_R) . The equilibrium job-match rate q and the shares of workers (L_F, L_R) will also be the same. What will change are outputs (y_F, y_R) and wages (w_F, w_R) . These variables will change to a different extent depending on whether β_R or a_R/a_F is changing, as shown below:

$$\frac{y_R}{y_F} = \frac{w_R}{w_F} = \beta_R^{\frac{\rho}{1-\rho}} \left(\frac{a_R}{a_F} \right)^{\frac{1}{1-\rho}}.$$

Based on the different elasticities, β_R and a_R/a_F can be identified separately. In particular, with no coordination cost (i.e., if $\rho = 0$), a change in β_R will not change at all wages (w_F, w_R) or outputs (y_F, y_R) in equilibrium.

C.3 Derivation

Equilibrium job applications across work modalities

Wage w_k is determined under the asymmetric Nash bargaining conditional on job type k by the following first-order condition:

$$b\{x_k w_k - u\} + (1-b)x_k w_k = (1-b)x_k y_k \Rightarrow x_k w_k = bu + (1-b)x_k y_k \Rightarrow w_k = b \frac{u}{x_k} + (1-b)y_k.$$

Then, the Nash product conditional on job type $k \in \{F, R\}$, denoted by Φ_k , becomes:

$$\begin{aligned} \Phi_k &\stackrel{\text{def}}{=} [y_k - w_k]^b [x_k w_k - u]^{1-b} = \left[b y_k - b \frac{u}{x_k} \right]^b [(1-b)x_k y_k - (1-b)u]^{1-b} \\ &= b^b (1-b)^{1-b} \left[y_k - \frac{u}{x_k} \right]^b [x_k y_k - u]^{1-b} = b^b (1-b)^{1-b} (x_k)^{-b} [x_k y_k - u]. \end{aligned}$$

If $u = 0$ holds, we have:

$$\Phi_k = b^b(1-b)^{1-b}y_k(x_k)^{1-b} \Leftrightarrow \left\{ \frac{\Phi_k}{b^b(1-b)^{1-b}} \right\}^{\frac{1}{1-b}} = y_k^{\frac{1}{1-b}}x_k.$$

Since $z^{\frac{1}{1-b}}$ is increasing in $z \in [0, \infty)$ and $b^b(1-b)^{1-b}$ is positive, we have:

$$P\left[\Phi_k \geq \max_{j \neq k} \Phi_j\right] = P\left[\left\{ \frac{\Phi_k}{b^b(1-b)^{1-b}} \right\}^{\frac{1}{1-b}} \geq \max_{j \neq k} \left\{ \frac{\Phi_j}{b^b(1-b)^{1-b}} \right\}^{\frac{1}{1-b}}\right] = P\left[y_k^{\frac{1}{1-b}}x_k \geq \max_{j \neq k} \left\{ y_j^{\frac{1}{1-b}}x_j \right\}\right].$$

By assumption, x_F and x_R independently follow a Fréchet distribution $F_0(x) \stackrel{\text{def}}{=} e^{-\beta_k x^{-\theta}}$ with parameters $\beta_k > 0$ and $\theta > 0$, implying that the distribution of $y_k^{\frac{1}{1-b}}x_k$, denoted by $F_k(z)$, is:

$$F_k(z) = P\left[y_k^{\frac{1}{1-b}}x_k \leq z\right] = P\left[x_k \leq y_k^{\frac{-1}{1-b}}z\right] = F_0\left(y_k^{\frac{-1}{1-b}}z\right) = e^{-\beta_k y_k^{\frac{\theta}{1-b}}z^{-\theta}},$$

and we obtain:¹⁵

$$P\left[y_k^{\frac{1}{1-b}}x_k \geq \max_{j \neq k} \left\{ y_j^{\frac{1}{1-b}}x_j \right\}\right] = \int_0^\infty \prod_{j \neq k} \{F_j(z)\} dF_k(z) = \frac{\beta_k y_k^{\frac{\theta}{1-b}}}{\sum_j \left\{ \beta_j y_j^{\frac{\theta}{1-b}} \right\}},$$

implying that a job of type k is chosen more often if per-unit production y_k is larger than other $\{y_j\}_{j \neq k}$. Note that the probability of $y_k^{\frac{1}{1-b}}x_k$ being exactly equal to any other $y_j^{\frac{1}{1-b}}x_j$, $j \neq k$, is zero. Therefore, p_k is simply equal to the probability above, and we have:

$$p_k = P\left[y_k^{\frac{1}{1-b}}x_k \geq \max_{j \neq k} \left\{ y_j^{\frac{1}{1-b}}x_j \right\}\right] = \frac{\beta_k y_k^{\frac{\theta}{1-b}}}{\sum_j \left\{ \beta_j y_j^{\frac{\theta}{1-b}} \right\}} = \frac{\beta_k y_k}{\sum_j \left\{ \beta_j y_j \right\}},$$

noting that θ is normalized to be equal to $1-b$. Substituting $y_k = a_k h_k$ and $h_k = \left(\frac{L_k}{L_F + L_R}\right)^\rho = p_k^\rho$, we have:

$$\begin{aligned} p_F &= \frac{\beta_F a_F p_F^\rho}{\beta_F a_F p_F^\rho + \beta_R a_R p_R^\rho} \Rightarrow (p_F - 1)\beta_F a_F p_F^\rho + p_F \beta_R a_R p_R^\rho = 0 \\ &\Rightarrow \beta_F a_F p_F^{\rho-1} = \beta_R a_R p_R^{\rho-1} \quad \text{or } (p_F, p_R) = (0,1) \text{ or } (1,0). \end{aligned}$$

¹⁵ We use a formula for \mathbb{R} -valued random variables $\{Z_i\}$ that independently follow distributions $\{G_i\}$ for each i , as follows:

$$P\left[Z_k \geq \max_{j \neq k} \{Z_j\}\right] = E\left[P\left[Z_k \geq \max_{j \neq k} \{Z_j\} \mid Z_k\right]\right] = \int_{\mathbb{R}} P[Z_j \leq Z_k, j \neq k \mid Z_k = z] dG_k(z) = \int_{\mathbb{R}} \prod_{j \neq k} \{P[Z_j \leq z]\} dG_k(z) = \int_{\mathbb{R}} \prod_{j \neq k} \{G_j(z)\} dG_k(z),$$

where the first equality follows the law of iterated expectations, the second equality assumes that $P[Z_j \leq Z_k, j \neq k \mid Z_k = z]$ as a function of z is Riemann-Stieltjes integrable with respect to G_k (see, e.g., Theorem 17 of Chapter 4, Fristedt and Gray 1997), and then the third equality uses independence across $\{Z_i\}$ for each i . We also use a standard formula for the Fréchet distribution. See also, e.g., Eaton and Kortum (2002).

We also assume away the possibilities of having only one job type, i.e., $(p_F, p_R) = (0,1)$ or $(1,0)$, in equilibrium (with a definitional condition of $(w_F, w_R) > 0$), and obtain:

$$\left\{ \frac{\beta_F a_F}{\beta_R a_R} \right\}^{\frac{1}{\rho-1}} p_F = p_R = 1 - p_F \Rightarrow p_F = \frac{1}{\left\{ \frac{\beta_F a_F}{\beta_R a_R} \right\}^{\frac{1}{\rho-1}} + 1} = \frac{\{\beta_F a_F\}^{\frac{1}{1-\rho}}}{\{\beta_F a_F\}^{\frac{1}{1-\rho}} + \{\beta_R a_R\}^{\frac{1}{1-\rho}}}$$

If $\rho = 1$ holds, there is no equilibrium unless $\beta_F a_F = \beta_R a_R$ holds, and in that case, there are a continuum of multiple equilibria for any $p_F \in [0,1]$ and $p_R = 1 - p_F$. We assume away $\rho = 1$ for simplicity. Also, we have:

$$\frac{\partial p_F}{\partial a_F} = - \left(\left\{ \frac{\beta_F a_F}{\beta_R a_R} \right\}^{\frac{1}{\rho-1}} + 1 \right)^{-2} \frac{1}{\rho - 1} \left\{ \frac{\beta_F a_F}{\beta_R a_R} \right\}^{\frac{1}{\rho-1} - 1} \frac{\beta_F}{\beta_R a_R},$$

implying that p_k increases when a_k increases if $\rho < 1$ holds, but otherwise, p_k decreases when a_k increases. We therefore assume $\rho < 1$ so that equilibrium outcomes depend on a_k more intuitively.

Equilibrium employment rate and output

Assuming free entry for job posting, we have:

$$q \frac{N}{n} \sum_{k \in \{F,R\}} p_k \{y_k - w_k\} = \eta \Rightarrow \frac{1}{n} \sum_{k \in \{F,R\}} q N p_k b y_k = \eta \Rightarrow \frac{1}{n} b \sum_{k \in \{F,R\}} L_k y_k = \eta \Rightarrow n = \frac{b}{\eta} Y.$$

We normalize $\eta = b$, which is a normalization of the unit of output (see section C.1), resulting in $n = Y$. Together with other normalizations of $q_0 = 1$ and $N = 1$, we have:

$$q = \left(\frac{q_0 n}{N} \right)^b = Y^b = \left(\sum_{k \in \{F,R\}} a_k h_k L_k \right)^b = \left(q \sum_{k \in \{F,R\}} a_k p_k^{\rho+1} \right)^b \Rightarrow q = \left(\sum_{k \in \{F,R\}} a_k p_k^{\rho+1} \right)^{\frac{b}{1-b}}.$$

Substituting p_k with the formula above, we have:

$$q = \left(\sum_{k \in \{F,R\}} a_k \left(\frac{\{\beta_k a_k\}^{\frac{1}{1-\rho}}}{\{\beta_F a_F\}^{\frac{1}{1-\rho}} + \{\beta_R a_R\}^{\frac{1}{1-\rho}}} \right)^{\rho+1} \right)^{\frac{b}{1-b}} = \left(\frac{\beta_F^{\frac{1+\rho}{1-\rho}} a_F^{\frac{2}{1-\rho}} + \beta_R^{\frac{1+\rho}{1-\rho}} a_R^{\frac{2}{1-\rho}}}{\left(\{\beta_F a_F\}^{\frac{1}{1-\rho}} + \{\beta_R a_R\}^{\frac{1}{1-\rho}} \right)^{1+\rho}} \right)^{\frac{b}{1-b}}.$$

Therefore, equilibrium outcomes are uniquely determined from a set of parameters.

A parameter restriction for equilibrium existence

A set of parameters needs to satisfy a condition such that $q \leq 1$ holds for the associated equilibrium to exist. As is common in the literature (see, e.g., Wright and others 2021), the matching function is assumed to be of the Cobb-Douglas form, which does not guarantee that matching probability q is within $[0,1]$. Although $q > 0$ holds, $q \leq 1$ is not guaranteed.

The condition $q \leq 1$ can be visualized as an area in the first quadrant of the $(a_F h_F, a_R h_R)$ -plane, with a boundary of the shape of an ellipse. The normalization assumptions (i.e., $N = 1$, $q_0 = 1$, $\eta = b$) lead to $q = Y^b$ as shown above, and $Y^b \leq 1$ is equivalent to $Y \leq 1$ for any $b > 0$. Then, the equilibrium relationship between Y and $(a_F h_F, a_R h_R)$ can be written as follows:

$$Y = \sum_{k \in \{F, R\}} a_k h_k p_k = \sum_{k \in \{F, R\}} \frac{\beta_k (a_k h_k)^2}{\beta_F a_F h_F + \beta_R a_R h_R} \Rightarrow \beta_F \left[a_F h_F - \frac{Y}{2} \right]^2 + \beta_R \left[a_R h_R - \frac{Y}{2} \right]^2 = \frac{Y^2 (\beta_F + \beta_R)}{4}.$$

In the $(a_F h_F, a_R h_R)$ -plane, this equation forms an ellipse, whose center is $(Y/2, Y/2)$, whose size is increasing in Y , and passing the origin. It means that the values of $(a_F h_F, a_R h_R)$ in an equilibrium associated with Y and $(a_F, a_R, \beta_F, \beta_R)$ as well as other parameters must be located on this ellipse. Since the ellipse is monotonically larger for a larger value of Y , inequality $Y \leq 1$ is satisfied in the inside of an ellipse defined by the equation above with $Y = 1$, leading to the following inequality:

$$\beta_F \left[a_F h_F - \frac{1}{2} \right]^2 + \beta_R \left[a_R h_R - \frac{1}{2} \right]^2 \leq \frac{\beta_F + \beta_R}{4}.$$

Conversely, each point $(a_F h_F, a_R h_R) > 0$ inside the ellipse with $Y = 1$ in the first quadrant corresponds to an equilibrium. Starting from $Y = 1$, reducing Y continuously will find a unique ellipse that includes point $(a_F h_F, a_R h_R)$. Then, Y is equal to two times the x- or y-coordinate of the center of this ellipse. Then, an equilibrium condition $\frac{p_R}{p_F} = \frac{\beta_R a_R h_R}{\beta_F a_F h_F}$ enables us to pin down the value of p_R/p_F as the slope to the line from the origin to $(a_F h_F, a_R h_R)$ times β_R/β_F , and then each of (p_F, p_R) is uniquely determined together with $p_F + p_R = 1$. Since an ellipse with a certain value of Y and a line passing the origin has a unique intersection for in the first quadrant (because the ellipse always passing the origin), there is a unique mapping between the values of $(a_F h_F, a_R h_R)$ and equilibrium outcomes (Y, p_F, p_R) , for any values of $(\beta_F, \beta_R) > 0$. Then, the values of (a_F, a_R) are uniquely determined from the values of $(a_F h_F, a_R h_R)$, if the values of (β_F, β_R) and ρ are given, as follows:

$$a_F h_F = a_F p_F^\rho = a_F \left[\frac{\beta_F a_F h_F}{\beta_F a_F h_F + \beta_R a_R h_R} \right]^\rho \Rightarrow a_F = \left[1 + \frac{\beta_R a_R h_R}{\beta_F a_F h_F} \right]^\rho a_F h_F,$$

and a_R can be obtained similarly, which identifies an equilibrium, uniquely.

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