Why Working from Home Will Stick

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Abstract: Work from home (WFH) has stabilized at about 25% of all paid workdays as of 2025, 3.5 times its 2019 level. To understand this shift, we collect and analyze over 250,000 survey responses from US workers since 2020. To assess its economic consequences, we build a quantitative equilibrium model that endogenizes work arrangements, workhours, and productivity. By designing our survey and model jointly, we capture key choices and tradeoffs related to WFH. According to our calibrated model, returning to pre-pandemic work arrangements would lower output per hour (inclusive of commute time) by 3.5% and reduce worker welfare by 2.6% on average, with large differences across workers. These results explain the persistence of WFH while raising a broader question: why didn't the shift happen before 2020? Our answer is that the pandemic compelled workers and firms to experiment with WFH at scale, yielding new information and a re-optimization of work arrangements. We estimate that pandemic-induced experimentation can account for over 90% of the large rise in WFH from 2019 to the post-pandemic period, when the economy settled into a new equilibrium with higher welfare.

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1. Introduction

COVID-19 drove a mass social experiment in work from home (WFH). Americans supplied more than half of paid workdays from home in spring 2020, as compared to seven percent before the pandemic.[1] This seismic shift raised questions about whether WFH would stick and no shortage of opinions about whether it is good for businesses and workers. In 2020 Netflix's then-CEO Reed Hastings offered one view: "I don't see any positives. Not being able to get together in person, particularly internationally, is a pure negative." At the other end of the spectrum, Rite Aid CEO Heyward Donigan said, "We have adapted to work-from-home unbelievably well… We've learned that we can work remote, and we can now hire and manage a company remotely." Apple CEO Tim Cook took an intermediate view: "In all candor, it's not like being together physically.…[But] I don't believe that we'll return to the way we were because we've found that there are some things that actually work really well virtually."[2]

Partly motivated by this range of views, we have tracked WFH in the United States since May 2020, designing and fielding a survey that collects thousands of individual-level responses each month. Our Survey of Working Arrangements and Attitudes (SWAA) yields the longest-running monthly series on WFH back to 2020.[3] Our SWAA-based WFH measures are now distributed via the St. Louis Fed's FRED database and have garnered considerable interest from researchers and policy makers.[4] Data from early SWAA waves led us to forecast in the first version of this paper (Barrero et al., 2021) that high WFH rates would stick after the pandemic ended, as did Bick et al. (2023) using separate survey evidence. That prediction has come to pass. US workers supply about 25% of paid workdays from home as of 2025, 3.5 times the 2019 percentage, with little change since early 2023 (Figure 1).[5]

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[1] See Figure 1 below and Ozimek (2020), Bick et al. (2023), and Brynjolfsson et al. (2025) for evidence on the extent of WFH in spring 2020.

[2] The quotations are from Cutter (2020).

[3] The Real-Time Population survey of Bick et al. (2023) also tracked WFH rates monthly between April 2020 and June 2021. After that it runs two to three times annually. The Current Population Survey began collecting data on the share of workhours supplied from home in 2022 (https://data.bls.gov/timeseries/LNU0201B46B and https://www.bls.gov/cps/telework.htm). From May 2020 to September 2022, the CPS collected data on the share of persons who teleworked or worked from home in the past 4 weeks *because of the pandemic* (https://www.bls.gov/cps/effects-of-the-coronavirus-covid-19-pandemic.htm).

[4] See https://fred.stlouisfed.org/series/WFHCOVIDMATQUESTION. Our WFH measures feature prominently in the Economic Report of the President (Council of Economic Advisers, 2024 and 2025).

[5] Kmetz et al. (2023) and Bick et al. (2023, 2025) also provide individual-level survey evidence that high WFH rates persist. Business surveys like the Census Business Trends and Outlook Survey confirm that WFH levels remain

How did the pandemic lead to a large *and lasting* rise in WFH? After all, government restrictions on in-person interactions are long gone, as is widespread anxiety about COVID-19. The answer, according to our evidence and analysis, turns on the pandemic's role in driving workers and firms to experiment with WFH at scale and at the same time. That experimentation yielded new information, much experience with remote work, and a resulting re-optimization of work arrangements. In this way, the pandemic brought a lasting shift to a new equilibrium characterized by much higher WFH rates, with net benefits for workers. This episode illustrates how large shocks that drive experimentation – like the COVID-19 pandemic and the reaction to it – can lead to enduring and welfare-improving changes in the organization of work.

Our paper draws on rich SWAA data, interpreted with the aid of a structural model, to support this narrative and quantify its implications. Relative to prior work, we collect new post-pandemic data on individual work arrangements, workhours, and wages, which we use to calibrate the model. We also use our survey data and quantitative model to ask whether learning can account for the lasting shift in WFH rates. Three facts in our post-pandemic data underscore that firms and workers select work arrangements based on productivities, preferences, and time savings. First, workers with stronger assessments of their relative efficiency in remote work also WFH more days per week. Separate survey evidence for senior managers yields the same pattern: managers who believe their employees are more productive when working remotely report twice as much WFH at their firms as managers with the most negative assessments of WFH. Second, workers rate their own WFH productivity more highly when their commutes are longer, and they attribute much of their WFH productivity advantage to commute time savings. Third, workers with long commutes also want to WFH more often. The second and third facts suggest that time savings are a key reason why workers value WFH, and why they favorably assess their own productivity in remote work.

By enabling workers to produce similar amounts while devoting less time to work, we argue that WFH boosts the economy's *effective* labor productivity, defined as output divided by all hours devoted to work inclusive of time spent commuting. Even if WFH makes individual workers somewhat less productive because of communication and coordination frictions (Battiston et al., 2021, Atkin et al., 2023, Gibbs et al., 2023, and Emanuel and Harrington, 2024), commute time savings can raise effective productivity and welfare relative to pre-pandemic work

elevated in 2025 and project stable WFH rates into the future (Barrero et al., 2025). Non-survey sources also indicate that high WFH persists, as in Abraham et al. (2024) and Monte et al. (2026).

arrangements. If some workers are more productive when working remotely part of the week, as our analysis finds, then WFH further raises productivity and welfare. Preferences over work arrangements also differ among workers, with potentially important welfare implications.

To explore these and related issues, we build an equilibrium model that endogenizes workhours, work arrangements, productivity, and wages – all while accommodating rich agent-level heterogeneity in ability, commute time, and preferences. The model's flexible structure lets us capture the observed variation in work arrangements across industries, occupations, and persons. Because we design the survey with the model in mind, we are well positioned to assess the tradeoffs among WFH, productivity, and welfare at aggregate and individual levels.

We calibrate the model to SWAA data from 2023 to 2025 and use it to quantify the productivity and welfare implications of observed WFH levels compared to counterfactual scenarios. Returning to pre-pandemic WFH levels, for example, would reduce measured labor productivity (output per paid workhour) by 0.7%, because some workers are more productive when working remotely some of the time. The drop in effective labor productivity is five times as large at 3.5% because of added commute time. Returning to pre-pandemic WFH levels would also lower consumption-equivalent worker welfare by 2.6%, on average, with large differences across workers. Official statistics don't capture the effective productivity and welfare effects, leaving them largely invisible. One of our key contributions is to quantify these hard-to-measure benefits of the pandemic-induced rise in WFH. We also assess the consequences of returning to "lockdown" levels of WFH and of return-to-office policies that impose a minimum number of onsite workdays per week. Both yield lower welfare and effective productivity than currently observed work arrangements, even though measured productivity and output rise under a limited push to onsite work. We also extend our model to account for positive spillovers of onsite work on productivity and wages. Those in-person externalities must be substantial (about twice as large as recent estimates) to avoid welfare losses when imposing a return to pre-pandemic WFH rates in our basic model.

If current WFH levels raise welfare relative to pre-pandemic levels, why wasn't WFH more prevalent before 2020? We address this question with theory and evidence. A simple theoretical model shows how uncertainty, adoption costs, and strategic complementarities can discourage experimentation and WFH adoption. When the pandemic forced experimentation with remote work, some workers and firms learned that WFH is viable in certain jobs and tasks. Having

incurred the sunk costs of experimentation and adoption, workers and firms with sufficiently favorable WFH experiences stuck with it after the pandemic ended. That is, they re-optimized in light of new information and altered circumstances. These direct effects of forced experimentation are amplified if WFH is more attractive when many coworkers, customers, and suppliers also WFH, reflecting the strategic-complementarity logic of Cooper and John (1988).

Several pieces of evidence derived from our SWAA data support this interpretation of how the pandemic shifted the WFH equilibrium. First, many workers report being positively surprised by their WFH productivity experiences during the pandemic. Second, the average surprise value is positive, suggesting that prior views about WFH were overly pessimistic. Third, looking across individuals, more favorable productivity surprises are associated with more WFH as of the survey date, stronger desires to continue to WFH, and employer plans for higher WFH rates in the future. Fourth, the mechanism is quantitatively important. Interpreted through the lens of our model, the scale of re-optimization implied by our data on productivity surprises suggests the WFH rate would be 8.4% without learning. That is close to our 2019 estimate of 7.2%, implying that learning can account for over 90% of the WFH rise since 2019. Finally, most workers report a decline in the stigma associated with WFH in surveys we fielded from July 2020 to May 2022. This finding points to a change in work norms that further reinforced the shift to WFH.

The pandemic-era WFH experiment, thus, resembles the experience of London Underground commuters reported by Larcom et al. (2017). After a labor strike forced commuters to try new routes, many learned that they preferred their new routes and stuck to them long after the strike ended. The mechanism is similar in our setting, but the scale is vastly greater and so are the economic and societal consequences.

Altogether, our paper offers four main sets of contributions. First, we show that WFH has persisted at high levels – about 25% of paid workdays in 2025 – long after the pandemic ended. Second, we collect post-pandemic data on individual work arrangements, workhours, and commute times, and fit them to a model that endogenizes those variables. Third, we quantify WFH's effects on labor productivity and welfare at the aggregate and individual levels. Fourth, we provide evidence from our survey on how the pandemic catalyzed a lasting shift to higher WFH rates by compelling workers and managers to experiment with WFH, leading them to reoptimize work arrangements. Our model and data imply that learning and re-optimization account for over

90% of the shift in WFH rates since 2019. Strategic complementarities in experimentation and adoption likely helped amplify and entrench the shift to a new equilibrium with higher WFH rates.

This paper relates to four active literatures. First, survey efforts to measure WFH include the SWAA, Bick et al. (2023), Barrero et al. (2025), and various government surveys. Some studies measure WFH using other sources of data such as internet activity (Kwan et al., 2022) and cell phone mobility (Abraham et al., 2024). Kmetz et al. (2023), Bick et al. (2025), Brynjolfsson et al. (2025), and Buckman et al. (2025) seek to reconcile differences in WFH measures across sources.

Second, we contribute to a literature on how WFH affects the productivity of firms and workers. Bloom et al. (2015) provide experimental evidence on call centers and find positive productivity effects, while Battiston et al. (2021), Atkin et al. (2023) and Emanuel and Harrington (2024) find negative effects due to communication frictions or slower on-the-job learning. Choudhury et al. (2021) find that US patent examiners experienced a productivity gain of 4.4% when allowed to work remotely but note that patent examiners (like call center workers) don't collaborate much. Choudhury et al. (2024) study NGO employees in Bangladesh and find that hybrid WFH led to more emails and higher productivity. Bloom et al. (2024) study college-educated workers in a Chinese travel agency and find little productivity impact of hybrid WFH but a large drop in turnover. Gibbs et al. (2023) consider college-educated employees in an Asian IT firm who switched to WFH during the pandemic. Fenizia and Kirchmaier (2025) exploit quasi-random variation in the WFH status of police staff in a crime reporting and resolution unit. Finally, Emanuel et al. (2025) study how performance and collaboration respond to the pandemic-induced shift to WFH and a later return to office among software engineers who differ by co-location status.

A third literature evaluates the equilibrium effects of WFH, including the spatial analyses of Delventhal et al. (2022), Delventhal and Parkhomenko (2026), Duranton and Handbury (2023), Davis, Ghent, and Gregory (2024a, 2024b), Monte et al. (2026), and Richard (2025). Bick et al. (2023) forecast the persistence of WFH and provide evidence that it reflected re-optimization among knowledge workers for whom it was feasible before the pandemic. We corroborate those predictions using post-pandemic data and contribute a new model to quantify the consequences and the scope for re-optimization. Bagga et al. (2025) use a search-and-matching framework to argue that a shift in preferences for WFH explains unemployment, vacancy, and worker reallocation dynamics in the early 2020s. Sedlacek and Shi (2025) study how the rise of WFH alters scale economies and affects firm entry and exit.

Fourth, we contribute to research on the broader economic and social ramifications of WFH. Liu and Su (2025) and Choi et al. (2026) provide evidence on how the shift to WFH affects wages. Harrington and Kahn (2023) find that WFH shrinks the motherhood penalty in jobs that facilitate remote work. Agrawal et al. (2025) and Gupta et al. (2026) study WFH effects on local taxes and real estate values.

The next section describes our survey. Section 3 uses the survey data to develop several findings that motivate and guide our model design. Section 4 sets forth and calibrates our equilibrium model, and Section 5 uses the model to quantify the productivity and welfare implications of WFH. Section 6 considers why the big shift to WFH didn't happen before the pandemic, and Section 7 offers concluding remarks. Appendices offer additional empirical results, explain how we track WFH rates over time, and set forth a formal theory of how the pandemic shifted the economy to a new equilibrium with higher WFH rates.

2. Survey Methodology

We have fielded the Survey of Working Arrangements and Attitudes (SWAA) since May 2020. Each month, we sample up to 10,000 U.S. residents aged 20 to 64. We ask about demographics, labor force status, industry and occupation of current or most recent job, attitudes towards remote work, work arrangements, and other matters. Our monthly survey instruments are posted at https://wfhresearch.com/survey-design-and-question-repository/. For the purposes of tracking WFH rates, we focus on persons who earn at least $10,000 in a prior year.[6]

To implement the SWAA, we contract with market research firms like IncQuery. They provide a platform to program the survey questions and intermediate with other firms (e.g., Cint, formerly known as Lucid) to access pre-recruited panels of prospective survey participants. When a survey wave goes to field, the market research firm issues invitations to prospective respondents and continues until reaching the desired number and mix of participants. Recipients are selected based on their US locations and demographic characteristics. The invitation states the estimated

[6] Before June 2022 we sampled 5,000 workers per month and before early 2021 it was 2,500. Most recently, we have obtained responses from 8,000 workers each month. Initially, we adopted a prior earnings requirement to cost-effectively sample persons with recent working experience and attachment to the labor force. As our funding grew, we relaxed that requirement and in mid-2022 began collecting data from all persons 20 to 64. In this paper, we impose a prior-year earnings requirement unless noted. From May 2020 to March 2021, we required respondents to report labor earnings of at least $20,000 in 2019. From April to September 2021, we transitioned to a lower earnings threshold of $10,000 in 2019 and kept that threshold from October to December 2021. From January to March 2022, we transitioned to a threshold of $10,000 in 2021 and have kept a threshold of $10,000 in the previous year for most of the data used in this paper.

survey completion time, but does not describe the topic, and links to an online questionnaire. Respondents who complete the survey receive cash, vouchers, or non-cash awards, which they can donate. We do not contact respondents ourselves, do not collect personally identifiable information, and have no way to re-contact them.[7]

Our approach aligns closely with Stantcheva's (2023) recommendations on how to conduct high-quality survey research. To address a potential lack of attention by respondents, we routinely conduct two quality control steps before our empirical analyses. First, we drop "speeders" – those who take too little time to carefully answer questions. In practice, we drop those who take less than two-thirds of the median completion time – or about 15% of the raw sample. Second, we drop respondents who fail any of four attention-check questions: (1) Early on, we ask "*What is 3 + 4?*" and drop respondents who don't answer 7. (2) A third of the way into the survey, we ask "*In how many cities with more than 500,000 inhabitants have you lived? Irrespective of your answer please insert the number 33",* dropping respondents who don't report 33. (3) Two-thirds into the survey, we ask "*What color is grass?... Make sure that you select purple as an answer so we know you are paying attention*…" and keep respondents who answer purple (high attention) or green (medium attention). (4) We ask respondent age near the middle of the survey and birth year near the end, dropping respondents when (implied) ages differ by more than two years. These checks lead us to drop 12% of non-speeder responses.[8]

We reweight the SWAA data to match Current Population Survey (CPS) employment shares in cells defined by the cross product of age, sex, education, and earnings categories.[9] Appendix Figure A.1 shows how the distribution of raw data in 2025 (after dropping speeders) compares to the CPS distribution for key demographics. Middle-aged, highly educated, and higher-

[7] Our survey was declared exempt by the IRB at Stanford University and National Bureau of Economic Research.
[8] We first included attention-check questions in late 2021 and did not include the two questions about age until March 2024. So, for consistency, we do not apply the attention check filter in Figure 1.
[9] We obtain the target share of persons aged 20 to 64 in each cell from a pooled sample of CPS Annual Social and Economic Supplement (ASEC) across 2010 to 2019 and keep this target constant so that any variation reflects variation in the survey data rather than the target. To avoid large monthly changes in the weight on any given cell, we use a rolling-weights scheme since April 2021. In month *t*, we compute the share of observations in each age-sex-education-earnings cell during the two months covering *t-1* to *t*. We construct the weights for month *t* by up- or down-weighting those proportions to match the CPS share of the population in each cell. Prior to October 2023 our rolling weights scheme pooled 6 months (*t-5* to *t*) of SWAA data, at which time we switched to our current two-month pooling to be more responsive to high-frequency changes in sample composition. For the sample period covering May 2020 to March 2021, we pool across all observations collected during that period, and the resulting weights are identical for the same demographic cell across months during that period.

earning persons are materially over-represented before reweighting. After reweighting, our survey data look representative along non-targeted dimensions.

One validation exercise compares SWAA respondents' political preferences to voting outcomes. Since January 2022 the survey includes a question about party affiliation that we borrow almost verbatim from the General Social Survey. Figure A.2 compares the share of respondents who identify with the Democratic party (among those who identify with the major parties) to the share of the two-party vote for the Democratic Presidential candidate in the respondent's county in the 2020 or 2024 elections (whichever is closest to the survey date). The overall and county-level party affiliation shares in the SWAA align closely with Democratic vote shares. Similarly, Buckman et al. (2025) find that SWAA partisan affiliation shares align with those in Pew survey data. The left panel of Figure A.3 also shows that the demographic mix of respondents who complete the SWAA aligns closely with the mix of those who start but don't finish.

To track the extent of WFH using SWAA data, we calculate the percentage of full paid days worked from home based on responses to the following question put to employed respondents: "*For each day* **last week,** *did you* **work a full day (6 or more hours)**, *and if so* **where?**" There are three response options for each day of the prior week: *"Worked* **from home***,"* *"Worked* **at employer or client site***,"* or *"Did not work 6 or more hours."* This formulation has been in effect since November 2021, and Figure A.4 shows how it appears in the online survey. From May to October 2020, we asked respondents to categorically report their work arrangements since most people then worked 100% remotely or 100% in person. From November 2020 to October 2021, we asked the number of days worked from home and at the workplace during the reference week, without asking what they did on each specific day. By November 2021 we changed to the question design in Figure A.4 to improve our measurement, after testing several designs in parallel and in A/B tests. To generate a consistent WFH series back to 2020, we impute WFH levels from November 2020 to October 2021 using a regression model that maps responses between the current and earlier question, based on subsamples with responses to both questions.[10]

Since 2021 we have posted our SWAA data and made it freely available at http://www.wfhresearch.com/. Researchers can download a spreadsheet with key time series for

[10] For more information about this imputation and about the nature of the earlier questions, see Appendix B, which reproduces the methodological note we have posted at https://wfhresearch.com/wp-content/uploads/2025/07/Methodological-Note-July-2025.pdf.

WFH rates, among other variables, at https://wfhresearch.com/data. Reflecting ongoing interest from researchers and policymakers, the St. Louis Fed's FRED Database carries several of our WFH measures. Researchers can also create a free account on http://www.wfhresearch.com/data to access our anonymous SWAA microdata back to 2020. Each month, we post an updated version of our monthly series and microdata that incorporate the latest survey wave. For this paper we use the data release covering May 2020 to December 2025 (Barrero et al., 2026).

Figure 1 shows our main WFH series from May 2020 to December 2025. WFH peaked at about 60% of paid workdays in May 2020. Most people who could WFH did so full time, and many who could not were unemployed, furloughed, or employed but not working. The rapid fall in WFH rates over the rest of 2020 reflects both a return to employment and a return to onsite work by some who had been working from home. WFH rates fell more slowly in 2021 and even more slowly in 2022 and later.[11] As of late 2025, WFH accounts for about 25% of paid workdays, 3.5 times the level in 2019 based on American Time Use Survey (ATUS) data.[12] Figure 1 also shows that our WFH series tracks estimates from the Census Household Pulse Survey (CHPS) from mid-2022 to mid-2024. The CHPS series draws on a question about whether people in the household WFH in the past 7 days, and, if so, whether they did so 1 to 2, 3 to 4, or 5 days that week. We impute a 30% WFH rate for 1 to 2 days, 70% for 3 to 4 days, and 100% for 5 days. After mid-2024 the Census Bureau stopped posting updated CHPS microdata with all the variables required to generate a time series, so we cannot benchmark our series against it in recent months.

3. Self-Assessed Productivity and Time Savings When Working from Home

Why does WFH persist near 25% of paid workdays more than 5 years after the onset of the pandemic? We hypothesize that this outcome reflects the choices of workers and firms, many of whom find WFH to be a productive and welfare-enhancing arrangement. In Section 4 below, we build and calibrate an equilibrium model that encompasses this perspective. But first we assess the basic hypothesis using SWAA data from January 2023 to December 2025. Here, our analysis

[11] Appendix Figure A.5 supports the view that WFH rates largely stabilized by 2023 and have declined mildly since then. Starting in 2020 we asked workers to tell us, in a post-pandemic future *"…how often* **is your employer planning** *for you to work full days at home?"* The series based on this question rises until mid-2022, when it meets the contemporaneous level of actual WFH. The two series move in tandem after that.

[12] We count paid workdays as those in which ATUS respondents do six or more hours of paid work for their main job, just as in our SWAA question, shown in Figure A.4. We count ATUS workdays as WFH when at least six hours of work on the main job is supplied from home.

sample starts about one year after the last large wave of COVID-19 deaths, following which mask mandates largely ended and pandemic-related concerns diminished.

For respondents with some WFH experience since 2020, we ask a two-part question about their own efficiency while WFH. The first part reads, *"How does your efficiency working from home compare to your efficiency working on business premises?"* The response options are:

- *Better -- I am **more** efficient at home than working on business premises*
- *About the same -- I'm equally efficient in both places*
- *Worse -- I am **less** efficient at home than working on business premises*

We randomly place "Better …" or "Worse …" first to address primacy bias. We follow up with *"How much* **more [less] efficient** *are you working from home than on business premises?"* Response options range from *"Under 5% more [less] efficient"* at the low end to *"Over 35% more [less] efficient"* at the high end. Those who say *"About the same…"* get no follow-up question. 41% of workers believe they are more efficient in WFH mode, and 13% believe they are less efficient. Figure A.6 reports the full response distribution.

We recognize that workers may favorably assess own WFH efficiency to justify their desires to WFH, whether the productivity advantage is real or not. Even when truthful, workers might be poor judges of their efficiency. Indeed, several papers find that WFH can lower productivity. Emanuel and Harrington (2024), for example, find negative productivity effects for call-center workers who went remote amid the 2020 lockdowns, even though they estimate *positive* effects on profitability due to reduced floorspace. Gibbs et al. (2023) also find negative productivity effects under lockdown. Bloom et al. (2024) run a randomized control trial comparing hybrid and fully in-person work, finding higher retention and little impact on performance.

That said, worker self-assessments exhibit strong regularities that suggest they are informative about the underlying WFH efficiency and about worker preferences. Figure 2 shows a positive relation between self-assessed WFH efficiency and actual WFH rates. While not always monotonic, the pattern is one of higher WFH rates for persons with more favorable assessments of own WFH efficiency. We fielded analogous questions to senior managers (CEOs, CFOs, etc.) in the October 2025 and April 2026 waves of the Atlanta Fed's Survey of Business Uncertainty.[13] In the SBU data, actual firm-level WFH rates rise monotonically with how favorably senior

[13] See https://www.atlantafed.org/research-and-data/surveys/business-uncertainty; specifically, the special question archive for October 2025 and April 2026. Altig et al. (2022) describe the survey and its methodology.

managers assess the relative efficiency of WFH in their own firms (Figure A.7). On average, senior managers hold less favorable views about WFH efficiency than workers, but both sets of survey responses reveal that WFH rates rise with subjective assessments of WFH efficiency.

If work arrangements reflect joint decisions by workers and their employers, it's hard to see how the relative productivity of WFH would not matter. We expect higher (relative) WFH efficiency among those who choose it, and lower WFH efficiency among those who commute regularly. That's what we see in Figures 2 and A.7, suggesting that subjective WFH efficiency assessments are not pure noise or motivated reasoning. We thus interpret these assessments as informative signals about the relative efficiency of WFH, which is why they predict WFH rates. In fact, the relationship between self-assessed WFH efficiency and contemporaneous WFH rates has steepened over time. A linear regression of Percent of Full Paid Workdays WFH on Self-Assessed Relative WFH Efficiency in the SWAA microdata yields a slope of 0.64 (0.02) in 2023, rising to 0.76 (0.02) in 2024 and 0.77 (0.02) in 2025.[14] Figure A.8 displays the corresponding bin scatters. As WFH stabilized at about 25% of paid workdays, it persisted especially for those who believe it's productive for them. Beliefs about relative WFH efficiency among those with WFH experience strengthened after the shift to WFH and have stabilized since 2023 (Figure A.9).

Other questions in our survey point to the reasons why workers rate their efficiency more highly when working from home. Five out of six respondents with positive self-assessments say *time savings from not commuting* are part of the reason. We obtain more data on those time savings using a series of SWAA questions about commute times and time spent getting ready for work.[15] The data reveal a positive relationship between self-assessed relative WFH efficiency and two-way commute times (inclusive of extra grooming time on commute days), as shown in the left

[14] We assign a relative efficiency value of zero to responses that say "About the same," and use mid-point values for the range specified in the follow up question posed to those who specify "more" or "less" efficient. We assign a value of 40% to those who say they are "Over 35% more efficient" in WFH and -40% at the other extreme.

[15] For workers who had at least one onsite day during the reference week, we ask "On the days that you commute to work, how much time (in minutes) does it typically take?" For fully remote workers (with no onsite days during the reference week), we ask "How long would it take to travel (one-way) from your home to your employer's location?" We also ask "How much time do you spend on grooming and/or getting ready for work when: - You commute to your employer's or client's worksite? - You work from home?" We measure grooming time saved as the difference between the length of time spent grooming on commute days and the amount on WFH days (or zero, if the difference is negative). See, for example, the May 2024 questionnaire at https://wfhresearch.com/wp-content/uploads/2024/06/May-2024-SWAA-Questionnaire.pdf. In our 2025 surveys we did not ask about time spent getting ready for work, so for responses in those months we impute grooming time based on mean responses by age, sex, education, and earnings in prior waves.

panel of Figure 3. Lengthening the daily two-way commute by one hour is associated with a 1.5 percentage point (ppt) increase in self-assessed WFH efficiency.

Time savings also help explain why many workers like WFH. The right panel of Figure 3 shows a binned scatter plot of two-way commute times (including grooming) against workers' desired number of WFH days. The latter variable comes from "***Looking one year ahead***, how often would you ***like to*** have paid workdays at home?" with response options "Never," "About once or twice per month," "1 day per week," "2 days per week," and so on up to "5+ days per week."[16] Expressing responses as percentages of a 5-day workweek, we find that an additional hour of commuting + grooming time predicts a 6.4 ppt increase in the desired WFH days per week (i.e., 0.32 extra WFH days). Figure 3 reinforces other evidence that commuting is a key driver of WFH adoption and its implications for firms and workers as in Aksoy et al. (2023), Davis, Ghent, and Gregory (2024a and 2024b), Delventhal and Parkhomenko (2026), and Richard (2025).

Summing up, Figures 2 and 3 yield several facts that motivate our approach of treating WFH as a choice variable in a model of labor supply and demand. First, for both workers and managers, actual WFH rates rise with subjective assessments of relative WFH efficiency. Second, commute time savings are an important reason why many workers like WFH. Not surprisingly, they regard (unpaid) time spent commuting and grooming as a job-related disamenity. Third, time savings are a key reason that many workers regard WFH as relatively efficient. Implicitly, many workers appear to assess "productivity" in terms of work accomplished divided by total time devoted to work, which is our concept of effective labor productivity. In the next section, we use the evidence in Figures 2 and 3 to guide the design of a quantitative model that speaks to the impact of WFH on productivity and welfare in the post-pandemic era.

4. An Equilibrium Model of Labor Supply and Work Arrangements

We present an equilibrium model that endogenizes workhours, work arrangements, wages, and productivity. Workers value WFH because it reduces time spent on commuting and getting ready for work, allowing more time for leisure. Each worker, and hence firms, face diminishing marginal returns in remote workhours. In equilibrium, workers and firms settle on work arrangements, workhours, and compensation. The model identifies worker-specific productivity parameters from data on wages, workhours, and work arrangements, and it lets us estimate the

[16] Prior to August 2023, this question began with "As the pandemic ends…"

degree of substitution between remote and onsite work. We observe other key model parameters – e.g., daily commute time – directly in our survey data. These model elements and data ingredients provide a framework for the counterfactual exercises in Sections 5 and 6 below.

a. Worker preferences and time allocation

Workers, indexed by $i \in I$, get utility from consumption c_i and disutility from time devoted to work n_i:

$$u(c_i, n_i) = log(c_i) - \chi_i \frac{n_i^{1+\eta}}{1+\eta}. \quad (1)$$

Time devoted to work equals paid workhours h_i plus commuting and grooming time:

$$n_i = h_i + (t_i + g_i)DAYS_i(1 - \delta_i), \quad (2)$$

where $DAYS_i$ is paid workdays per week, $\delta_i \in [0,1]$ is the WFH share of paid workdays, t_i is round-trip commute time on non-WFH workdays, and g_i is the extra time spent on grooming and getting ready for work on non-WFH workdays. Here, we distinguish paid work hours h_i from total time devoted to work n_i.[17] The preference parameter χ_i governs the relative disutility of time devoted to work, and η is the inverse of the Frisch elasticity of labor supply. Consumption cannot exceed labor earnings, $c_i \leq w_i h_i$, where w_i is the wage per paid workhour. When we take the model to the data, we map h_i to survey reports of paid workhours.

According to (1) and (2), workers value WFH because it saves on commuting and grooming time. Later, we will consider a variant of the model with innate and heterogeneous preferences over δ_i to accommodate other reasons why workers like or dislike WFH.

b. Production technologies

A representative, price-taking intermediate firm transforms paid workhours into efficiency units of labor using the following technology:

$$L_i = A_i[(1 - \delta_i)h_i + B_i(h_i\delta_i)^\alpha],$$

where A_i is i's productivity level, B_i is a shifter for i's relative productivity when working remotely, and $\alpha \in (0,1)$ limits the returns to WFH and the substitutability between work modes. Given $B_i > 0$, each individual's remote workhours $(\delta_i h_i)$ are subject to diminishing marginal returns. This captures the idea that a job is a bundle of tasks that differ in how well they can be executed in WFH mode.

[17] Equation (2) omits any baseline grooming time required on all workdays. In fact, we collected data on baseline grooming time. It is small, varies modestly across persons in our sample, and matters little for our quantitative results. Hence, we suppress the baseline grooming time for simplicity.

The intermediate firm sells labor efficiency units to a price-taking final goods producer that generates output according to a linear technology, $Y = \int_{i \in I} L_i \mathrm{d}F(i)$. The final goods producer pays W per labor efficiency unit. The final and intermediate firms are owned by entrepreneurs with linear utility who consume any operating profits or losses.[18]

c. Firm and worker optimality in equilibrium

The final goods producer maximizes its profits by choosing how many labor efficiency units to buy. It sells to consumers in the form of the output good, the numeraire:

$$\max_{L_i} \int_i (1 - W) L_i dF(i) . \qquad (3)$$

Thus, the final goods producer is willing to supply any amount of output as long as the wage per labor efficiency unit W is no higher than 1.

The intermediate firm chooses weekly workhours h_i and work arrangements δ_i for each worker to maximize its profits, taking W and w_i as given:

$$\max_{\{h_i, \delta_i\}_{i \in I}} \int_{i \in I} (WA_i[(1 - \delta_i)h_i + B_i(\delta_i h_i)^\alpha] - w_i h_i) dF(i). \quad (4)$$

Treating h_i and δ_i as continuous, the firm's first-order conditions pertaining to worker i are:

$$h_i: \; WA_i \left((1 - \delta_i) + B_i \alpha h_i^{\alpha - 1} \delta_i^\alpha \right) = w_i,$$

$$\delta_i: WA_i(-h_i + B_i \alpha h_i^\alpha \delta_i^{\alpha - 1}) = 0,$$

which yield two optimality conditions that hold at an interior solution:

$$w_i = WA_i \qquad (5)$$

$$\delta(h_i) = \frac{[\alpha B_i]^{\frac{1}{1-\alpha}}}{h_i}. \quad (6)$$

These conditions determine the set of labor contracts acceptable to the firm, under the assumption that it pays a linear wage w_i for each workhour h_i. Together, these two conditions let us recover the productivity parameters A_i and B_i from observables – hourly wages w_i, work arrangements δ_i, and paid workhours h_i – given a value for α.

Equation (6) implies a positive relationship between B_i and δ_i, whereby the firm offers a higher WFH rate to workers with higher relative productivities in remote mode. Indeed, sufficiently high B_i values yield a corner solution with fully remote work. In that case, $\delta_i = 1$ and

[18] Our setup can be extended to one that requires capital and labor to produce aggregate output, as with $Y = K^\psi L^{1-\psi}$, $L = \int_{i \in I} L_i \, \mathrm{d}F(i)$, and a final goods producer that pays rental rate r for each unit of K and wage W for each labor efficiency unit. This type of extension would be useful in adapting our model to a dynamic setting.

the optimal h_i satisfies $w_i = W\alpha A_i B_i h_i^{\alpha-1}$.[19] This positive relationship between B_i and δ_i in (6) is the model analogue to Figure 2, which shows that higher self-assessed relative productivity in WFH predicts higher WFH rates in the SWAA data. Equation (6) also governs the firm's willingness to trade off WFH and compensation for any individual worker. Specifically, given B_i, the firm is willing to raise worker i's WFH rate only if the worker supplies fewer hours and, hence, earns less income. This tradeoff reflects the declining marginal product of WFH hours coupled with a flat hourly wage for any individual worker.

Workers maximize utility over consumption and hours devoted to work, taking w_i as given, subject to the budget constraint and the contractual requirement (6). Each worker chooses a combination of hours and work arrangements (h_i and δ_i) that makes for an attractive hire to the intermediate firm. At an interior solution, workers face the tradeoff given by (6): a higher value of δ_i economizes on commuting and grooming time, thereby reducing the disutility of hours devoted to work, but also involves fewer paid workhours, lower earnings, and less consumption. This tradeoff can be seen as the model counterpart to the idea that firms regard WFH as an amenity calling for lower compensation.

Substituting from (6) and the budget constraint, worker i's problem becomes

$$\max_{h_i} log\ (w_i h_i) - \chi_i \frac{\left[h_i + (t_i + g_i) DAYS_i \left(1 - \delta(h_i)\right)\right]^{1+\eta}}{1+\eta}, \qquad (7)$$

with first-order condition for an interior solution,[20]

$$\frac{1}{h_i} = \chi_i \left[h_i + \left(t_i + g_i\ \right) DAYS_i \left(1 - \delta(h_i)\right)\right]^{\eta} \cdot \left[1 - \left(t_i + g_i\ \right) DAYS_i \delta'(h_i)\right]. \qquad (8)$$

Equation (8) says workers trade off the consumption benefits of an extra workhour against the disutility associated with that extra workhour. Because $\delta'(h_i) < 0$ per (6), the firm will only accept more workhours from i if the WFH share δ_i goes down. For the worker, that means each extra workhour involves more disutility from commuting and grooming.

The compensation contracts in our model capture salient aspects of the tradeoffs associated with WFH. For example, Bagga et al. (2025) argue that workers will switch jobs or accept lower pay in exchange for the opportunity to WFH. Mas and Pallais (2017), Colonnelli et al. (2025), Lewandowski et al. (2026), and Drake et al. (2025) find a willingness to pay for WFH in

[19] When $B_i = 0$, no WFH ($\delta_i = 0$) is the optimal work arrangement.

[20] At a corner solution with $\delta(h_i) = 1$ and $\delta'(h_i) = 0$ the worker's first-order condition is $\frac{1}{h_i} = \chi_i [h_i]^{\eta}$.

experimental settings. Using data on job offers, Cullen et al. (2025) estimate that US workers in the tech sector will accept 25% lower pay for hybrid or fully remote jobs. Our compensation contracts endogenously yield a tradeoff for workers that involves lower earnings for higher WFH rates. There are other ways to build this tradeoff into a model, for example, by specifying different wage rates for remote and in-person hours. However, that would make it harder to take the model to the data, which rarely reports separate WFH and non-WFH wage rates for a given individual.

d. Equilibrium definition and solution

An equilibrium in this economy is a set of prices $\{W, \{w_i\}_{i\in I}\}$ and paid workhours and work arrangements $\{h_i, \delta_i\}_{i\in I}$ such that:

- the final goods producer maximizes (3) taking W as given;
- the intermediate firm maximizes (4) taking W and w_i as given;
- workers maximize (7) taking w_i as given; and
- entrepreneurs with linear utility consume the value of any profits or losses generated by the firms that produce intermediate and final goods.

In equilibrium, labor efficiency units have the same price as the consumption good ($W = 1$). From equation (5), the hourly wage for worker i then satisfies $w_i = A_i$ whenever there is an interior solution to the intermediate firm and worker problems.

As remarked, workers choose hours and work arrangements (h_i, δ_i) that satisfy (6). We will also consider models that (a) impose work arrangements exogenously, (b) impose a minimum share of in-person workdays per week, (c) let the firm set work arrangements unilaterally, (d) accommodate preferences over WFH that differ among workers, (e) let the production function parameter α vary by industry, and (f) allow work arrangements to have external productivity spillovers. We describe these model variants more fully below.

e. Calibrating the model

We combine SWAA data with model equilibrium conditions to infer productivity and preference parameters. Using data from 2023 to 2025 for respondents with 20 or more workhours in the reference week, and assuming the data reflect interior solutions at equilibrium, we have:

$$A_i = w_i \text{ and } B_i = \frac{(\delta_i h_i)^{1-\alpha}}{\alpha}. \qquad (9)$$

Thus, given α, we can obtain A_i and B_i directly from data on wages, workhours, and work arrangements.[21] The interiority assumption yields the smallest model-consistent B_i values for persons observed to work in a fully remote capacity. Similarly, given η, equation (8) yields the individual-level disutility parameters χ_i after plugging in data on workhours, work arrangements, daily commute time, and extra grooming time on non-WFH days. We set $\eta = 2$ based on Frisch labor supply elasticity estimates near 0.5 (Chetty et al., 2011). Inferring A_i, B_i, and χ_i from first-order conditions that hold in equilibrium is similar to the wedge-finding approach of Chari, Kehoe and McGrattan (2007), Hsieh and Klenow (2009), and Indarte et al. (2026) in other contexts.

That leaves one parameter to pin down, namely α. For any given value of α, (9) yields a vector of WFH productivity shifters, $\{B(\alpha; h_i, \delta_i)\}_{i \in I}$. To calibrate α, we exploit the observation that the model yields a relationship between B_i and δ_i that corresponds to the empirical relationship in Figure 2 between self-assessed relative productivities in WFH mode and WFH rates. Thus, we choose α to minimize the sum of squared deviations:

$$\alpha = argmin \sum_{i \in I} \omega_i \cdot \left(b_i - B_i(\alpha; h_i, \delta_i)\right)^2 \qquad (10)$$

where ω_i is the sample weight for individual i and b_i is their self-assessed relative productivity in WFH mode. We set $b_i = 0$ for workers with zero WFH experience since 2020, under the assumption that they (or their jobs) are unsuitable for WFH. We set $b_i = 1$ for those who report equal efficiency in both modes, $b_i = 1.05$ for those who report 5% higher efficiency in WFH mode, $b_i = 0.95$ for those who report 5% lower efficiency, and so on. Appendix Figure A.10 plots the objective function in (10) and shows a unique minimum at $\alpha = 0.975$. That is not far from $\alpha = 1$, which would imply perfect substitutability between work modes *among workers with* $B_i > 0$. Thus, our estimate broadly aligns with the literature, including Davis, Ghent, and Gregory (2024b) who find a high elasticity of substitution between onsite work and WFH of 3.6. Similarly, Eberly et al. (2021) consistently estimate elasticities of substitution above 1. We can easily let α vary by observable job or worker characteristics, as in Figure A.11 for industry and gender.

A potential concern with our approach to calibrating α is that survey respondents might report overly favorable assessments of their relative productivities in WFH mode. Suppose, for example, that respondents overstate relative WFH productivities by five percentage points.

[21] For paid workhours, we ask "*How many* **hours** *did you* **work for pay last week?***"* For hourly wages, we divide earnings in the prior year by fifty times weekly hours, where the earnings figure is based on bin-level responses to *"*Approximately how much did you **earn by working in [the previous calendar year], on a before-tax basis***?"*

Adjusting for this hypothetical bias and reoptimizing in (10) yields $\alpha = 0.986$, which implies more substitutability between work modes than our baseline value of $\alpha = 0.975$. Shifting the b_i values downward raises α, because we then need weaker diminishing returns to WFH to rationalize the observed WFH rates. For the quantitative exercises in Section 5, we will consider the sensitivity of our results to a range of α values. That said, Figure 2 suggests some respondents understate WFH efficiency: average WFH rates exceed 10% for those reporting 40% lower WFH efficiency.

Now consider the productivity parameters that emerge by taking our model to the SWAA data. Plugging $\alpha = 0.975$ and the individual-level WFH hours into (9) yields the vector of B_i values, with $B_i = 0$ for workers with zero WFH hours. To assess the reasonableness of the B_i values, Figure 4 reports means by industry and occupation. The industry means range from 0.2 in Hospitality & Food Services to 0.8 in the Information sector. The occupation means range from 0.2 in Transportation to 0.6 in Management, Business, and Financial. These values – and the fuller set of industry and occupation means – align well with our prior views on the practicality of WFH. They reflect the mix of fully on-site workers ($B_i = 0$) and those who WFH ($B_i > 0$) by industry and occupation. Indeed, most jobs in Hospitality & Food Services offer little scope for WFH, while Information often has the highest WFH rate among all U.S. industry sectors.

Figure 5 displays histograms of the A_i values for individual productivity levels and the B_i shifters for relative productivities in WFH mode. The A_i values differ by a factor of more than ten across workers. $B_i = 0$ for about 62% of the sample, while $B_i \in (1.054, 1.142)$ for the other 38%. Appendix Table A.1 reports regressions of the b_i and B_i values on age and education categories, sex, earnings, and time spent on commuting and (extra) grooming on onsite workdays. The conditional means of both b_i and B_i are highest among workers in their 30s and lowest for those over 50. The conditional means are higher for college graduates and those with longer commutes, and they rise steeply with earnings. The conditional mean of b_i is lower for men than women, while the conditional mean of B_i is greater for men. This pattern partly reflects a different sorting of men and women across industries that differ in their suitability for remote work.

5. Implications of Work from Home for Productivity and Welfare

a. Designing and implementing counterfactuals

We now use the calibrated model to assess the productivity and welfare consequences of WFH. In our first analysis, we consider the effects of a return to 2019 levels of remote work. We implement this analysis with counterfactual work arrangements $\{\delta_i'\}_{i \in I}$ as follows:

- Randomly select a fraction of fully remote workers ($\delta_i = 1$) in the 2023-2025 data to instead work fully onsite ($\delta_i' = 0$). Set this fraction so that 4.7% of workers are fully remote in the counterfactual, matching the fully remote share in the 2019 American Community Survey (ACS).[22]
- Randomly select a fraction of workers with hybrid arrangements ($0 < \delta_i < 1$) in the 2023-25 data to work fully onsite ($\delta_i' = 0$). Set this fraction so that WFH accounts for 7.2% of all paid workdays in the counterfactual.[23]
- Fully onsite workers ($\delta_i = 0$) in the 2023-25 data continue to work fully onsite in the counterfactual ($\delta_i' = 0$).

This counterfactual requires 27.2% of the workforce to cut back on WFH.

In a second analysis with the basic model, we consider policy interventions that curtail WFH by requiring a minimum number of onsite workdays. In a third analysis, we consider a scenario that resembles the pandemic-era lockdown episode, denying the option to work onsite in the counterfactual to all workers with WFH experience since 2020. Other workers retain their 2023-2025 work arrangements in this counterfactual.

Because we impose work arrangements exogenously in these counterfactuals, worker and firm optimality conditions take $\{\delta_i'\}_{i\in I}$ as given. The intermediate firm's problem now becomes:

$$\max_{\{h_i\}_{i\in I}} \int_{i\in I} (WA_i[(1-\delta_i')h_i + B_i(\delta_i' h_i)^{\alpha}] - w_i h_i)\mathrm{d}\,F(i),$$

yielding the first-order condition with respect to h_i

$$w_i = WA_i[(1-\delta_i') + \alpha B_i {\delta_i'}^{\alpha} h_i^{\alpha-1}].$$

Worker i's optimization problem now becomes:

$$\max_{h_i} \log(w_i h_i) - \chi_i \frac{[h_i + (t_i + g_i)\mathrm{DAYS}_i(1-\delta_i')]^{1+\eta}}{1+\eta},$$

with the first-order condition

[22] The ACS question reads *"How did this person usually get to work LAST WEEK? Mark (X) ONE box for the method of transportation used for most of the distance."* We interpret the share of people who respond "worked from home" as a measure of fully remote work.

[23] We focus on persons with annual earnings above $20,000 in the ATUS; count days with six or more workhours on the main job, regardless of location, as paid workdays; and treat WFH days as ones with six or more hours on their main job at home. This mirrors our approach in the SWAA data. We incorporate the 4.7% figure for fully remote workers in the target 7.2%.

$$\frac{1}{h_i} = \chi_i[h_i + (t_i + g_i)\text{DAYS}_i(1 - \delta_i')]^{\eta}.$$

Given work arrangements $\{\delta_i'\}_{i\in I}$, the counterfactual equilibrium entails prices $\{W, \{w_i\}_{i\in I}\}$ and hours $\{h_i\}_{i\in I}$ that solve the modified worker and firm optimization problems. As before, the (numeraire) output good and labor efficiency units have the same price in equilibrium, and entrepreneurs with linear utility consume profits or losses.

We are interested in how the counterfactual work arrangements affect *measured* labor productivity, *effective* labor productivity, output, and welfare – all relative to the observed equilibrium in the 2023-25 data. We compute measured labor productivity in the usual manner as output divided by paid workhours:

$$\frac{Y}{H} = \frac{\int_{i\in I} L_i \, dF(i)}{\int_{i\in I} h_i dF(i)}. \quad (11)$$

We compute effective labor productivity as output divided by total hours devoted to work, inclusive of commuting and (extra) grooming time on onsite days:

$$\frac{Y}{H + T + G} = \frac{\int_{i\in I} L_i dF(i)}{\int_{i\in I}[h_i + (t_i + g_i)DAYS_i(1 - \delta_i)]\, dF(i)}. \quad (12)$$

Because (12) captures time spent commuting and getting ready for onsite work, it is better suited than (11) for assessing how work arrangements affect the efficiency with which the economy transforms worker time into market output.

We measure welfare effects using consumption-equivalent proportional changes x_i,

$$log((1 + x_i)c_i) - \chi_i \frac{[h_i + (t_i + g_i)DAYS_i(1 - \delta_i)]^{1+\eta}}{1 + \eta}$$

$$= log(c_i') - \chi_i \frac{[h_i' + (t_i + g_i)DAYS_i(1 - \delta_i')]^{1+\eta}}{1+\eta} \quad (13)$$

where primes ($'$) denote counterfactual values. We focus on worker welfare for two reasons. First, entrepreneurs account for only a small slice of consumption and output. In the baseline equilibrium, profits of intermediate firms equal 0.7% of aggregate output, and the final goods producer has zero profit. Second, our survey data yield rich evidence on wages, commute times, grooming time, and WFH preferences for workers but not for firm owners.

b. Results for counterfactuals in the basic model

Returning to 2019 work arrangements: Table 1 compares counterfactual outcomes to the ones generated by the model when fit to 2023-25 data. As reported in row (1), returning to 2019

arrangements yields a 0.7% drop in measured labor productivity and a 1.1% loss of output. To understand these results, recall from Figure 5 that 38% of workers are more productive in WFH mode for *some* of their job-related tasks. Forcing many of them to cut back on WFH reduces measured productivity and output. It also raises the scarcity value of their time, which drives a reduction in paid workhours. A countervailing force is also in play because the WFH rate in the baseline equilibrium exceeds the rate that maximizes aggregate measured productivity. Hence, even qualitatively, our output and measured productivity results are not hard-wired into the model. Other calibrations can yield higher levels of measured productivity and output under 2019 work arrangements than at the baseline, as we show in our sensitivity analysis.

Returning to 2019 arrangements lowers *effective* productivity by 3.5%, five times the drop in measured productivity. Here, the explanation is straightforward: the 2019 arrangements involve more time devoted to commuting and grooming. The effective productivity measure captures this time savings, while the conventional measure does not. Returning to 2019 arrangements also lowers consumption-equivalent welfare by 2.6%, on average. This figure is greater than the output drop because it captures the value of lost time savings, which is the main source of the welfare loss associated with a return to 2019 arrangements in the calibrated version of our basic model.

The mean welfare loss of 2.6% masks a great deal of heterogeneity across workers. To highlight this point, Figure 6 shows the distribution of welfare changes among workers directly affected by a return to 2019 arrangements. About 6% of these workers experience welfare losses equivalent to a consumption cut of 25% or more. Those with shorter commutes, lower baseline WFH rates, and lower disutility of time devoted to work have smaller welfare losses. The high dispersion in welfare losses shown in Figure 6 offers some insight into why return-to-office mandates are so strongly resisted by some workers. We return to this point later.

Policies that curtail WFH directly: Some observers regard (too much) remote work as harmful to economic performance, giving rise to policy proposals that would discourage or restrict the extent of WFH. We now assess the economic effects of policies that cap individual-level WFH rates by requiring at least 1, 2, 3, 4 or 5 onsite workdays per week.[24] Figure A.12 depicts the effects of these interventions on output, productivity, and mean welfare, all expressed as percentage deviations from the baseline outcome with no compulsory minimum for onsite workdays. As the

[24] When the onsite requirement binds, we solve individual-level outcomes as explained in Section 5.a. When the requirement does not bind, we solve for outcomes as explained in Section 4.

figure shows, compelling everyone to work onsite at least 1 day per week (20% of workdays) *raises* measured productivity and output, in large part because it has a positive effect on hours. To understand this result, recall that WFH in the baseline equilibrium exceeds the rate that maximizes aggregate measured productivity. That happens because workers choose WFH rates with an eye toward time savings as well as productivity. Pushing them to work onsite somewhat more than in the unconstrained equilibrium can raise measured productivity and does so in our calibration. However, as Figure A.12 also shows, requiring 3 or more onsite workdays per week lowers both measured productivity and output. When $B_i > 1$ for some workers, measured productivity and output are maximized at positive WFH rates, not zero WFH rates.

Despite the output gains generated by modest restrictions on WFH, these policies always reduce welfare and effective productivity in our basic model. Moreover, those welfare and effective productivity costs rise with the number of compulsory onsite days. Those costs will be especially large for workers who optimized their residential location (and commute) for an equilibrium with high WFH rates (see Akan et al., 2026) and who would see large increases in commuting if forced back onsite. In the long run such workers might change jobs or move closer to work, which our model does not capture.

Lockdown-like work arrangements: Row (2) of Panel A in Table 1 reports results for a return to lockdown-like work arrangements. In our 2023-25 data, 12.5% of workers operate in a fully remote mode in the baseline equilibrium. These workers continue to work entirely from home in the counterfactual. WFH is feasible (possibly under duress) for 46% of our sample, as revealed by their WFH experiences since 2020, but not productive enough to warrant fully remote work in 2023-25. Requiring these workers to shift to fully remote work lowers output by nearly 19% relative to the 2023-25 baseline. Here, the output losses arise for two reasons: First, the lockdown pushes some workers out of employment – specifically, those among the 46% with $B_i = 0$. Second, for those among the 46% with $B_i > 0$, output per hour falls because of the requirement to work in a fully remote capacity.

Despite the output collapse, measured labor productivity rises by 1% relative to the 2023-25 baseline due to a composition effect. Specifically, those who get pushed to non-employment by the lockdown requirement have lower earnings, and hence lower values of A_i in our calibrated model. We see that pattern in Table A.1, which shows that both b_i and B_i rise strongly with individual-level earnings. This role for composition effects on measured productivity in our

quantitative analysis echoes observed outcomes in the early phases of the COVID-19 pandemic, which saw strong labor productivity gains amidst an employment and output collapse (Stewart, 2022). Because of reduced commuting and grooming time under lockdown arrangements, the counterfactual yields an even larger gain in effective productivity.

The lockdown scenario drives large welfare losses, with a mean loss of 18.8%. The welfare losses are 100% for workers who get pushed out of employment. Obviously, this is an extreme outcome that reflects an absence of risk-sharing mechanisms in our model. While those mechanisms were prominent aspects of the 2020 pandemic episode, they are not central to the issues tackled in this paper. Hence, we do not take them up here.

c. Counterfactuals with preference heterogeneity over WFH

Our basic model highlights the time-saving aspect of WFH, which aligns with the relationship between commuting and WFH desires in Figure 3. Survey respondents also point to the time-savings benefits of WFH when asked directly. As Figure A.13 reports, 45% of respondents identify "no commute" as a top benefit of WFH, while 35% point to "less time getting ready." Nearly half point to "save on gas & lunch," which is also closely tied to commuting. However, "flexible work schedule," "more time with friends and family," and "quiet" also feature prominently as WFH benefits. Moreover, the regression of desired WFH on commute time in Figure 3 yields an R-squared value of only 0.03. Similarly, Aksoy et al. (2022), Barrero et al. (2023), and Buckman et al. (2025) find low R-squared values when regressing actual or desired WFH rates on commuting time, children in the household, and many other covariates. These results suggest a great deal of heterogeneity in preferences over WFH that is not easily explained by commuting, family circumstances, or other readily observable worker characteristics.

To assess the implications of this preference heterogeneity, we modify our basic model so that an individual's utility now depends on consumption, workhours, and the gap between actual work arrangements δ_i and an innate desired WFH rate $\gamma_i \in [0,1]$:

$$u(c_i, h_i, \delta_i) = \log(c_i) - \chi_i \frac{h_i^{1+\eta}}{1+\eta} - \frac{\psi}{2}(\delta_i - \gamma_i)^2.$$

For persons with WFH experience, we calibrate the γ_i values using responses to "***Looking one year ahead,*** how often [per week] would you ***like to*** have paid workdays at home?"[25] We set $\gamma_i =$

[25] This wording is the one we've used since August 2023. Prior to that, the initial clause asked, "As the pandemic ends" and other references to the post-pandemic future.

0 for those who say zero days, $\gamma_i = 0.2$ for those who say one day, and so on. This question also yields the data for the vertical axis in the right panel of Figure 3. For simplicity, we assume no aversion to commuting other than that implied by individual preferences for WFH in γ_i.

The parameter ψ governs how strongly people dislike deviations from their desired WFH rates relative to their preferences over consumption and workhours. Hence, we calibrate ψ using evidence on the willingness to pay to WFH. Mas and Pallais (2017) estimate an average willingness to pay equal to 8% of earnings.[26] We associate their estimate with the consumption-equivalent welfare cost of the maximum possible gap between δ_i and γ_i. This maximum gap yields a utility loss of $\frac{\psi}{2} * (1)^2 = \frac{\psi}{2}$. Expressing this loss in consumption-equivalent terms:

$$-\frac{\psi}{2} = \log(1-x) \Rightarrow \psi = -2 * \log(1-x).$$

Setting $x = 0.08$ yields $\psi = 0.17$, which we treat as our preferred calibration value.

After substituting in the budget constraint and the restriction (6) on work arrangements, the worker's optimization problem becomes

$$\max_{h_i} \log(w_i h_i) - \chi_i \frac{h_i^{1+\eta}}{1+\eta} - \frac{\psi}{2}(\delta(h_i) - \gamma_i)^2,$$

and the first-order condition is now given by:

$$\frac{1}{h_i} = \chi_i h_i^{\eta} + \psi(\delta(h_i) - \gamma_i)\delta'(h_i). \qquad (14)$$

Because $\delta'(h_i) < 0$, the second term on the right side of (14) can be positive or negative, depending on whether the individual's WFH rate is more or less than their preferred WFH rate. We calibrate the χ_i parameters to satisfy (14) in the 2023-2025 data. Other equilibrium conditions and calibration elements follow our approach in the basic model, again under the assumption that the observed data reflect interior solutions at equilibrium.

Rows (3) and (4) in Table 1 report results for the "Return to 2019" and "2020 Lockdown" counterfactuals using this alternative model. The productivity effects associated with these counterfactuals are similar to the ones we obtained for the basic model. However, the changes in output, hours, and welfare losses associated with the "Return to 2019" counterfactual are smaller when using the alternative model, at least for our preferred calibration of ψ.

[26] See, also, Aksoy et al. (2022) and Cullen et al. (2025).

d. Sensitivity analysis

Thus far, we have assumed that workers choose work arrangements subject to (6). This assumption takes seriously the view that workers correctly perceive the tradeoff embodied in (6), which depends on the intermediate firm's production function, and that workers can sort across jobs to find their preferred point on the tradeoff. Both elements of this view can be questioned. In practice, we often see firms specify work arrangements that workers take as given. Assigning authority over work arrangements to the firm has advantages when the firm has better knowledge of the production function.

In light of these concerns, we now modify our models so that workers take work arrangements as given. The intermediate firm's optimality conditions are again given by (5) and (6), while the worker's first-order condition in the basic model is now

$$\frac{1}{h_i} = \chi_i[h_i + (t_i + g_i)DAYS_i(1 - \delta_i)]^{\eta}. \qquad (15)$$

To calibrate this version of the model, we set δ_i to the individual's observed WFH rate in the 2023-25 data and infer χ_i to rationalize the observed h_i value in (15).

Table A.2 reports results for this version of the basic model in Panel A. As reported in row (1) (and comparing to row (1) in Table 1), returning to 2019 work arrangements yields somewhat larger declines in productivity, output, and welfare than before. Lockdown arrangements also yield modestly greater output and welfare declines for this version of the basic model. Panel B in Table A.2 shows that how we determine work arrangements is even less consequential in the model with preference heterogeneity over WFH. We conclude that our results are not very sensitive to the details of how we model the determination of work arrangements.

Next, consider the sensitivity of our results to the choice of α, the production function parameter that governs diminishing returns in WFH hours. Figure A.14 shows how the productivity, output, and average welfare effects of returning to 2019 arrangements vary with α. The average welfare effect is insensitive to small changes in α. The productivity and output effects are more sensitive, but still stable in a broad vicinity of $\alpha = 0.975$. Recall that correcting for overly favorable assessments of own WFH productivity raises the calibrated α value modestly. So, Figure A.14 implies that over-optimism about own WFH efficiency leads us to overstate the productivity and output losses caused by a return to 2019 work arrangements but only to a modest extent. If SWAA respondents exaggerate their relative WFH productivities by five percentage points,

adjusting for the bias and reoptimizing in (10) yields $\alpha = 0.986$. Using this α value, a return to 2019 arrangements causes output to drop by 0.9% rather than 1.1% with our baseline $\alpha = 0.975$.

We also consider a version of the basic model that calibrates α separately by industry, using the values in Figure A.11. As reported in Table A.3, this more flexible model specification yields productivity, output, and welfare effects from a return to 2019 work arrangements, or a 2020 lockdown arrangement, that are very similar to the results reported in Tables 1 and A.2.[27]

Figure A.15 shows how the productivity, output, and welfare effects of returning to 2019 work arrangements vary with ψ. That parameter governs how strongly people dislike deviations from their desired WFH rates in the model with heterogeneous preferences over WFH rates. We set the baseline value for that parameter based on Mas and Pallais (2017). The figure shows little change in the productivity and output consequences of returning to 2019 work arrangements when using other values of ψ. In contrast, and unsurprisingly, the welfare costs of a compulsory return to 2019 work arrangements rise with ψ, because many workers want to WFH more than in 2019.

Finally, Figure A.16 shows the sensitivity of our key results to changes in the Frisch elasticity of labor supply, whose baseline value follows Chetty et al. (2011). Under high enough Frisch elasticities, workers respond to the imposition of 2019 WFH rates by working more, yielding higher hours, output, and (in extreme cases) measured productivity. This result shows that our model does not hardwire a drop in output or measured productivity from a drop in WFH. The welfare and effective productivity effects are less sensitive to changing the Frisch elasticity.

e. Additional discussion

Many CEOs and analysts argue that onsite work fosters productivity-enhancing spillovers among coworkers, boosting growth and innovation. If these spillovers are internal to a single firm, or to a group of firms that can readily cooperate, firms are incentivized to adopt work arrangements that reflect the spillovers. When the productivity spillovers of each firm's work arrangements diffuse over many other firms, it becomes harder to internalize them in a decentralized manner. That raises the possibility that policy interventions to reduce WFH could raise welfare relative to decentralized outcomes. Monte et al. (2026) argue that the persistent reduction of in-person workdays observed after 2020 leads to welfare losses on the order of 2% due to these externalities.

[27] Table A.3 looks identical to Table 1 after rounding to one decimal point, but the underlying numbers are not identical between the two. They look similar because our estimates of industry-specific α values are all very similar to the single α in the baseline results from Table 1, and our results are not sensitive to small changes in α (Figure A.14).

We can bring this idea into our models by modifying the production technology of intermediate firms to include a term that captures external effects of work arrangements:

$$L_i = A_i[(1-\delta_i)h_i + B_i(h_i\delta_i)^{\alpha}]\left(1-\bar{\delta}\right)^{\varepsilon},$$

where $\bar{\delta}$ is the mean WFH rate, and ε captures the strength of spillovers. The case of $\varepsilon = 0$ nests the earlier models, while $\varepsilon > 0$ corresponds to net positive spillovers that rise with the onsite work share. Because firms and workers treat $\bar{\delta}$ as outside their control, the optimality conditions have the same form as before. Hence, for a given value of ε, we can solve for decentralized equilibrium outcomes as before. The firm's optimization problem, when paying a linear wage w_i per hour of paid work h_i and choosing work arrangements δ_i and hours h_i, yields two optimality conditions:

$$w_i = WA_i\left(1-\bar{\delta}\right)^{\varepsilon} \quad (16)$$

$$\delta_i = \frac{[\alpha B_i]^{\frac{1}{1-\alpha}}}{h_i}. \quad (17)$$

Equation 17 is identical to (6) in the basic model. Equation 16 clarifies that the external effect of in-person work raises the marginal product of an hour of work and thereby raises wages. A counterfactual equilibrium that lowered $\bar{\delta}$ could raise worker welfare if this effect is big enough to offset the losses from extra commuting time. Given ε, we can infer the values of A_i and B_i that satisfy (16) and (17) using post-pandemic data on wages, paid workhours, and work arrangements. The worker's optimization problem is unchanged from the basic model.

How large must ε be for a return to 2019 work arrangements to raise output or average consumption-equivalent welfare? Figure A.17 in the appendix shows that higher values of ε lead to less negative effects on productivity, output and welfare, and to positive effects for high enough ε. Table 2 reports the "breakeven" ε value such that the baseline 2023-25 equilibrium outcomes and the counterfactual imposing a return to 2019 WFH rates yield the same amount of aggregate output or average welfare. The left panel assumes the externality depends on the equal-weighted mean WFH rate, and the right panel assumes it depends on the productivity- (i.e., A_i-) weighted mean WFH rate. When imposing a return to pre-pandemic WFH rates, our basic model requires $\varepsilon \geq 0.060$ to avoid a loss in aggregate output and $\varepsilon \geq 0.141$ to avoid a loss in mean consumption equivalent welfare for $\bar{\delta}$ determined by the equal-weighted WFH rate. The corresponding breakeven ε values are 0.046 and 0.108, respectively, for $\bar{\delta}$ determined by the A_i-weighted WFH rate. The breakeven values of ε are also smaller when we use the model with heterogeneous WFH

preferences, because the output and welfare losses arising from a forced return to 2019 WFH rates are smaller in that specification (see Table 1).

Monte et al. (2026) estimate an elasticity of wages to in-person work performed in the city center of 0.067 for the mean US city. Under a value of $\varepsilon = 0.067$, in-person spillovers would be large enough to avoid output costs in our basic model, but not enough to avoid some loss in average welfare and effective productivity when imposing 2019 work arrangements (Figure A.17). It's unclear whether their city-level estimates map one-for-one to our ε, however. If we interpret their estimates to include both within-firm and external spillovers, that points to a value of $\varepsilon < 0.067$. That is because the internal spillovers show up in A_i and B_i, which reflect firms' optimal choices, and leave only external spillovers to ε. Still, our analysis in Table 2 and Figure A.17 suggests that spillovers could meaningfully change our estimated welfare and productivity effects.

Our analysis abstracts from dynamic effects of WFH. Sedlacek and Shi (2025), for example, argue that availability of WFH induces entry of smaller, less-productive firms because it allows for operation with lower fixed costs, including those related to office floorspace. Consistent with this logic, since 2020 there has been a sustained surge in business applications (see Decker and Haltiwanger, 2023) which may partly reflect lower fixed costs when entrepreneurs can WFH most of the time. Gupta et al. (2025) and Kwan et al. (2025) also provide evidence to suggest WFH boosts entrepreneurship: they show remote startups grow faster, and fully remote employees are more likely to become entrepreneurs.

There are subtleties in the interpretation of our model's productivity parameters, especially B_i, which governs worker i's relative productivity in remote mode. B_i captures the *net* impact of WFH on relative productivity from the viewpoint of the employing firm. Several papers, including Battiston et al. (2021) and Emanuel and Harrington (2024), estimate a negative impact of remote work due to communication frictions. Atkin et al. (2023) report experimental evidence that on-the-job learning is faster onsite. But reduced floorspace requirements can make WFH profitable if they lower costs by enough to offset WFH productivity losses, implying positive B_is in our framework. Indeed, Flynn et al. (2025) show S&P 500 firms tend to allow their employees to WFH more when their headquarters are in cities with pricier office real estate.[28] That also means we will recover higher B_is when firms reduce floorspace per worker. Tangible and intangible investments by

[28] Gupta et al. (2026) also link higher levels of WFH to lower floorspace use and quantify the effect of WFH on commercial office real estate valuations.

workers and their employers that facilitate WFH also push up our inferred B_is. That includes investment in IT systems, computer hardware, management practices that support workers doing their job remotely, and utilization of latent or "potential" capital, as Eberly et al. (2021) note. Several studies show WFH has expanded labor markets geographically, including Coskun et al. (2025) and Akan et al. (2026).[29] If that expansion improves the quality of job matches, firms will choose more WFH as if B_i were higher.

Our model abstracts from the potential for WFH to encourage labor force participation. People with physical disabilities or psychological conditions that make it hard to work onsite, for example, will find it easier to get and keep jobs if WFH opportunities are abundant (Bloom et al., 2026). This logic extends to people who care for young children or the elderly. For example, Harrington and Kahn (2023) and Tito (2024) find that employment gaps of mothers narrow when they can WFH. Ho and Jalota (2024) and Ho et al. (2025) show experimentally that WFH opportunities raise female labor force participation in South Asia.

6. Why Didn't the Shift to WFH Happen Earlier?

If WFH raises effective labor productivity and welfare for many workers, why did workers and firms not adopt it more fully before the pandemic? The technologies and capital that support WFH, including video-conferencing software, personal computers, high-speed internet access, and dwellings were all in place in 2019, as Eberly et al. (2021) highlight. This section provides evidence from the SWAA that workers and their employers re-optimized work arrangements after forced experimentation with WFH during the pandemic, overcoming barriers to WFH adoption and eventually settling into a post-pandemic equilibrium with higher WFH rates.

We now sketch a theoretical framework of how forced, simultaneous experimentation can lead to persistent changes in work arrangements. Appendix C sets forth the formal theory for interested readers. We make the following assumptions. First, even if WFH technology is available, firms that have never operated the technology face a one-time adoption cost to try it out. Second, the individual firm and worker payoff to WFH rises with the WFH rate in the broader economy. For example, it is commercially more attractive for a law firm to let its employees WFH when the employees of competitors and customers also WFH. Third, firms and workers are uncertain about the payoffs to WFH. They can learn about those payoffs by paying the adoption

[29] Bick et al. (2024) also link the rise of WFH to a concurrent rise in US interstate migration that would also facilitate improved cross-firm labor allocations.

cost and experimenting with WFH technology. Fourth, their prior beliefs about the productivity of WFH need not be correct on average. Finally, experimenting with WFH could be more informative when other firms are also experimenting with WFH at the same time.

Under these assumptions, the economy can stay in an equilibrium with low WFH rates because adoption costs, payoff uncertainties, and strategic complementarities deter firms from experimenting with a potentially better, but unproven WFH technology. An event that temporarily lowers the payoff to onsite work (e.g., "lock down" mandates and social distancing in reaction to a pandemic) can induce many firms and workers to incur WFH adoption and experimentation costs. Some firms and workers then learn that WFH works well for them, and so they continue to WFH after the forcing event ends. Strategic complementarities embedded in WFH payoffs induce others to WFH as well, leading to an amplified response. These effects are stronger if concurrent experimentation helps workers and firms learn more about their WFH payoffs, and when prior views about WFH payoffs are overly pessimistic on average. Thus, the theory admits a pre-pandemic, pre-experimentation equilibrium with low WFH rates and a post-pandemic, post-experimentation equilibrium with higher WFH rates and higher welfare.

Several pieces of evidence from our SWAA data support this narrative of forced experimentation, learning, and re-optimization in reaction to the pandemic shock. Between July 2020 and April 2022, we asked SWAA respondents with WFH experience: *"Compared to your expectations* **before COVID (in 2019)** *how has working from home turned out for you?"* The response options range from *"Hugely better – I am 20%+ more productive than I expected"* to *"Hugely worse – I am 20%+ less productive than I expected."* Figure 7 shows the distribution of responses, revealing two key findings. First, workers on balance report having a better WFH experience than they expected. Only about 12% say it was worse than expected. This result suggests that overly pessimistic prior views inhibited workers and firms from experimentation with WFH until the pandemic forced the matter. The knowledge gained from experimentation then led many firms and workers to favorably revise their assessments of WFH, leading to persistently higher WFH rates after the pandemic ended. Second, Figure 7 reveals wide dispersion in productivity surprises, which stands regardless of whether prior expectations about WFH were correct on average. Assigning midpoint values to each response bin (and ± 25 for the two extremes) in Figure 7, the standard deviation of the productivity surprises is 12.6 percentage points (ppt), and the 10^{th} and 90^{th} percentiles are -5% and +25%.

The dispersion matters because it means the experiment revealed different information to different workers. Moreover, that information passes through to worker preferences, employer plans and actual WFH adoption, as shown in Figure 8 and Table 3. The left panel of Figure 8 relates WFH productivity surprises to: (1) the amount of WFH that workers want post-pandemic, measured before mid-2022 using the same question we tapped to specify idiosyncratic WFH preferences in Section 5 (*"...how often would you like to have paid days at home?")*; and (2) employer plans for post-pandemic WFH, also measured before mid-2022 (*"how often is your employer planning for you to have full workdays at home"*). In both cases we see a positive slope, meaning that workers with more positive WFH surprises want more WFH, and their employers plan for them to WFH at higher rates in the long term.[30]

Stated desires and plans need not translate into reality. The right panel of Figure 8 shows they do, and that the pattern sharpens over time. A more positive WFH productivity surprise predicts higher WFH in each of 2020, 2021, and 2022, with steeper gradients in later years. That means productivity surprises predict actual WFH outcomes more sharply near the end of the pandemic, once the force of lockdowns and anxiety about the virus receded and re-optimization became the primary force behind the staying power of WFH. Earlier, widespread WFH reflected the force of the pandemic, which is why overall WFH is higher in 2020 (when many more workers were fully remote) but rises much less with the productivity surprise. Table 3 shows this steepening over time is a robust feature of the data for WFH desires, plans, and rates. Even-numbered columns in Table 3 include detailed controls for demographic characteristics, earnings, and survey-wave effects, with little impact on the key productivity surprise coefficients. Each of the three dependent variables has a different time profile from 2020 to 2022. WFH desires change little, while employer plans for WFH rise (Figure A.5). Actual WFH levels drop significantly from 2020 to 2022 as the pandemic recedes. Yet, for all three dependent variables, the pandemic-era WFH productivity surprises become stronger predictors of the outcome over time, as the pandemic recedes.

We can use our basic model and the data behind Figures 7 and 8 to ask whether learning and re-optimization account for much of the WFH rise since 2019. Take worker i in 2023-2025, who, after experimenting with WFH since 2020, has WFH rate δ_i and productivity in remote mode B_i. We assume both the worker and her employer learned B_i after experimenting with WFH during

[30] Aksoy et al. (2022) show the same patterns for employer plans in all 27 countries covered by the 2021 and 2022 waves of the Global Survey of Working Arrangements.

the pandemic, where B_i' is the prior belief about i's productivity in remote mode. Learning entails drawing a shock s_i that leads the worker and employer to a revised belief $B_i = B_i'(1 + s_i)$. The shift from B_i' to B_i yields a shift in i's WFH rate from δ_i' before learning to δ_i afterwards.

By taking our evidence on learning and re-optimization at face value, we can reverse-engineer what beliefs about worker i's relative productivity in remote mode were before learning. Specifically, we generate a vector of beliefs $\{B_i'\}_{i\in I}$ by simulating learning shocks $\{s_i\}_{i\in I}$ that reflect the joint distribution of productivity surprises and re-optimized work arrangements in 2022.[31] Figure 8 says that workers who draw more positive shocks s_i learn they have higher B_i values and settle on higher δ_i choices. The flipside is that if we observe a high WFH rate δ_i for i in 2023-2025, she likely drew a positive learning shock when forced to experiment with WFH. Indeed, we can compute the distribution of learning shocks consistent with her post-pandemic WFH rate of δ_i, $\Pr(s|\delta = \delta_i)$.[32] We use this distribution to draw a learning shock $s_i \sim \Pr(s|\delta = \delta_i)$ for each worker i in our 2023-2025 sample who experimented with WFH since 2020. Because we have B_i in our baseline calibration (Section 4), we recover $B_i' = B_i/(1 + s_i)$ for all such workers. For those with no WFH experience, we assume $B_i' = B_i = 0$. We then use the vector $\{B_i'\}_{i\in I}$ to compute a counterfactual equilibrium with pre-pandemic beliefs about WFH, while fixing productivities (A_i), preferences (χ_i), and commuting and grooming times (t_i and g_i). To quantify the impact of learning, we compare the average WFH rate in this counterfactual economy against what we observe in our SWAA data in 2023-2025 and in the 2019 ATUS.

Table 4 shows the results. Panel A reports the 2023-2025 WFH rate of 23.1% for the sample used to calibrate the model's post-pandemic equilibrium, alongside the 2019 WFH rate of 7.2% in the American Time Use Survey. Our pre-learning counterfactual yields a similar WFH rate of 8.4%, even though nothing in our calibration or the construction of the counterfactual uses pre-pandemic data. Thus, according to our basic model, learning and re-optimization account for 92% (100*(23.1-8.4)/(23.1-7.2)) of the rise in WFH rates from 2019 to 2023-2025. The rest likely

[31] We stopped asking the question about productivity surprises in mid-2022 out of concern about recall bias. Thus, we do not observe productivity surprises for workers after 2022. Our exercise assumes the link between WFH productivity surprises and lasting WFH rates is consistent with what we see in 2022.

[32] Computing this distribution is easy because δ_i is the ratio of WFH days to all workdays in the survey reference week. Since the numerator and denominator are both integers from 0 to 7, δ_i takes a finite number of values. Additionally, the survey question underlying the shock distribution in Figure 7 has a finite number of response options. As in Figure 8 and Table 3, we assign a value of 0 to the option "About the same," +25% or -25% to "Hugely better" and "Hugely worse," and the midpoint of the range specified for the other responses.

reflects other channels not captured by the model, like investments by firms and workers that make WFH more productive. Cross-worker differences in the size and sign of the productivity surprises are also critical for the model's prediction of an 8.4% WFH rate absent learning. If we create $\{B_i'\}_{i\in I}$ by scaling down every B_i by the average productivity surprise implied by Figure 7, the model predicts a 0.9% WFH rate, greatly undershooting the 7.2% figure from 2019.

Panel B of Table 4 reports the change in productivity, output, hours, and welfare from our counterfactual, pre-learning equilibrium to the one implied by the 2023-2025 data. This panel assumes output and welfare in the counterfactual are generated from the pre-learning $\{B_i'\}_{i\in I}$. Learning yields modest effects on measured productivity (0.1%), output (0.6%), and hours (0.4%). It yields larger gains in effective productivity (2.8%) and in mean consumption-equivalent welfare (2.4%), with wide dispersion in welfare effects (Figure A.18).[33] These results are broadly consistent with our earlier exercise that imposed a return to 2019 work arrangements (Table 1). Learning about WFH yields large, but hard-to-measure, improvements in welfare and effective productivity. Conventional statistics, instead, imply modest effects.

Other research provides related explanations for the lasting shift to WFH. Monte et al. (2026) build a model in which a temporary cutback in commuting (as in the pandemic) can persistently shift city-level work patterns due to agglomeration externalities. Davis, Ghent, and Gregory (2024b) attribute the shift to WFH to a large increase in its relative productivity, aided by an adoption externality, that leads workers and firms to reoptimize. Bick et al. (2023) show that the rise in WFH after 2020 is consistent with a higher adoption rate in WFH-suitable jobs.

We also find evidence that the pandemic reduced the stigma previously associated with WFH. More than 60% of SWAA respondents surveyed between July 2020 and May 2022 report that perceptions about WFH improved "among people you know" since the COVID pandemic began (Figure A.19). That attitudinal shift made it easier for workers to press for WFH privileges, and harder for their bosses to say no. Higher WFH rates in the broader economy may also have

[33] We assume that workers' and firms' beliefs $\{B_i'\}_{i\in I}$ before learning reflect the technology available, so counterfactual output and welfare use $\{B_i'\}_{i\in I}$. We cap two-way commute time (plus extra grooming time) in the counterfactual at 3.5 hours per day (near the 98th percentile of the raw variable), since some workers may have chosen to live far from work based on the availability of WFH, and would not have commuted that far before learning. Some workers suffer welfare losses because they have learning shocks $s_i < 0$ and therefore $B_i' > B_i$. Experimentation shifts these workers from a technology that enabled them to WFH at high rates to one that allows for less WFH. If we assume that learning cannot lower worker welfare, the average welfare gain rises to 2.9%.

amplified the pandemic's impact on WFH attitudes, a strategic complementarity that operates through attitudes or social norms rather than the aggregate production function.

7. Conclusion

We offer a unified explanation of how the COVID-19 pandemic led to a large and lasting shift to WFH, why the shift did not happen sooner, and why it will stick into the indefinite future. The central idea is that the pandemic triggered a mass social experiment in WFH, yielding a huge flow of new information about the viability and benefits of WFH, much first-time experience with WFH, revisions to prior views, and a resulting re-optimization of work arrangements that persisted long after the pandemic receded. We draw heavily on our original survey data to develop and assess this explanation.

We also use our rich micro data to calibrate an equilibrium model that endogenizes individual-level work arrangements, workhours, wages, and productivities. We use the model to quantify the implications of WFH for productivity, output, and consumption-equivalent welfare at aggregate and individual levels and to highlight a key distinction between measured labor productivity (output per paid workhour) and effective labor productivity (output per hour devoted to work, inclusive of commuting and grooming time). When we take our data on individual-level WFH productivity surprises to the calibrated model, we find that learning and re-optimization account for more than 90% of the shift to WFH between 2019 and 2023-2025.

This shift to WFH raised effective labor productivity by 3.5%, according to our basic model, five times its modest impact on measured labor productivity. Our basic model also implies that the shift to WFH raised consumption-equivalent welfare by 2.6%, on average, with wide variation across workers. Similar results hold for several variants of the model. We also extend the model to allow for the possibility that onsite work generates positive external spillovers on productivity and wages. To overturn our basic model's conclusions about the welfare gains associated with the shift to WFH requires spillover effects that are roughly twice as large as recent estimates in the literature.

In sum, we show that a large temporary forcing event can, under empirically verified conditions, drive a lasting shift in equilibrium work arrangements that raises effective labor productivity and average welfare.

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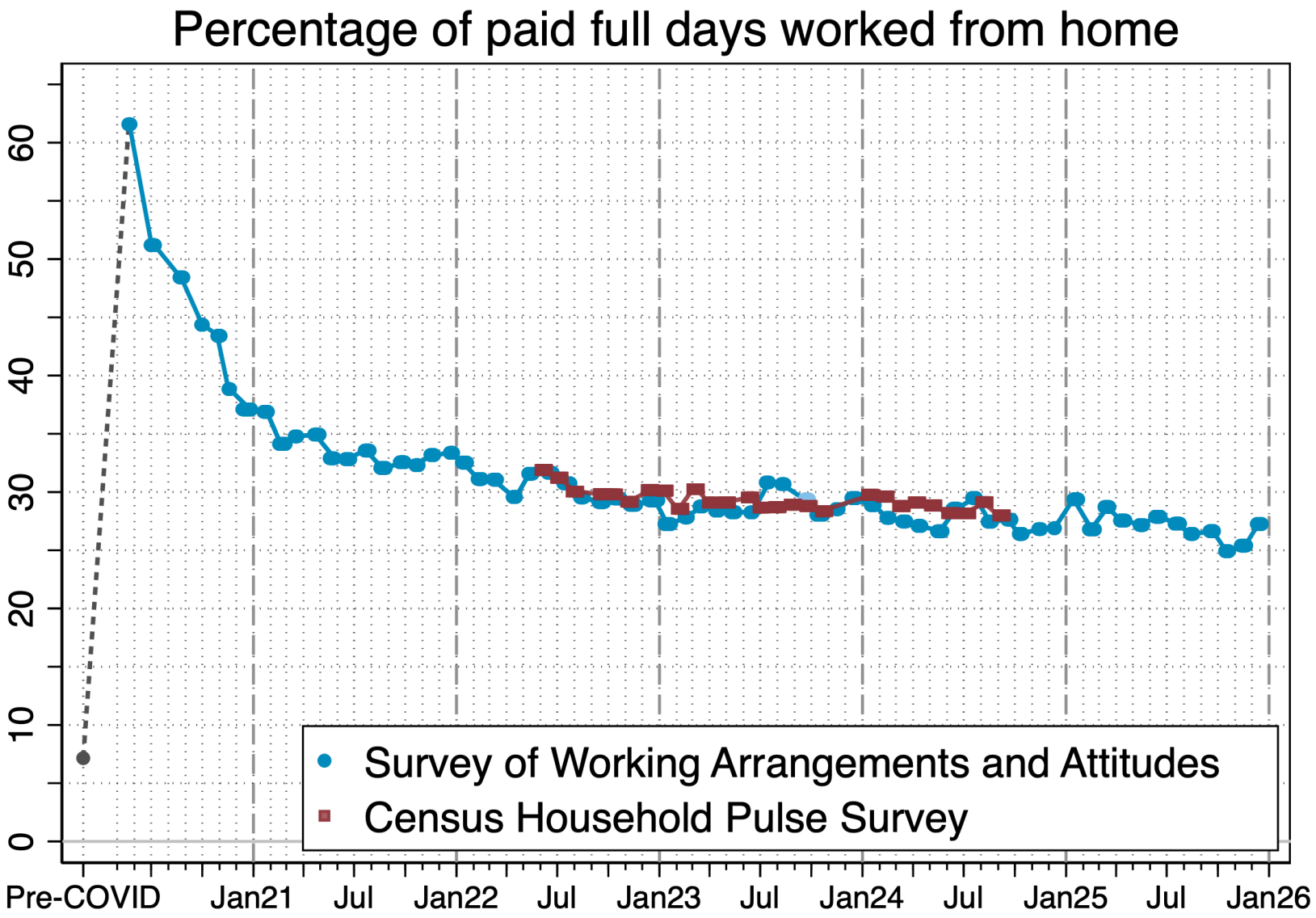
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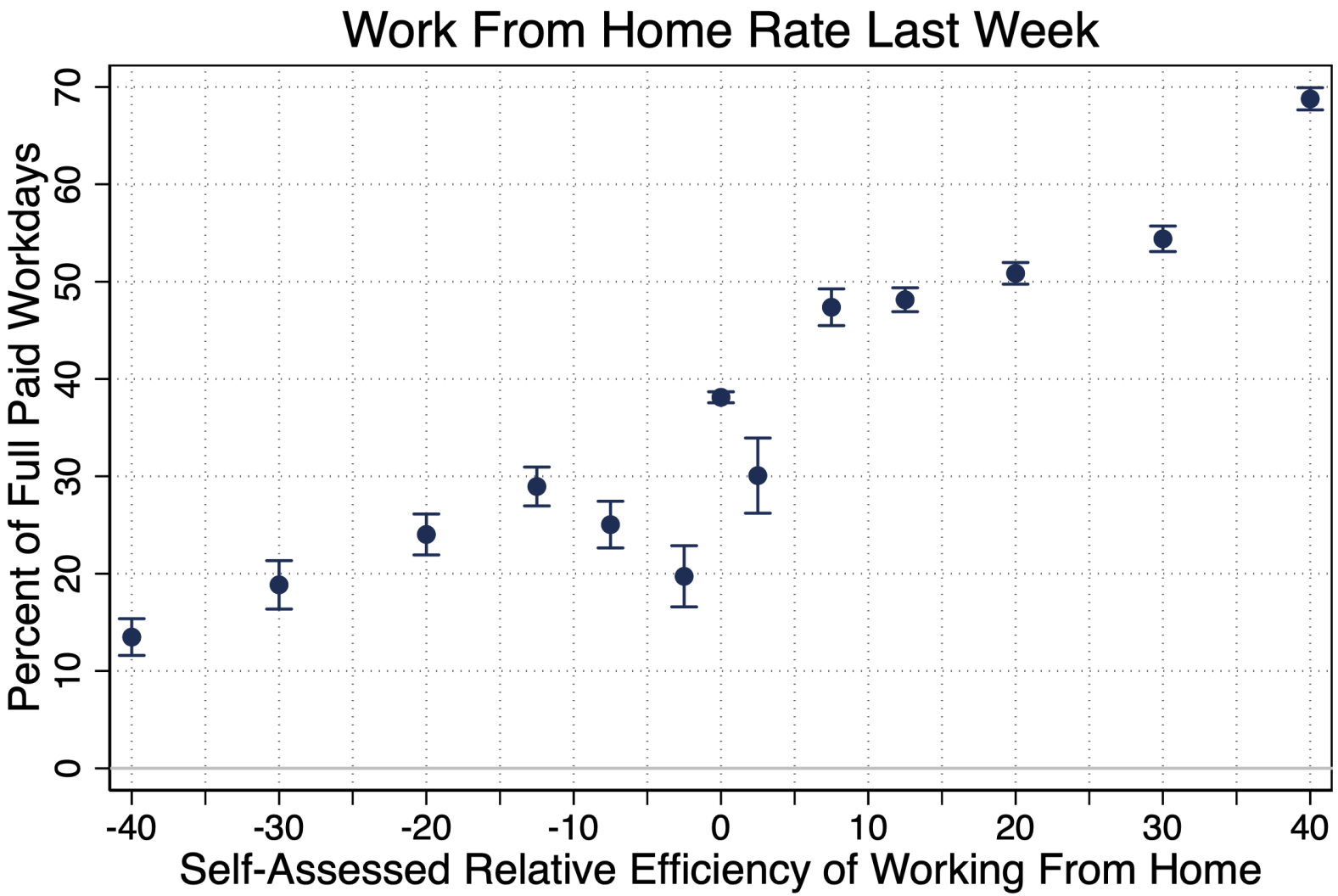
Figure 1. Working from Home Has Stuck



Notes: The figure shows the percent of full paid days that are work-from-home (WFH) days in the US. The 2019 estimate is based on that year's ATUS, counting full workdays as those in which the respondent worked 6 or more hours on their main job, and WFH if they worked at least six hours at home. SWAA estimates for November 2020 and later are based on questions that record the number of days of the reference week the respondent worked for pay for at least 6 hours and whether they WFH or worked on business premises. We compute $100\times(no.of\ WFH\ days)/(no.of\ workdays)$ and average across respondents. May to October 2020 estimates use questions that ask whether the respondent is working on business premises or WFH, showing the share for the latter. CHPS data come from a question that asks whether people in the household WFH 1 to 2, 3 to 4, or 5+ days per week, or none in the past 7 days. See Appendix B for more details.

N = 271,229 (SWAA), N = 923,587 (CHPS).

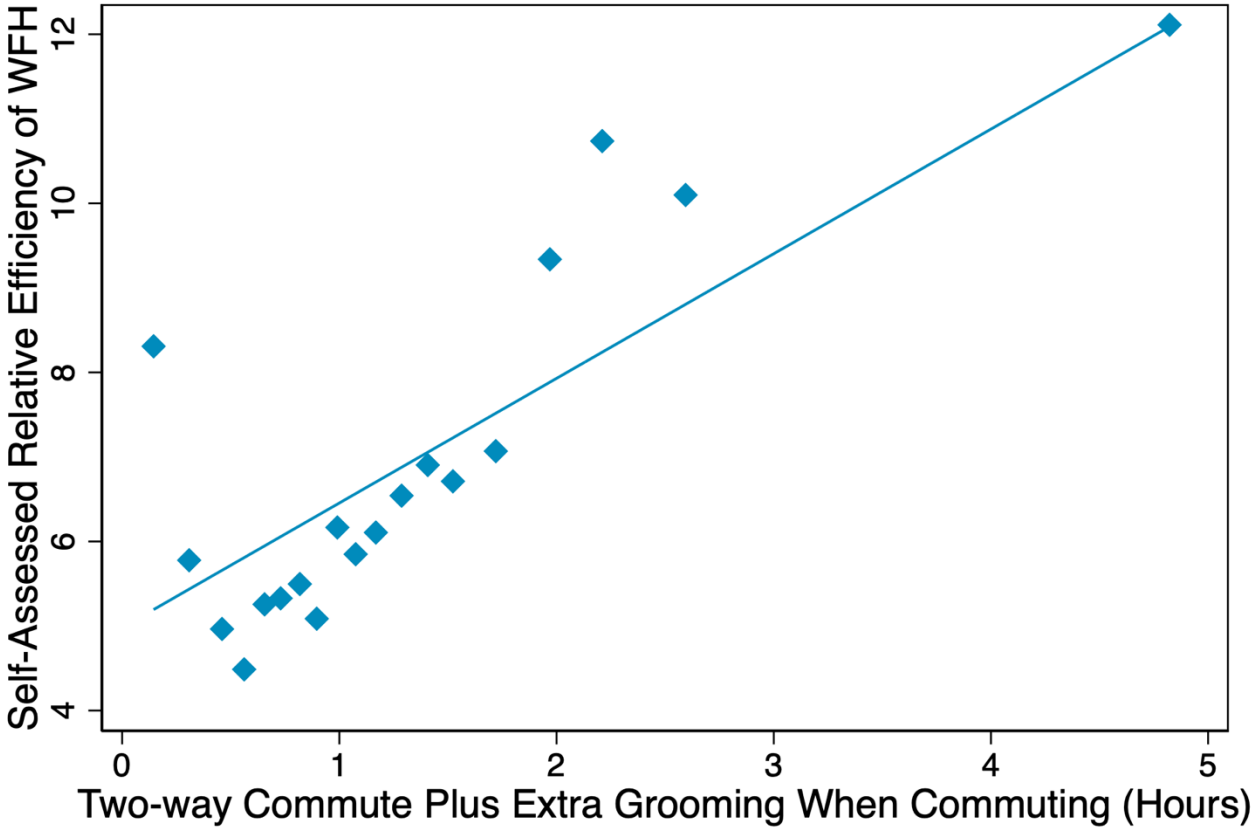
Figure 2. Worker Self-Assessments of Their Relative Efficiency While Working From Home Predict Actual Work From Home



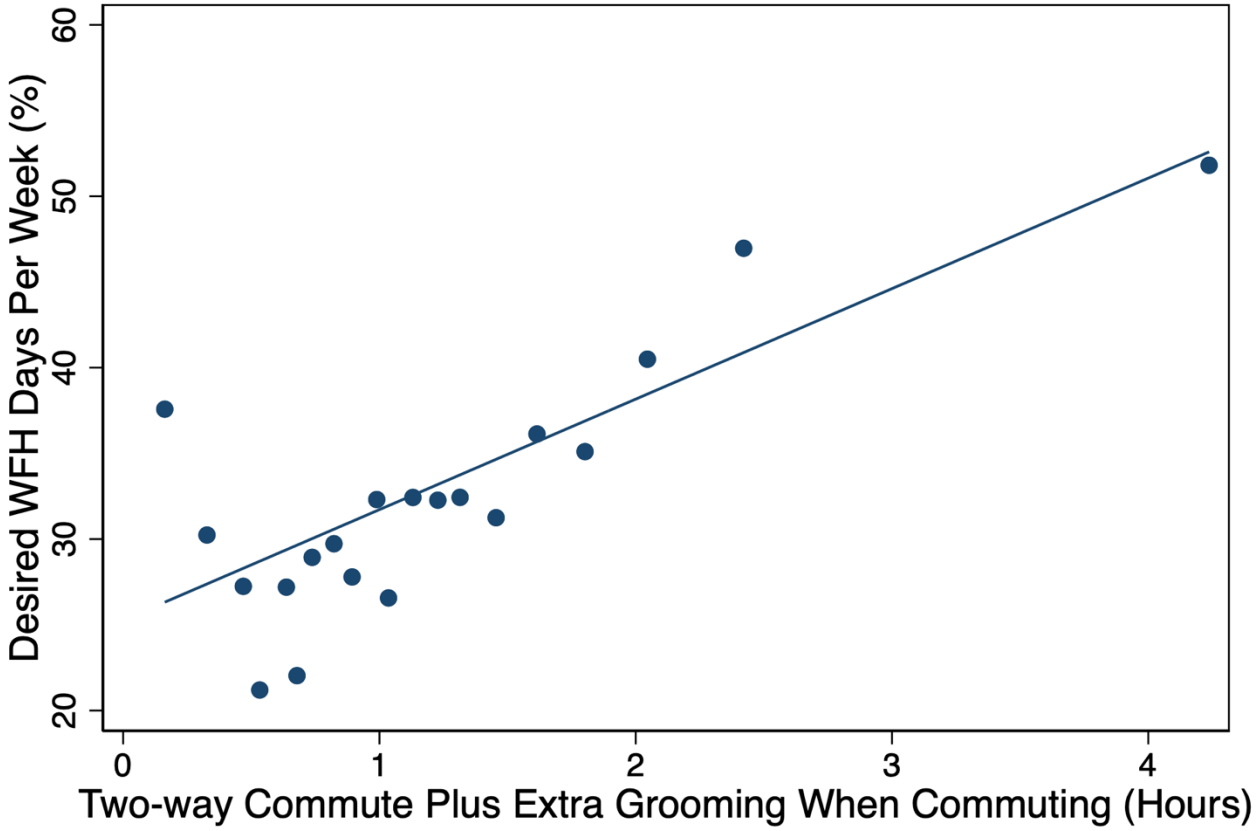
N = 93718

Notes: The figure shows the average WFH rate for each possible choice of self-assessed relative efficiency while WFH and its 95% confidence interval. We measure the WFH rate as the percent of paid workdays that are WFH days in the survey's reference week. (The survey question asks, *"For each day* **last week** *did you* **work a full day (6 or more hours)** *and if so* **where?***").* We measure self-assessed relative efficiency with a two-part question that first asks whether efficiency is better at home, about the same, or worse at home than on business premises, and then asks a follow-up question to ask how much better or worse. We interpret *"about the same"* to mean zero relative efficiency while WFH. Data are from SWAA waves covering **January 2023 to December 2025**, reweighted to the CPS by age, sex, education, and earnings.

Figure 3. Commuting and Grooming Time Savings Predict Self-Assessed Relative WFH Efficiency and Desired WFH Rates



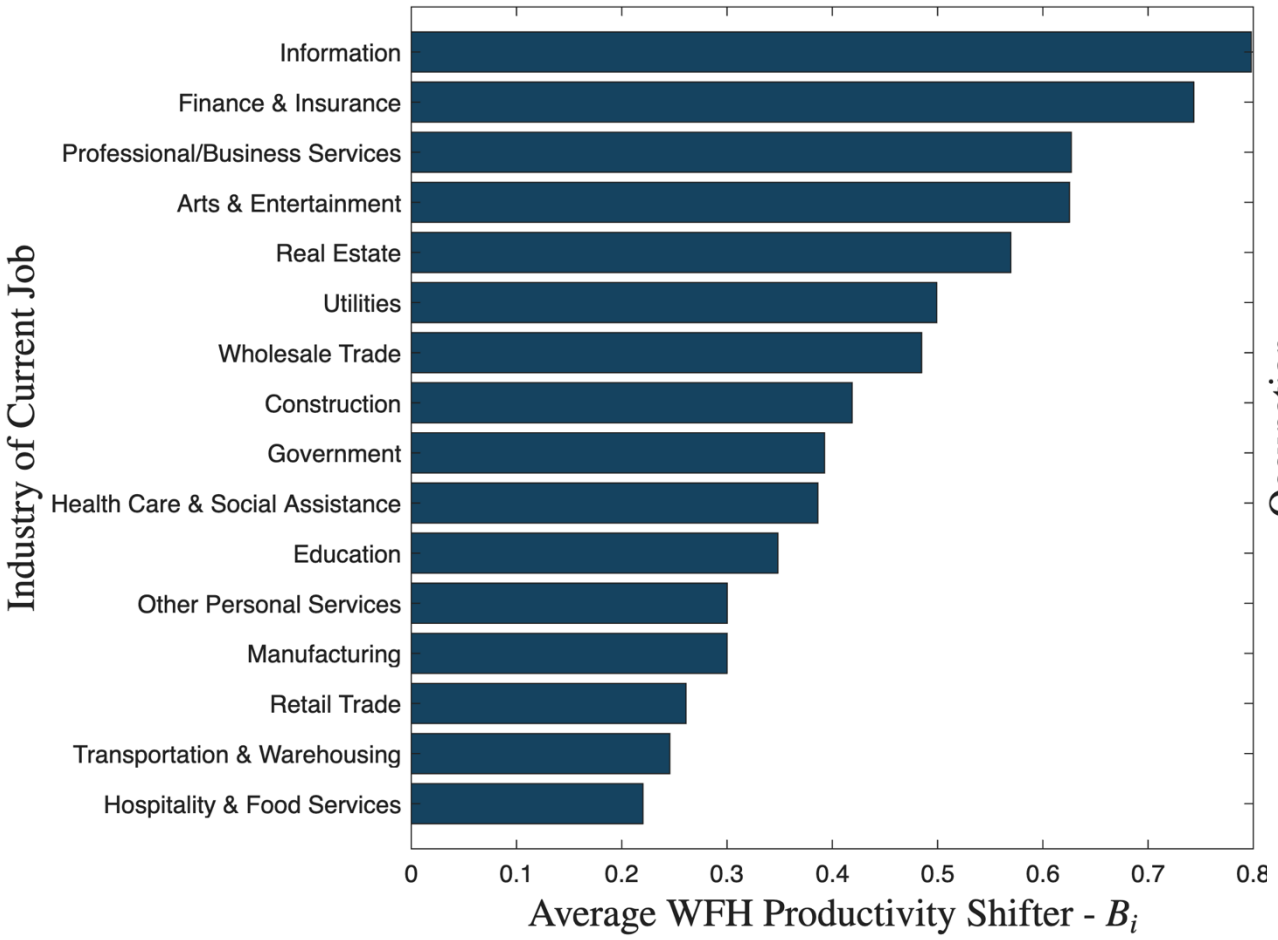
Coef (SE): 1.5 (0.1). N = 53520

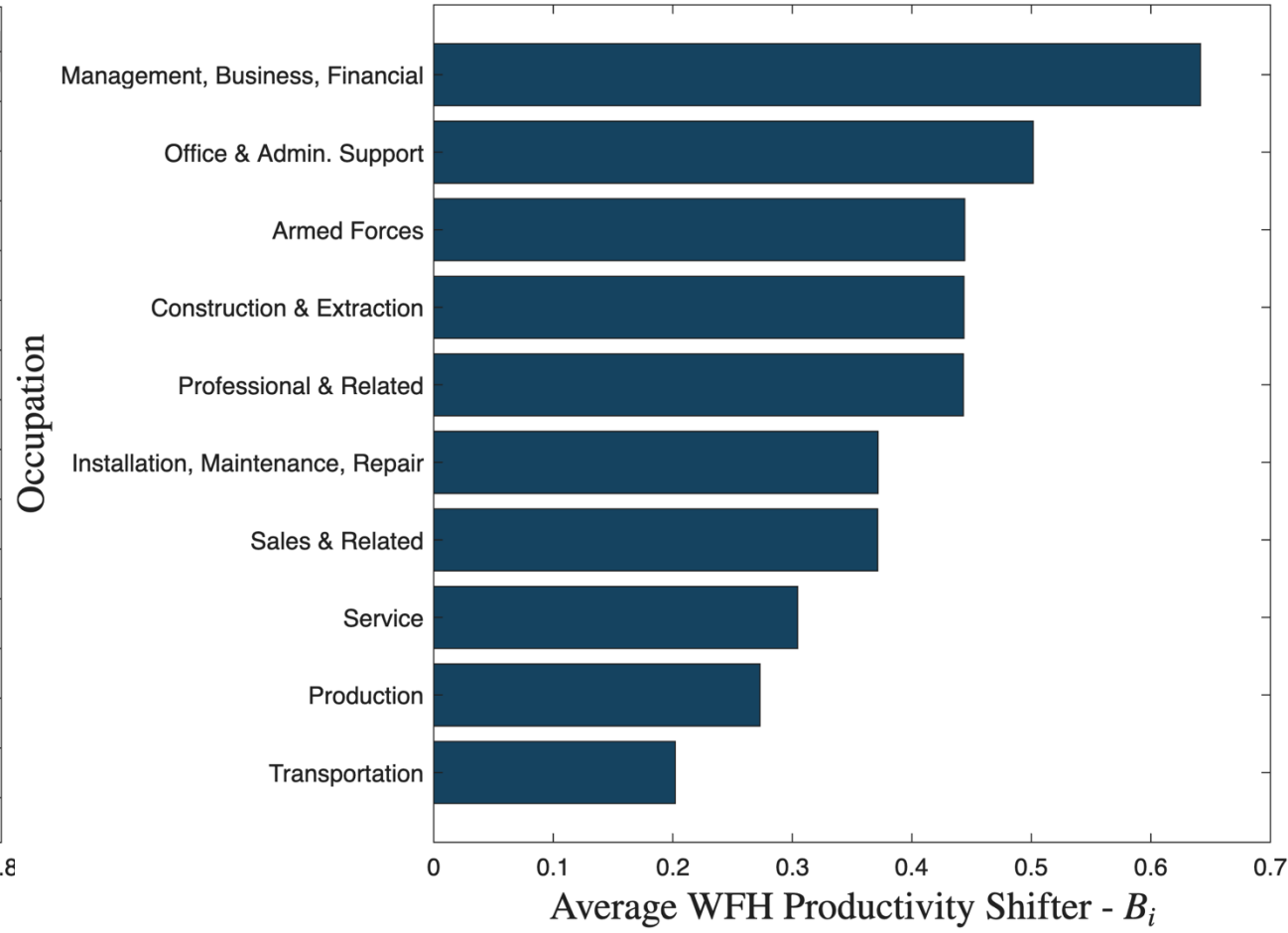


Coef (SE): 6.4 (0.2). N = 75461

Notes: Both panels show binned scatter plots with total two-way commute time and extra grooming time when commuting to the workplace on the horizontal axis. The left panel has self-assessed relative efficiency while WFH and the right panel has desired WFH days as percent of a five-day workweek. We measure self-assessed relative efficiency with a two-part question that first asks whether efficiency is better at home, about the same, or worse at home than on business premises, and then asks a follow-up question to ask how much better or worse. We interpret *"about the same"* to mean zero relative efficiency while WFH. We measure desired WFH using a question that asks "***Looking one year ahead,*** how often would you ***like to*** have paid workdays at home?" with responses ranging from "Never" to "5+ days per week." Data are from the SWAA covering the **January 2023 to December 2025** waves, reweighted to the CPS by age, sex, education, and earnings.

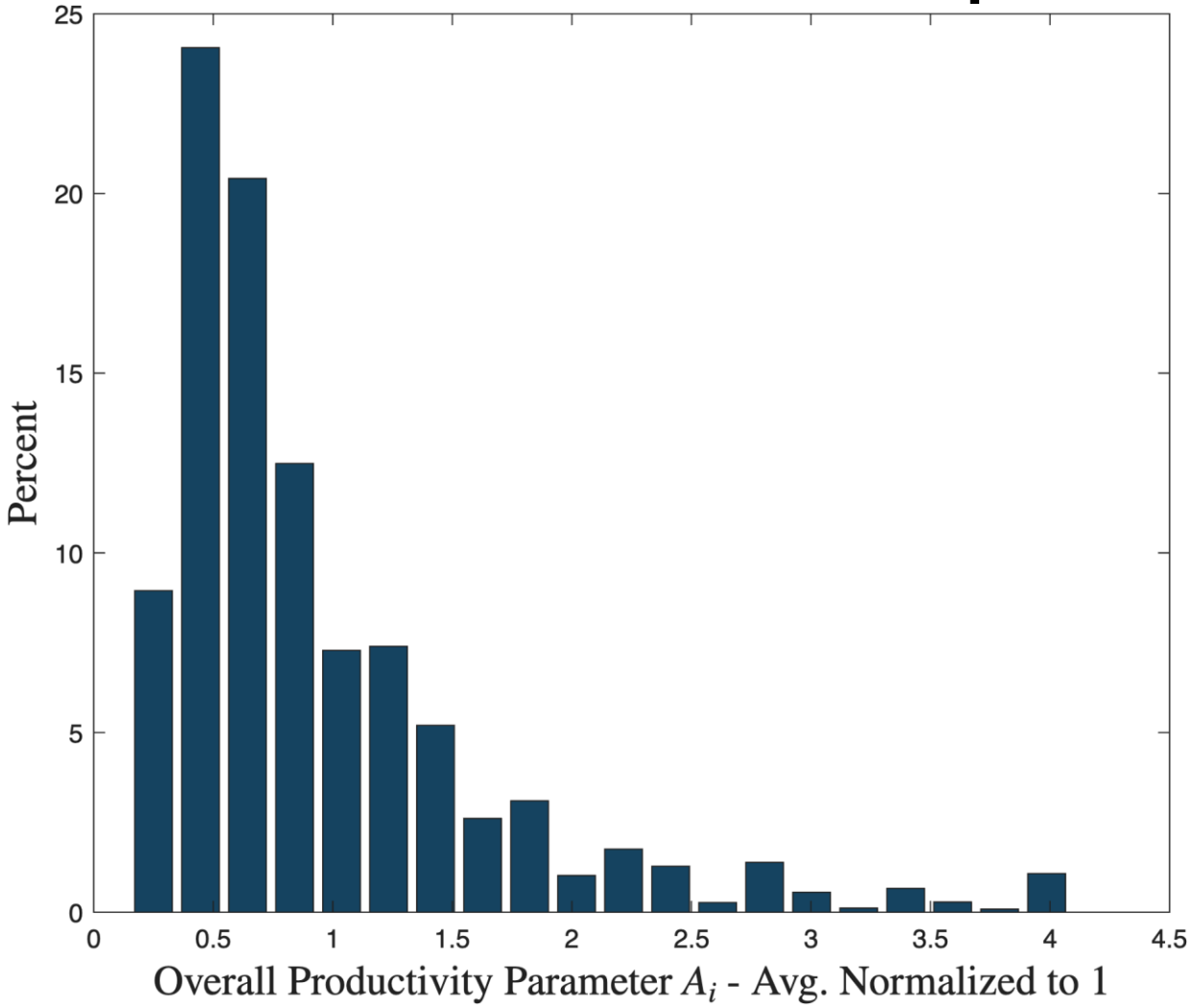
Figure 4. Mean Productivity Shifters in Remote Mode Are Higher in Industries that Are More Amenable to Work From Home

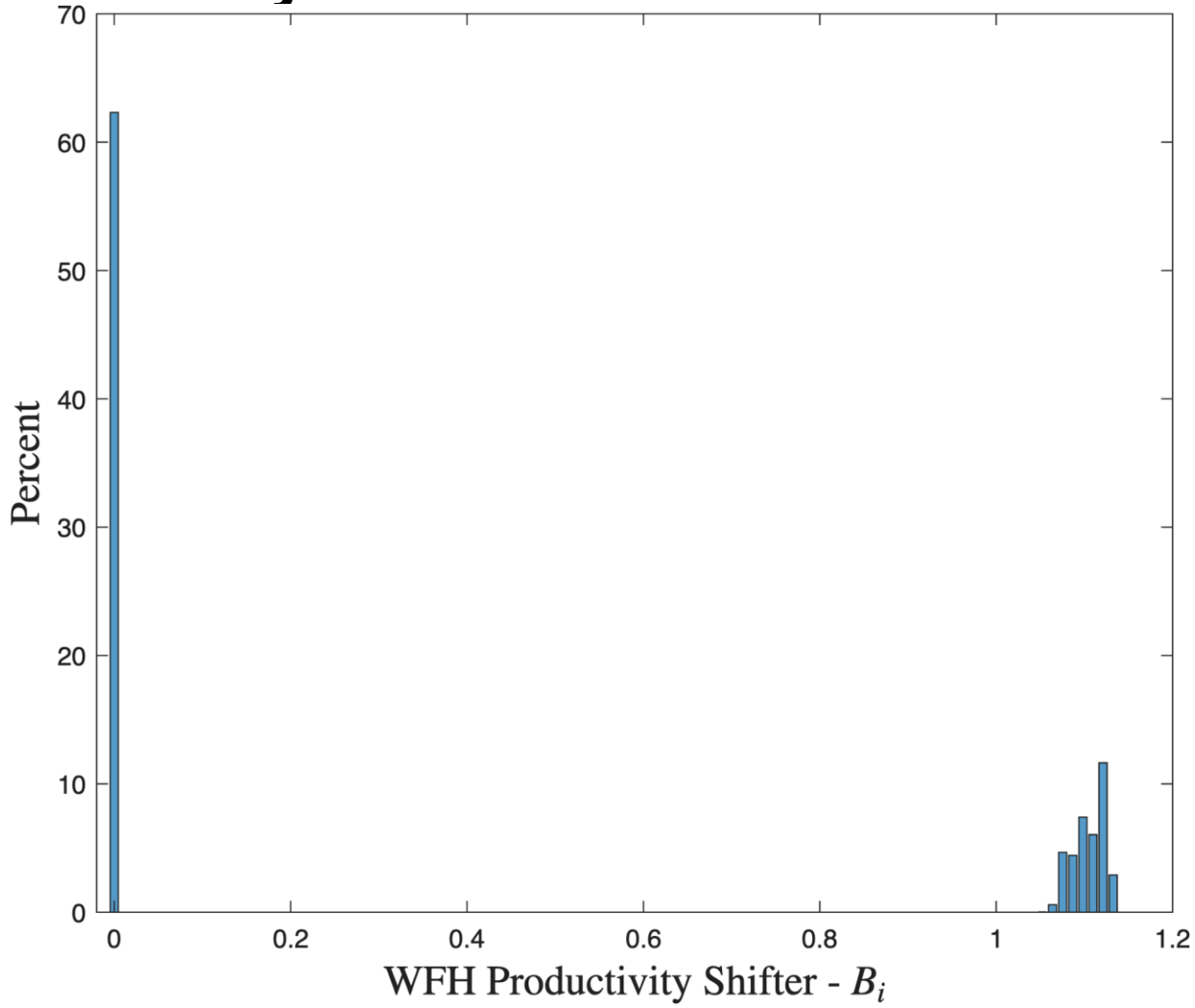




Notes: Each figure shows the mean of B_i, the worker-specific shifter that governs the relative productivity of worker i in WFH mode, by industry of the respondent's current job (left) and by occupation (right). We use SWAA data from **January 2023 to December 2025**, focusing on workers who reported at least 20 hours of work in the week prior to the survey. We drop the mining industry and agriculture, fishing, and forestry due to small samples and lack of suitability for remote work.

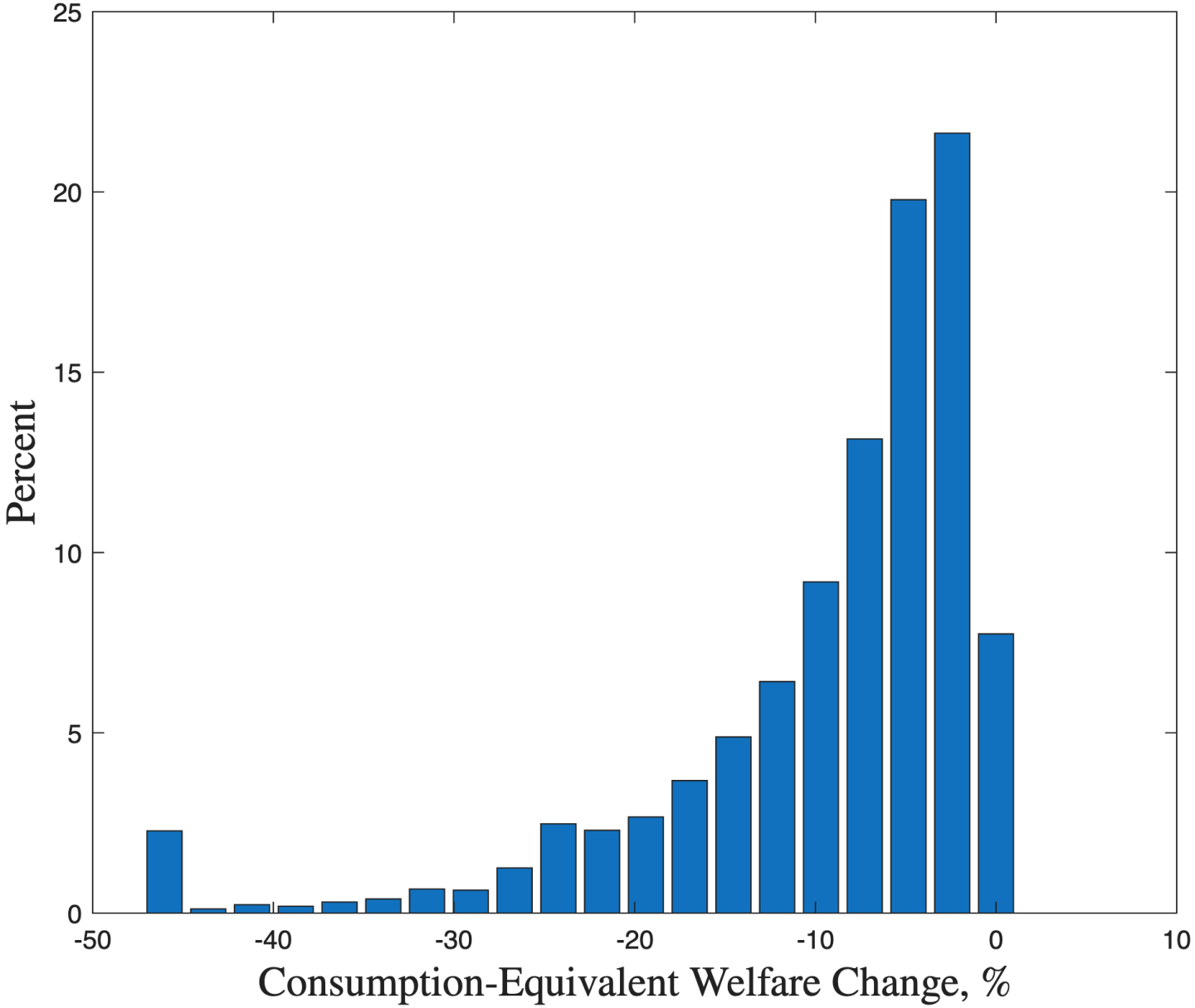
Figure 5. Model Calibration: The Distributions of Model-Implied Productivity Parameters





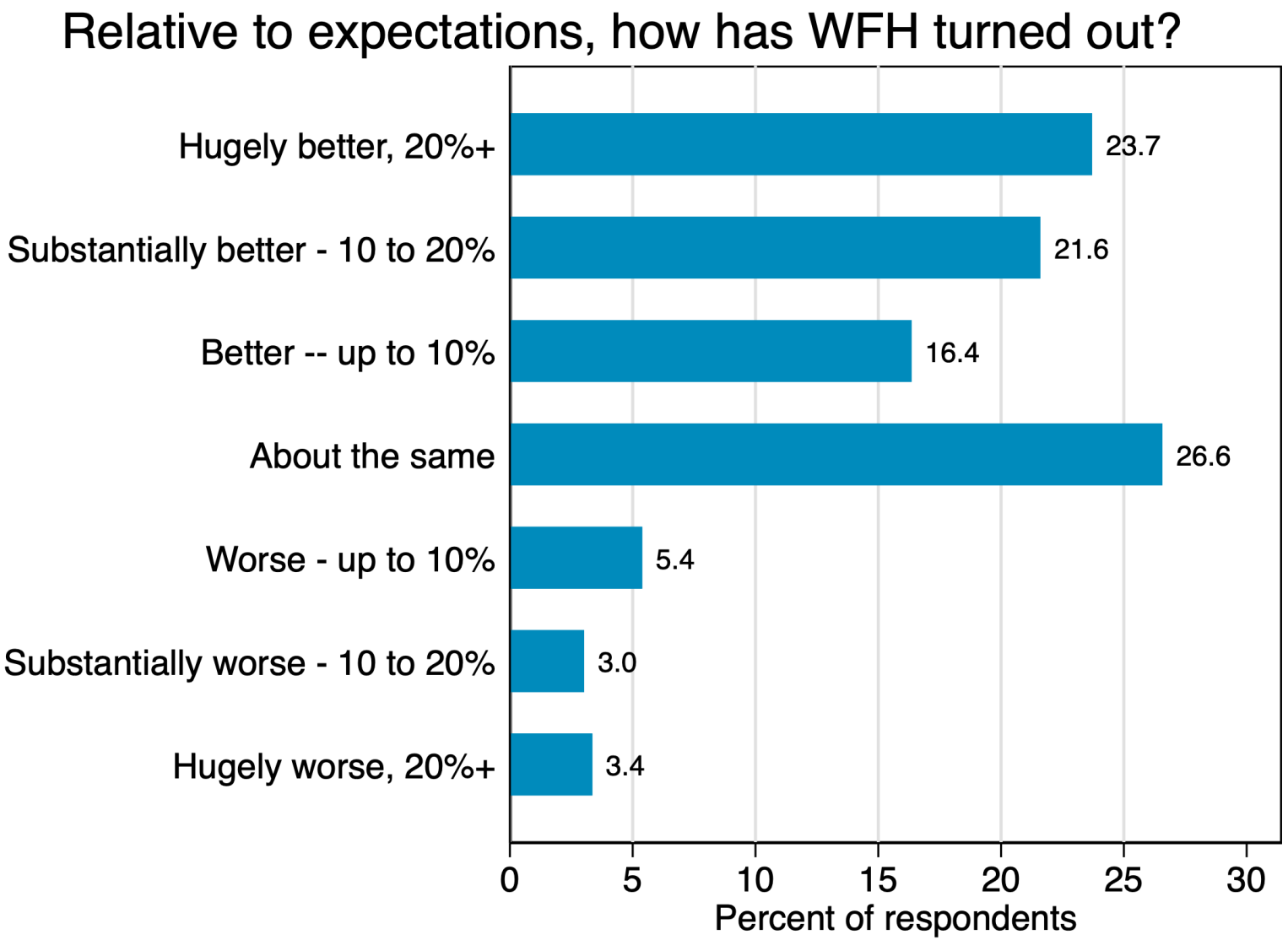
Notes: The charts show histograms of worker-specific productivities A_i (left, normalized to a cross-sectional mean of 1) and B_i (right). We winsorize the left chart at the 1st and 99th percentiles. We use SWAA data from **January 2023 to December 2025** for workers who report at least 20 hours of work in the survey reference week.

Figure 6. Returning to 2019 Work Arrangements Lowers Average Welfare, With High Cross-Sectional Variation



Notes: This figure shows a histogram of consumption-equivalent welfare changes for the 27.2% of workers who are directly affected by a return to 2019 arrangements. The welfare changes for other workers are small and not displayed here. We calculate welfare changes relative to the 2023-25 baseline outcomes.

Figure 7. Most Workers Who Tried Work from Home During COVID Report Better Experiences than They Expected



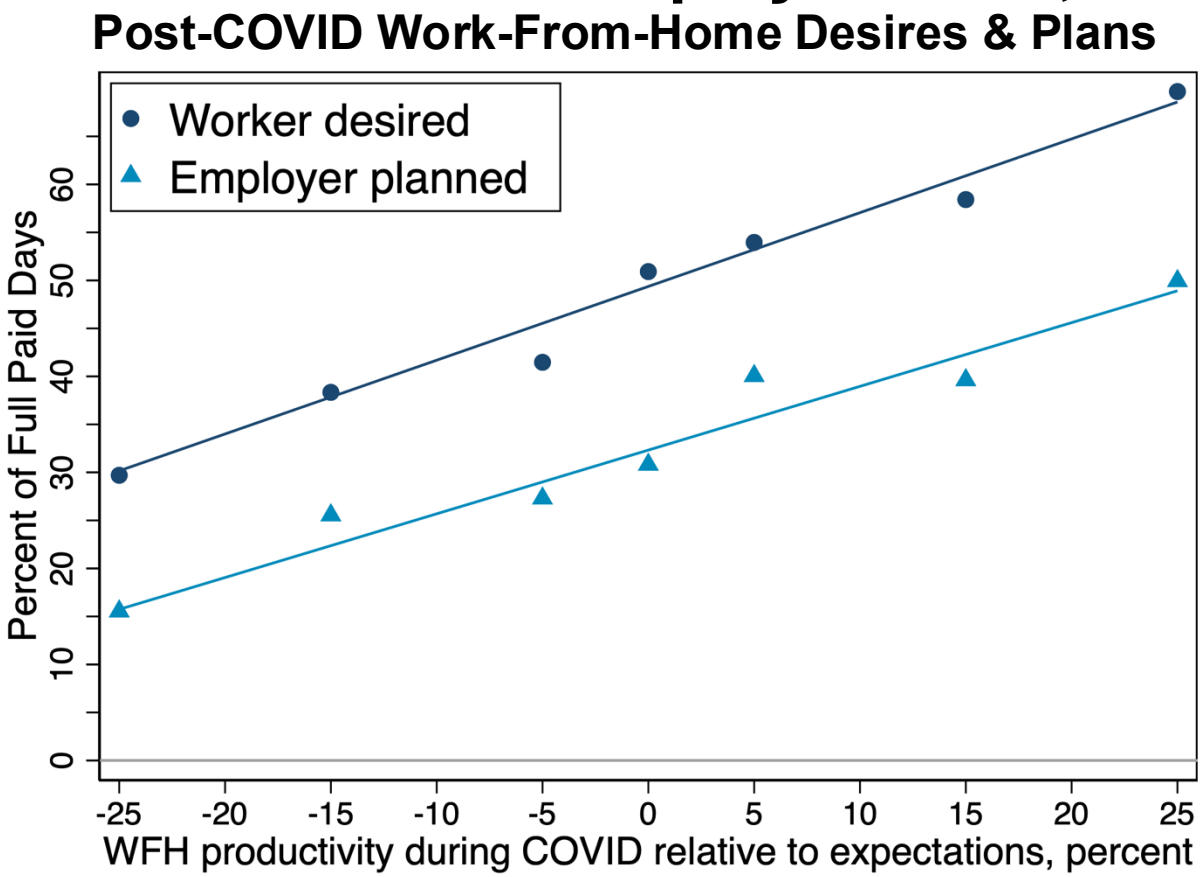
Responses to the Question:

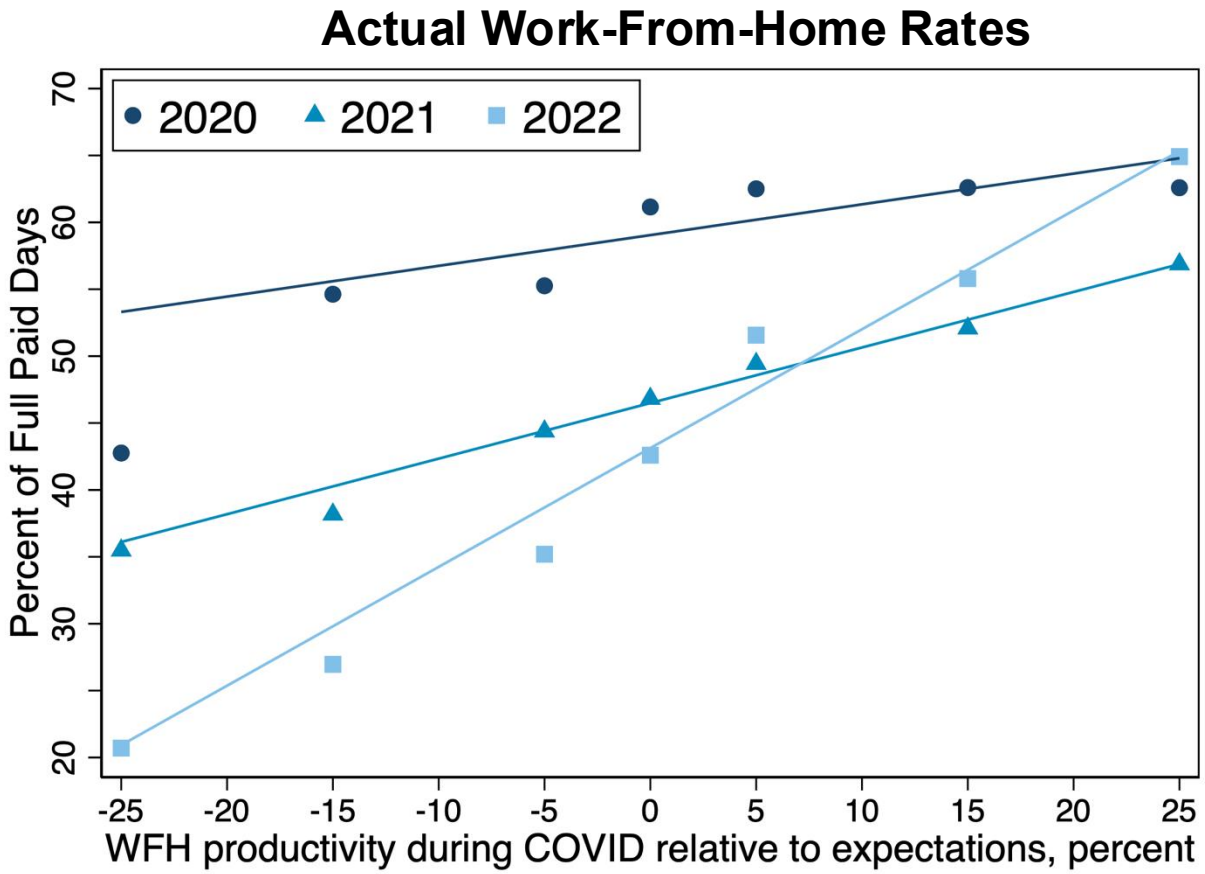
- *Compared to your expectations* **before COVID (in 2019)** *how has working from home turned out for you?*

Notes: The figure shows the distribution of responses to the question above, focusing on SWAA respondents who participated in the July 2020 to April 2022 waves of the SWAA and report having WFH at some point since 2020. We reweight the SWAA to match the CPS population in cells defined by age x sex x education x earnings.

N = 53,004

Figure 8. Learning and Experimentation Shape Worker Preferences, Employer Plans, and Outcomes Over Time





Notes: The left panel shows binned scatter plots of desired WFH (*"…how often would you like to have paid workdays from home"*) and employer plans (*"…how often is your employer planning for you to have paid workdays at home"*) in the post-pandemic future against the WFH productivity surprise (*"compared to your expectations* **before COVID (in 2019)** *how has working from home turned out for you?"*). We assign numerical values to the horizontal axis using the midpoint of the ranges referenced in each response option, shown in Figure 7. The right panel shows binned scatter plots using actual WFH rates on the vertical axis and splitting the sample by year across 2020, 2021, and 2022. The sample includes SWAA respondents who participated in the July 2020 to April 2022 waves and report having WFH at some point since 2020. We reweight the SWAA to match the CPS population in cells defined by age x sex x education x earnings.

Table 1. Counterfactual Work Arrangements: Effects on Productivity, Output, and Average Welfare

Counterfactual Work Arrangements	100 × difference between counterfactual and baseline outcomes				Mean Consumption-Equivalent Welfare Change, Percent
	$\Delta \log(Y/H)$	$\Delta \log(Y/(H+T+G))$	$\Delta \log(Y)$	$\Delta \log(H)$	
	Measured Productivity	**Effective Productivity**	**Output**	**Hours**	
A. Basic Model					
(1) Return to 2019	-0.7	-3.5	-1.1	-0.4	-2.6
(2) 2020 Lockdown	1.0	4.8	-18.8	-19.8	-18.8
B. Model with Preference Heterogeneity over WFH					
(3) Return to 2019	-0.5	-3.3	-0.6	-0.1	-0.8
(4) 2020 Lockdown	-0.2	3.4	-23.7	-23.5	-21.6

Notes: Negative table entries indicate lower values in the counterfactual equilibrium than in the 2023-2025 baseline equilibrium. Y, H, T, and G are aggregate output, total paid workhours, aggregate commuting time, and aggregated (extra) grooming time, respectively. See Section 5 in the text for a full description of how work arrangements in each counterfactual differ from the baseline equilibrium.

Table 2. External Spillovers from Onsite Work: How Large Must They Be to Rationalize a Compulsory Return to 2019 Arrangements?

	"Breakeven" value of ε, the strength of spillovers			
	$\bar{\delta}$ = equal-weighted mean WFH Rate		$\bar{\delta}$ = productivity(A_i)-weighted mean WFH Rate	
	Output	**Average Welfare**	**Output**	**Average Welfare**
(1) Basic Model	0.060	0.141	0.046	0.108
(2) Model with Preference Heterogeneity over WFH	0.030	0.045	0.023	0.034

Notes: Each table entry reports the minimal value of ε such that a return to 2019 work arrangements yields the same level of output or average welfare that prevails in the 2023-25 baseline equilibrium. The two left-most columns assume the relevant quantity for in-person spillovers is the equal-weighted mean WFH rate in the economy. The two right-most columns assume the relevant quantity is the productivity-weighted mean WFH rate, using workers' relative productivity to others A_i as weights.

Table 3. Learning and Experimentation Shape Worker Preferences, Employer Plans, and Outcomes Over Time

Dependent Variable	(1)	(2)	(3)	(4)	(5)	(6)
	Worker Desired Post-COVID Work From Home		Employer Planned Post-COVID Work From Home		Actual Work From Home	
WFH Productivity Relative to Expectations	0.60***	0.63***	0.50***	0.45***	0.23***	0.25***
	(0.04)	(0.04)	(0.04)	(0.04)	(0.05)	(0.04)
x 1(2021)	0.16***	0.14***	0.16***	0.15***	0.19***	0.17***
	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)
x 1(2022)	0.31***	0.29***	0.28***	0.30***	0.66***	0.65***
	(0.05)	(0.05)	(0.06)	(0.06)	(0.06)	(0.06)
1(2021)	0.30		4.10***		-12.53***	
	(0.69)		(0.68)		(0.75)	
1(2022)	-2.62***		10.35***		-15.89***	
	(0.84)		(0.83)		(0.98)	
Constant	50.90***	50.43***	27.85***	32.83***	59.03***	48.47***
	(0.58)	(0.27)	(0.57)	(0.27)	(0.68)	(0.27)
Fixed Effects for Survey Month, Age Category, Sex, Education, and Earnings		Y		Y		Y
Observations	52,935	52,935	49,097	49,097	45,647	45,647
R-squared	0.06	0.08	0.06	0.08	0.05	0.10

Notes: The units for all dependent variables are percent of full paid days, assuming a five-day workweek for worker desires (columns 1 and 2) and employer plans (columns 3 and 4). We give numerical values to the responses to the question, "Compared to your expectations before COVID (in 2019) how has working from home turned out for you?" using the midpoint of the range for each response option and assuming the top and bottom response correspond to a range that is equal in length to the others. We use 2020 as the baseline year for the slope coefficient and the year effects in columns 1, 3, and 5. Robust standard errors in parentheses. Data are from the Survey of Working Arrangements and Attitudes waves from July 2020 to April 2022, inclusive and focusing on workers who report having worked from home since the start of the pandemic. *** p<0.01, ** p<0.05, * p<0.1

Table 4. Experimentation and Learning Explain Most of the Rise in WFH According to Our Model and Drive a Sizable Gain in Average Welfare

A. WFH Rates in the Data and in the Model Counterfactual that Simulates the Economy Without Learning & Reoptimization

	2023-2025 Data	2019 Data	Implied by the Model Absent Experimentation and Learning
(1) WFH Rate, Percent of Paid Workdays	23.1	7.2	8.4
(2) Increase to 2023-2025 Level (p.p.)		15.9	14.7
(3) Percent of 2019 to 2023-2025 Increase			$100 \times (14.7/15.9) = 92.4$

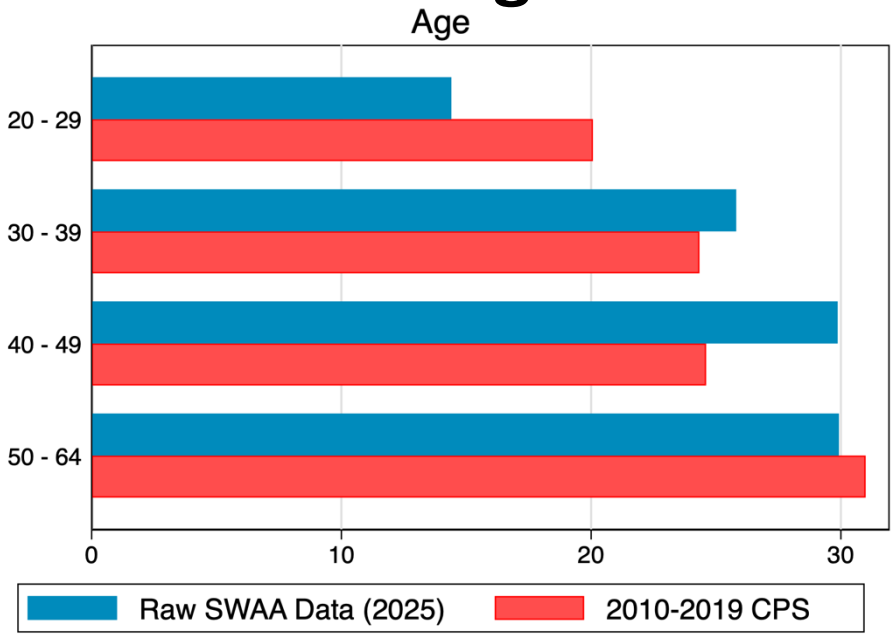
B. Gains from Learning

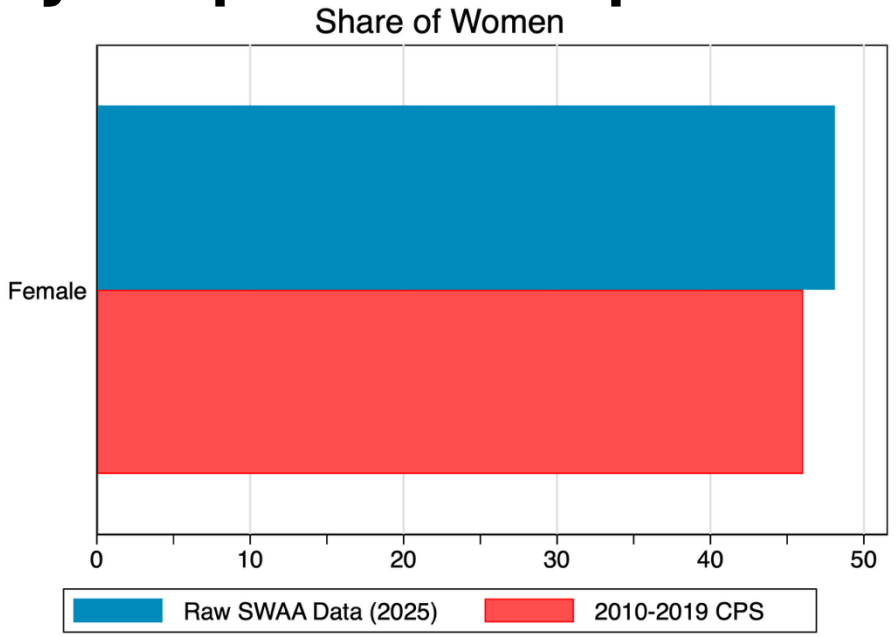
	$100 \times$ difference in outcomes between baseline and counterfactual (before learning)				
	$\Delta \log(Y/H)$	$\Delta \log(Y/(H+T+G))$	$\Delta \log(Y)$	$\Delta \log(\mathrm{H})$	**Consumption-Equivalent Welfare Change, Percent**
	Measured Productivity	**Effective Productivity**	**Output**	**Hours**	**Mean**
(4)	0.1	2.8	0.6	0.4	2.4

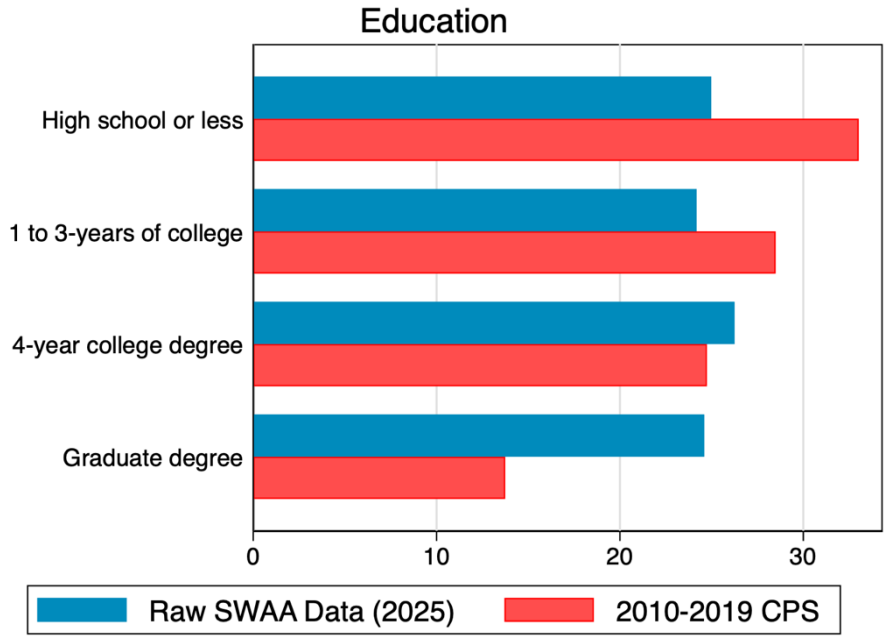
Notes: Panel A reports (1) WFH rates in the data and the model; (2) the increase in percentage points between 2019 and 2023-2025 in the data and implied by the model counterfactual without learning and re-optimization; and (3) the percent of the total increase implied by learning. Panel B reports gains from learning which compare outcomes in the baseline 2023-2025 equilibrium with the no-learning counterfactual. Positive entries indicate lower values in the counterfactual equilibrium without learning. Y, H, T, and G are aggregate output, total paid workhours, aggregate commuting time, and aggregated (extra) grooming time, respectively. Row (4) reports outcomes under the assumption that before learning the economy operates using the vector of pre-pandemic beliefs $\{B_i'\}_{i \in I}$ and capping two-way commute time (and extra grooming time) in the counterfactual at 3.5 hours per workday. See Section 6 in the text for more details.

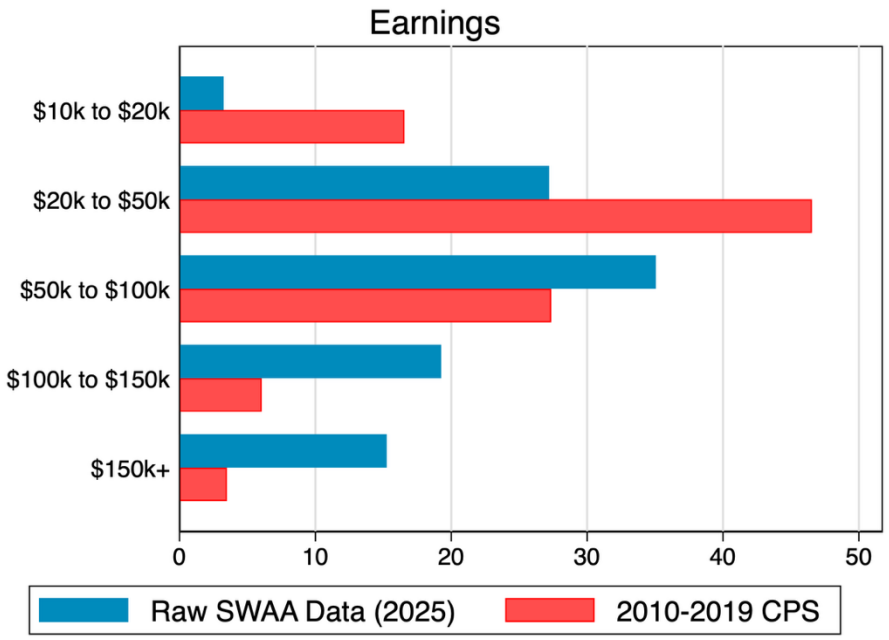
Appendix A. Additional Tables and Figures

Figure A.1. Survey Responses Compared to the CPS



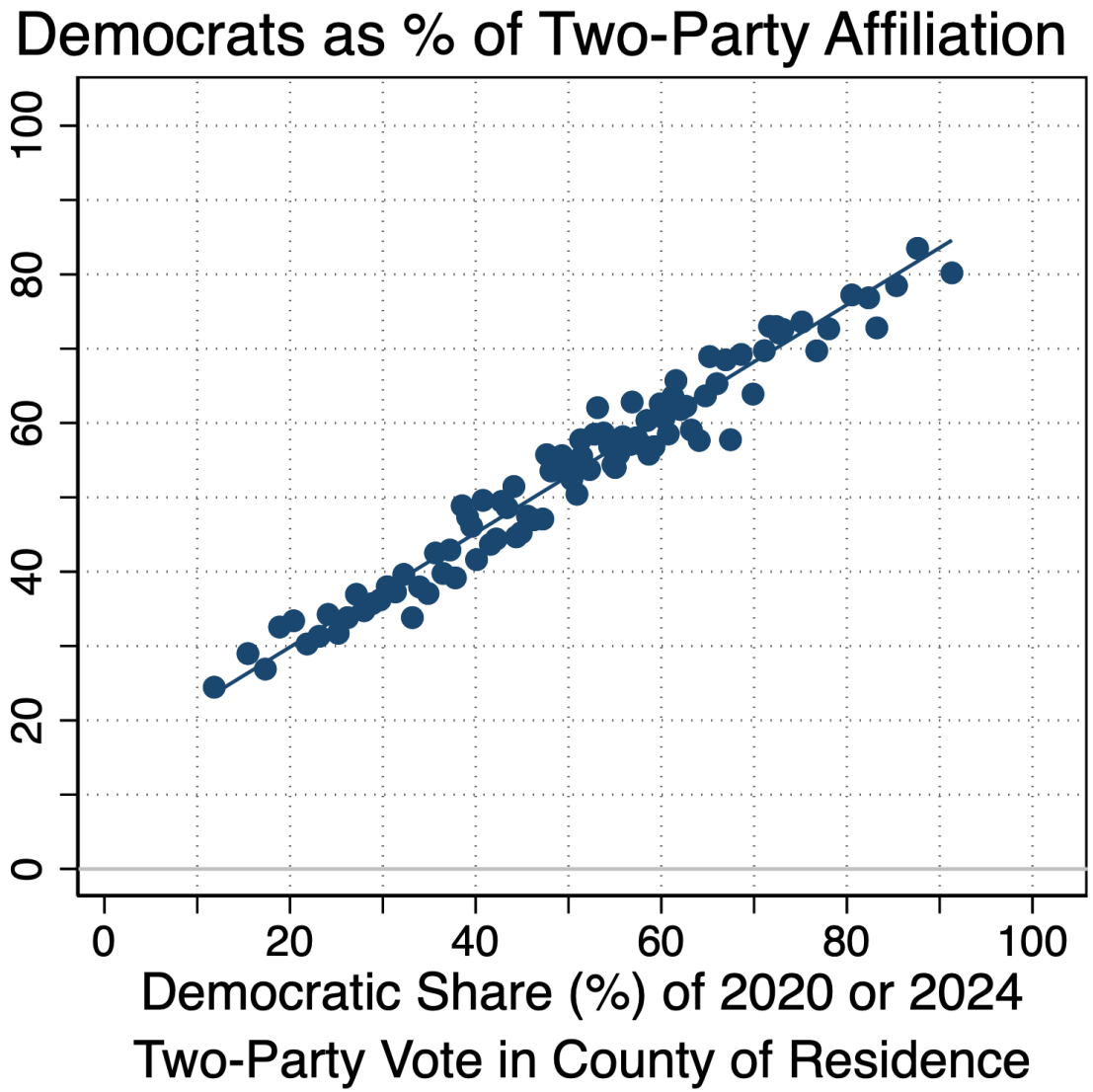






Notes: Each figure shows the distribution of raw SWAA survey responses and 2010 – 2019 CPS, focusing on those who earned more than $10,000 in the prior year. SWAA data are from 68,725 respondents collected from **January to December 2025.**

Figure A.2. Vote Share by County Matches SWAA Share by Political Preference



Slope of linear regression = .77 (.01). N = 188524.

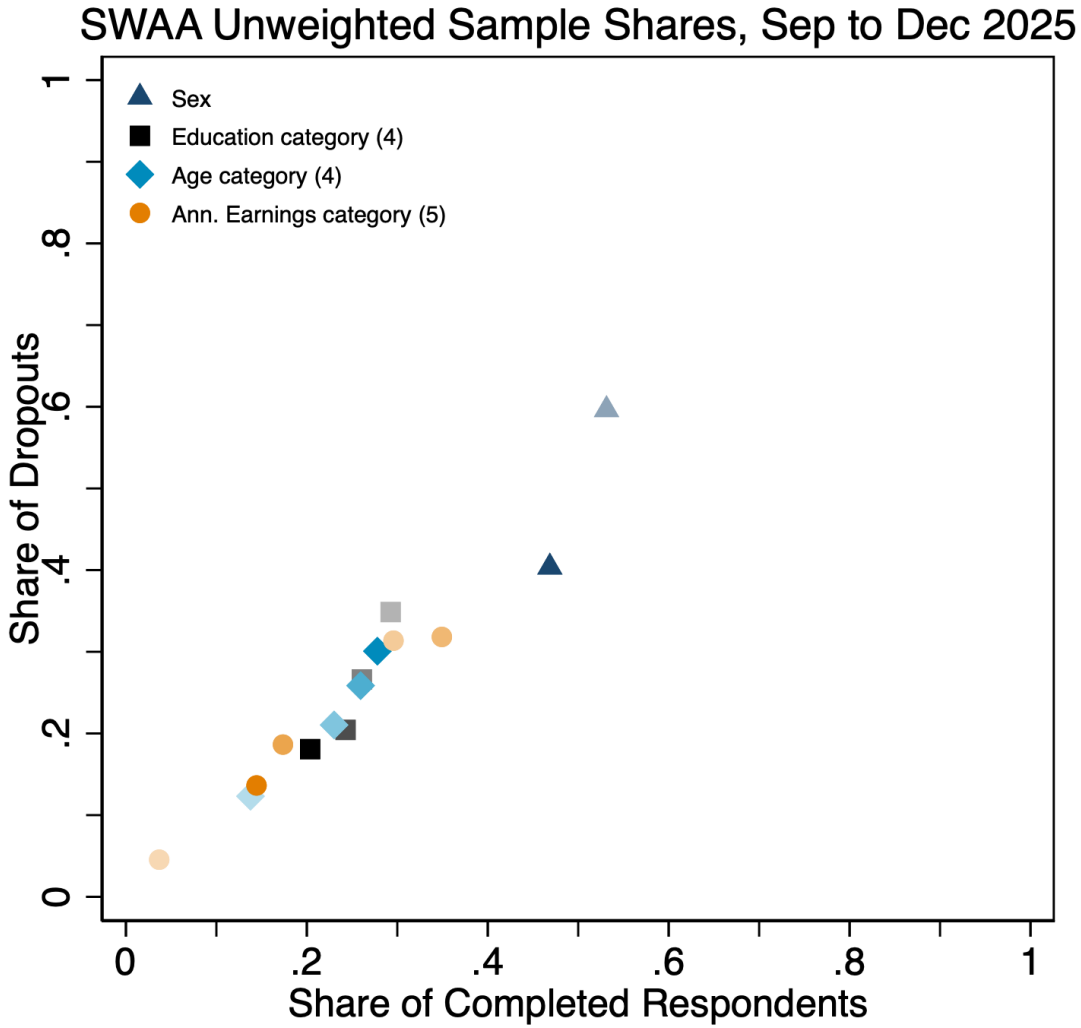
Responses to the Question:

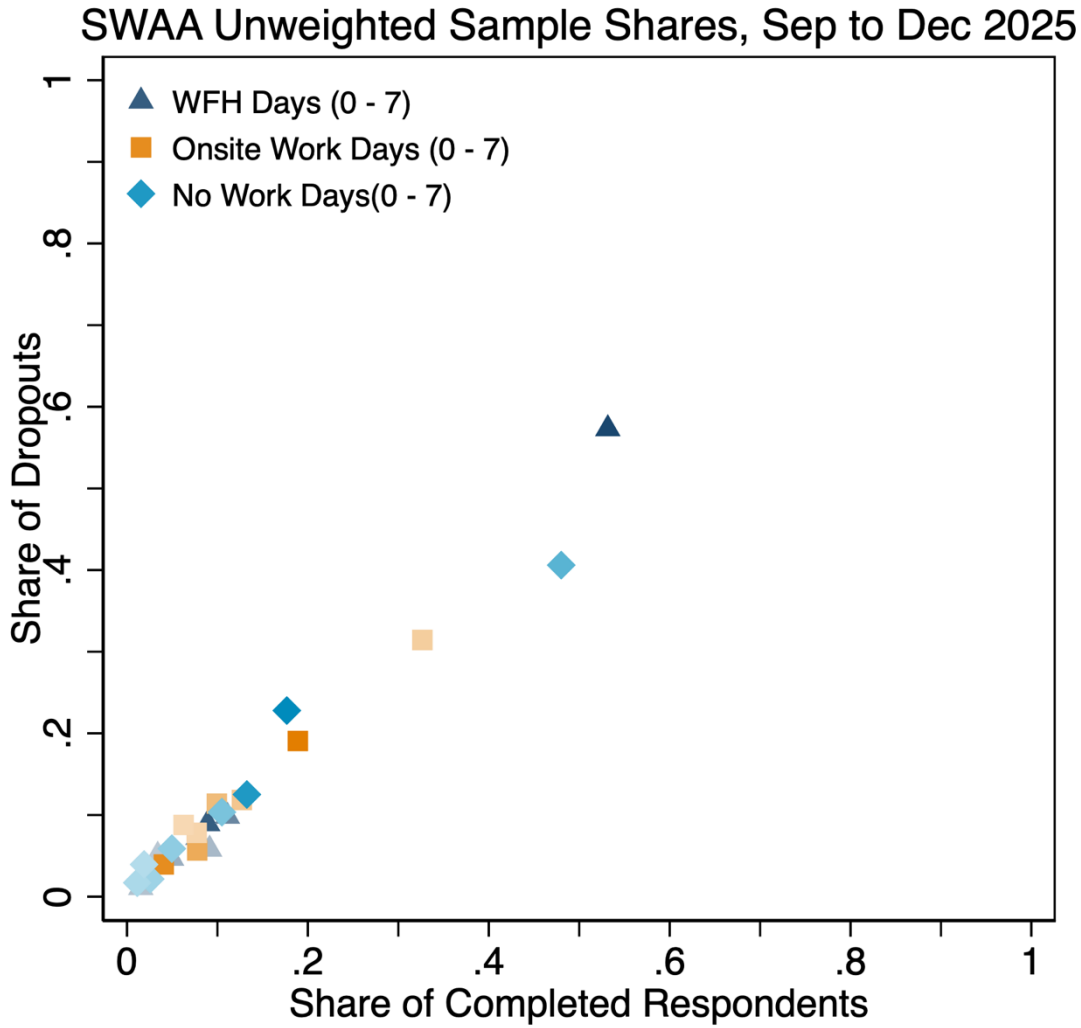
- *Generally speaking, do you usually think of yourself as a Republican, Democrat, Independent, or what?*

Notes: The figure shows the share of SWAA respondents who self-identify with the Democratic rather than the Republican party against the Democratic share of the two-party vote in the respondent's county of residence in the 2020 or 2024 election. We count respondents as affiliating with the Democratic party if they identify as a "Strong Democrat", "Not very strong Democrat" or "Independent close to Democrat", and similarly for Republicans. We exclude independents and those who prefer not to respond.

The sample includes SWAA respondents from the January 2022 through December 2025 waves. Data are reweighted to match the CPS by age x sex x education x earnings cells. We omit data for September 2023 due to data quality issues in that month.

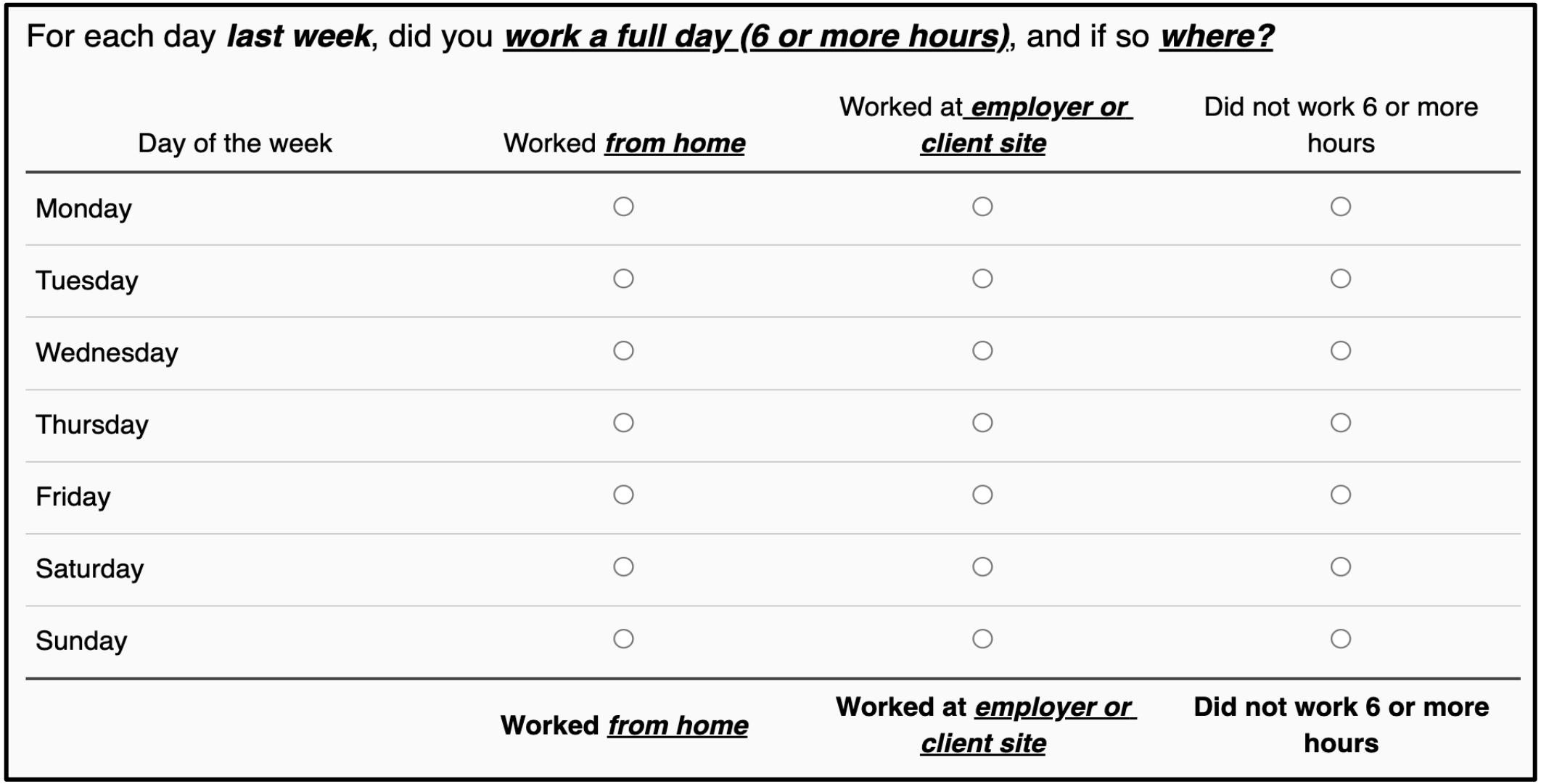
Figure A.3. Respondents Who Complete the Survey and Those Who Don't Have Similar Demographics and Work-From-Home Rates





Notes: These figures take raw survey responses from the September to December 2025 waves of the SWAA and compare the share of responses (unweighted) among respondents who complete the survey and those who drop out before the end, by key demographic categories (sex, education, age, and earnings) in the left panel. The right panel shows the share of responses by the number of days they report WFH, working onsite, or not working the prior week in response to the question shown in Figure A.4 among those who complete and drop out of the survey.

Figure A.4. Survey Question About Working Arrangements Last Week

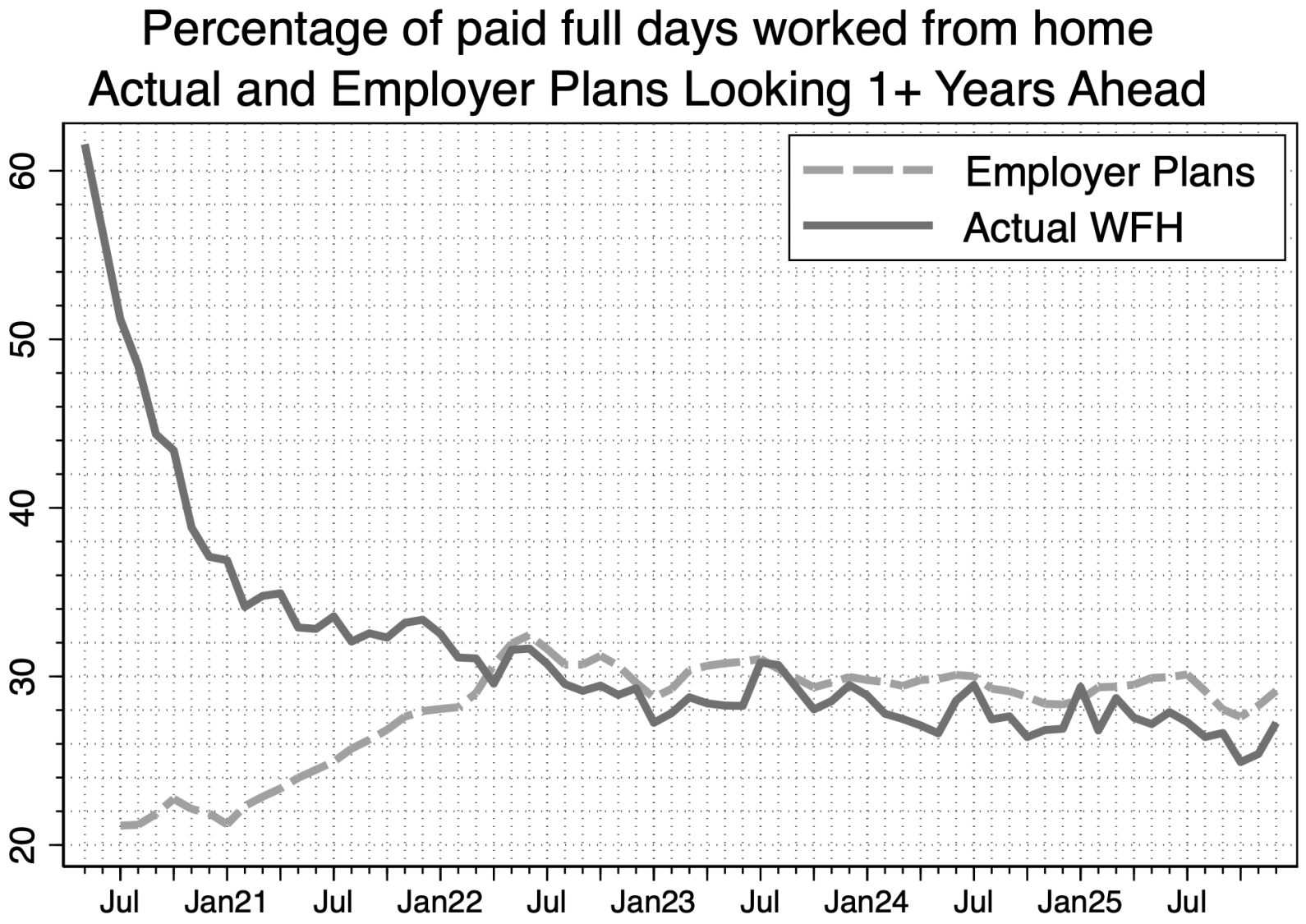


For each day ***last week***, did you ***work a full day (6 or more hours)***, and if so ***where?***

Day of the week	Worked ***from home***	Worked at ***employer or client site***	Did not work 6 or more hours
Monday	○	○	○
Tuesday	○	○	○
Wednesday	○	○	○
Thursday	○	○	○
Friday	○	○	○
Saturday	○	○	○
Sunday	○	○	○
	Worked *from home*	**Worked at *employer or client site***	**Did not work 6 or more hours**

Note: This is a screenshot of the question posed in November 2021 and later survey waves, which we use to measure WFH. See Appendix B for more details about those measurements.

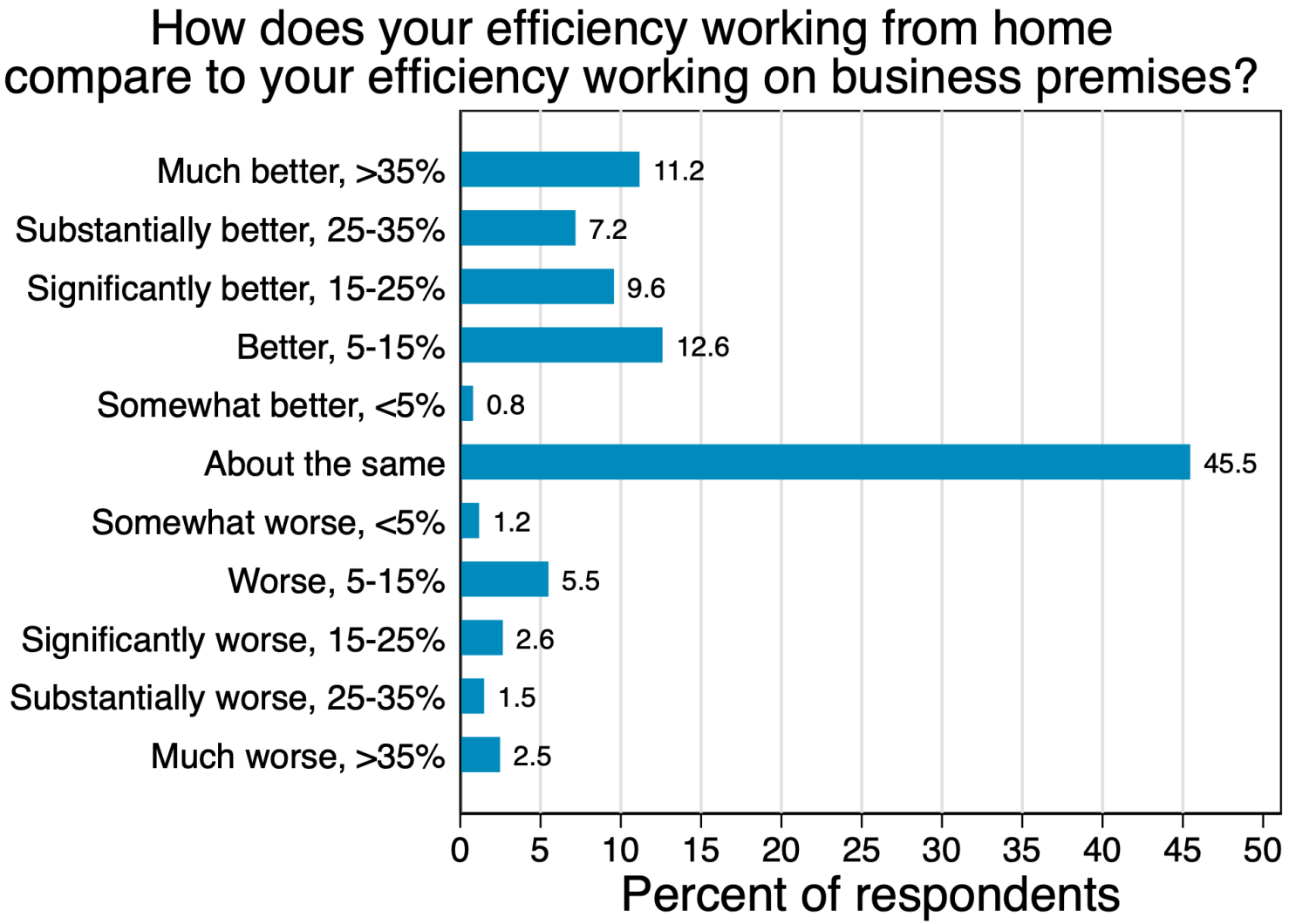
Figure A.5. Employer Plans for Long-term or Post-Pandemic WFH Converge with Actual WFH Rates in Mid-2022



Notes: The figure shows actual WFH rates using the same methodology and data as the SWAA series in Figure 1, starting from May 2020. The series for employer plans uses SWAA data, starting in July 2020, assumes a five-day workweek, and imputes no planned WFH if the respondent reports their employer has not provided any announcement or communication about future working arrangements. For employer plans, we report a 3-month moving average.

N = 271,229 (Actual WFH)
N = 310,790 (Employer Plans).

Figure A.6. About 40% of Respondents With Work-from-Home Experience Report Higher Efficiency When Doing So

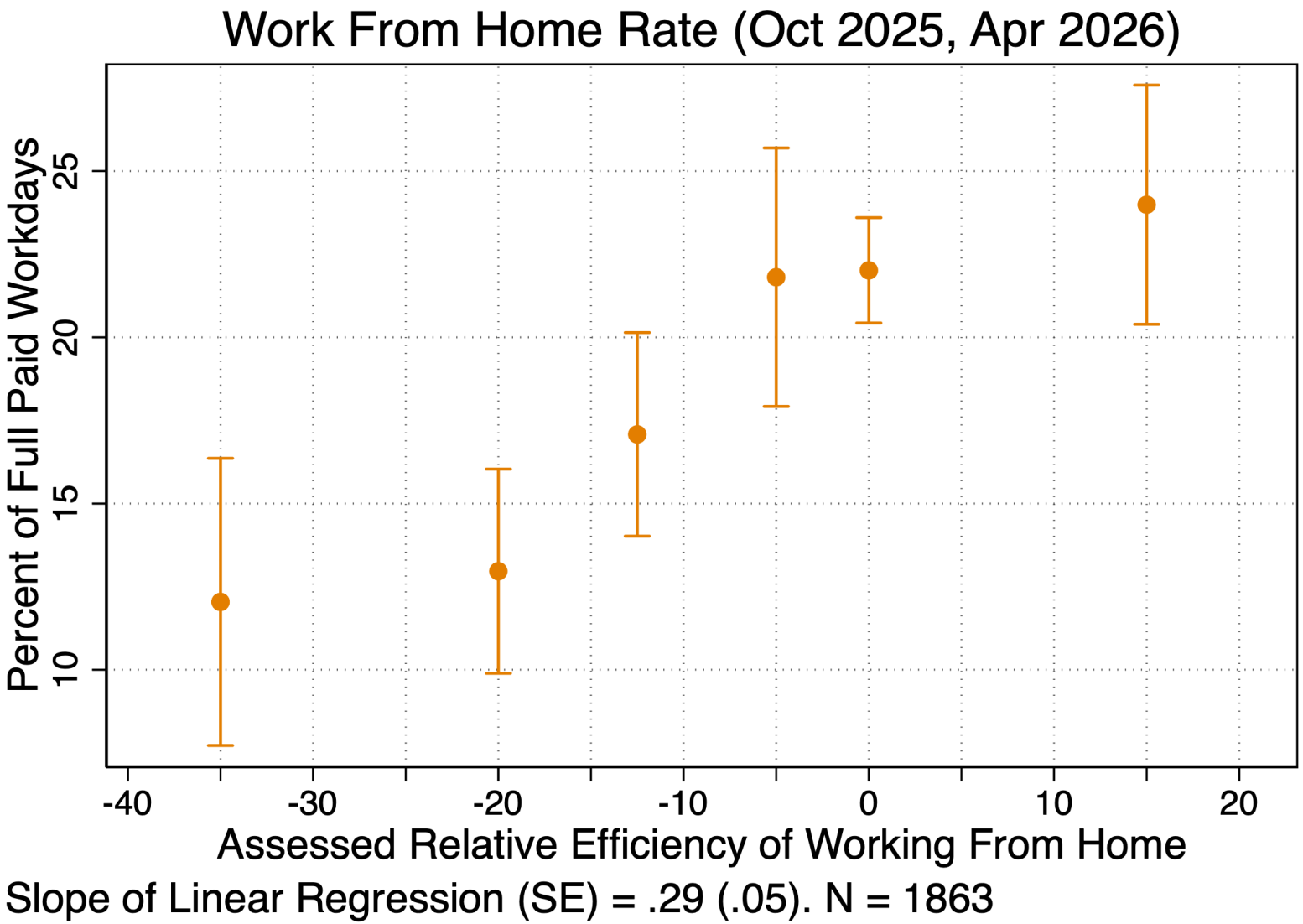


Responses to a two-part question:

- *How does your efficiency working from home compare to your efficiency working on business premises?*
  - *Better – I am more efficient at home…*
  - *About the same…*
  - *Worse – I am less efficient at home…*
- *How much* **more efficient [less efficient]** *are you working from home than on business premises?*

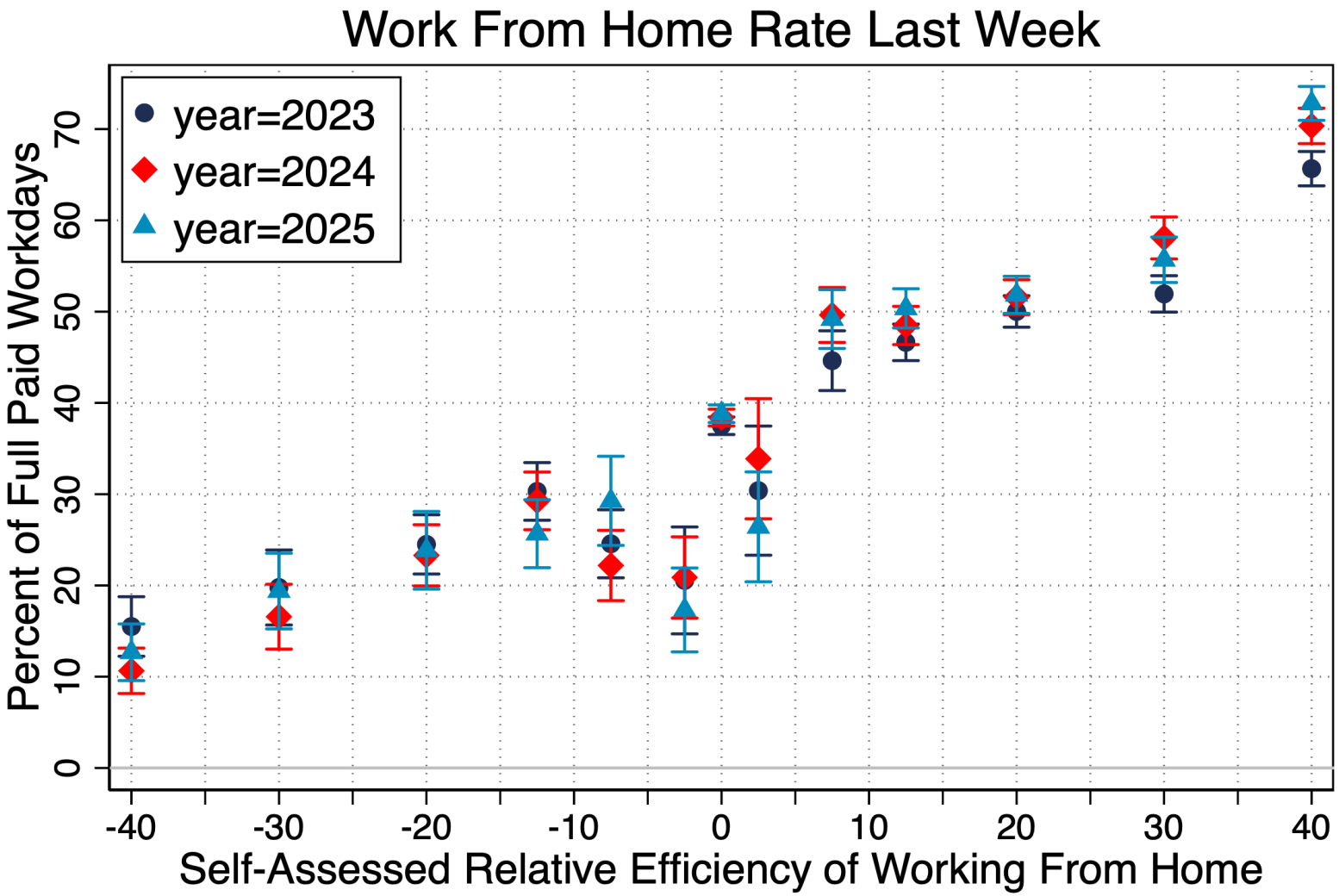
Notes: We randomize the order of the response options to the first question, with 50% seeing *"better"* on top and the other 50% on the bottom. The response options to the follow-up question are shown on the left side of the figure (for "*better*" or "*worse,*" respectively). Respondents who choose *"about the same*" in response to the first question do not see any follow-up question. Data are from the SWAA covering **January 2023 to December 2025**, reweighted to match the 2010 to 2019 CPS by age x sex x education x earnings cells. **N = 93,718.**

Figure A.7. Senior Managers with More Positive Views of WFH Productivity Report Higher Levels of Work from Home



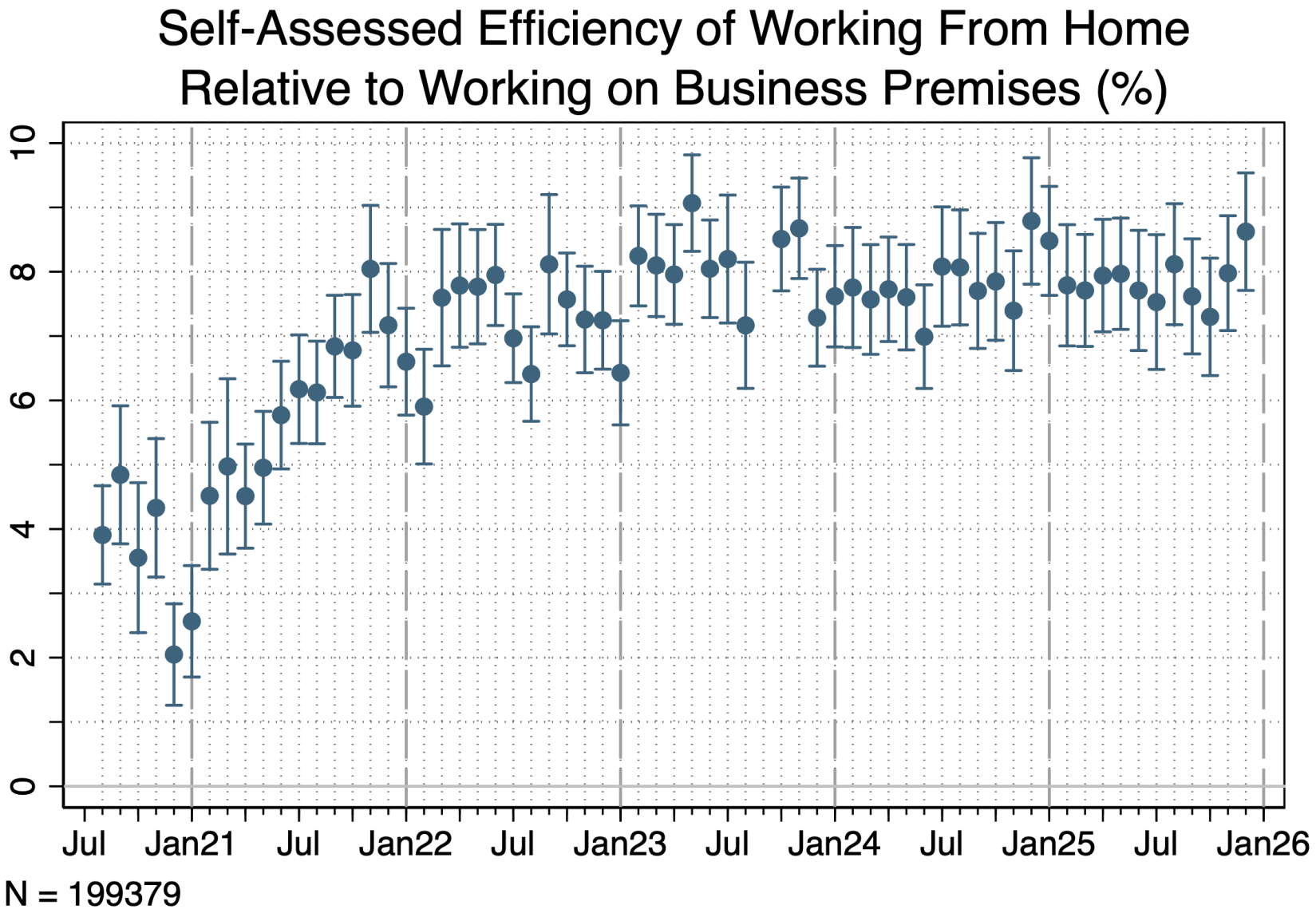
Notes: The figure shows a binned scatter plot of firm-level WFH rates against manager-assessed relative efficiency while WFH alongside 95% confidence intervals. We use the *binsreg* command of Cattaneo et al. (2024) and control for broad sector and survey wave effects. The data are based on survey responses from senior managers participating in the Atlanta Fed Survey of Business Uncertainty (SBU), based on their assessment of employees who can do at least part of their job while WFH. We measure WFH rates from the reported share of full-time employees who are fully on-site, on-site 3-4 days/week, on-site 1-2 days/week, or fully remote, expressed as a percent of WFH days in a 5-day workweek. We elicit relative efficiency assessments with a two-part question that first asks whether efficiency is better at home, about the same, or worse at home than on business premises for employees who can WFH, and then asks a follow-up question about how much better or worse. We interpret *"about the same"* to mean zero relative efficiency while WFH. The SBU data cover the October 2025 and April 2026 waves.

Figure A.8. The Gradient Between Self-Assessed Relative Efficiency and Work from Home Has Steepened Over Time



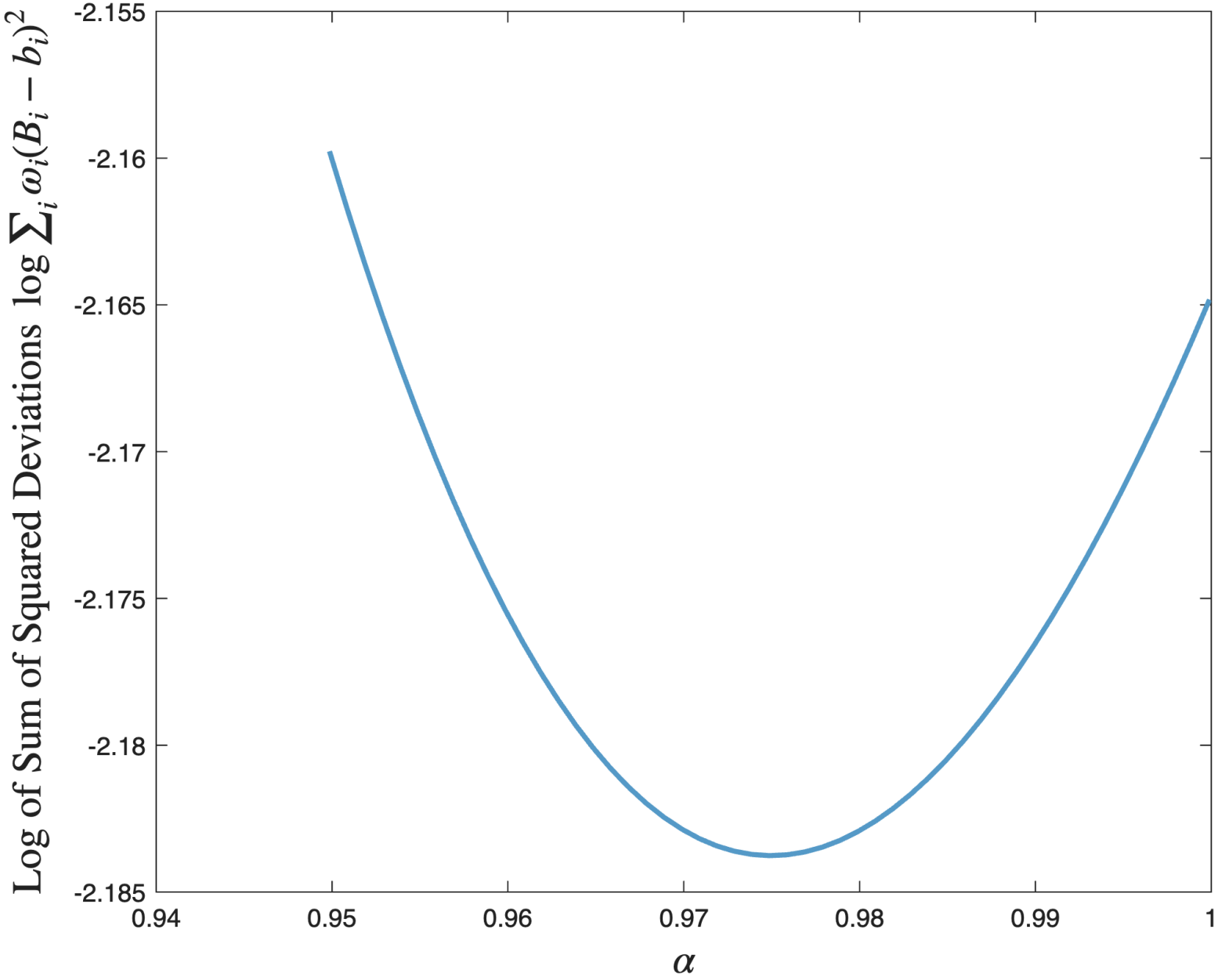
Notes: The figure shows the average WFH rate for each possible choice of self-assessed relative efficiency while WFH and its 95% confidence interval by year. We measure the WFH rate as the percent of paid workdays that are WFH days in the survey's reference week. (The survey question asks, *"For each day* **last week** *did you* **work a full day (6 or more hours)** *and if so* **where?***").* We measure self-assessed relative efficiency with a two-part question that first asks whether efficiency is better at home, about the same, or worse at home than on business premises, and then asks a follow-up question to ask how much better or worse. We interpret *"about the same"* to mean zero relative efficiency while WFH. Data are from SWAA waves covering **January 2023 to December 2025**, reweighted to the CPS by age, sex, education, and earnings.

Figure A.9. Self-Assessed Relative Efficiency of Work from Home (Among Those with WFH Experience) Rises Over 2021 and then Stabilizes



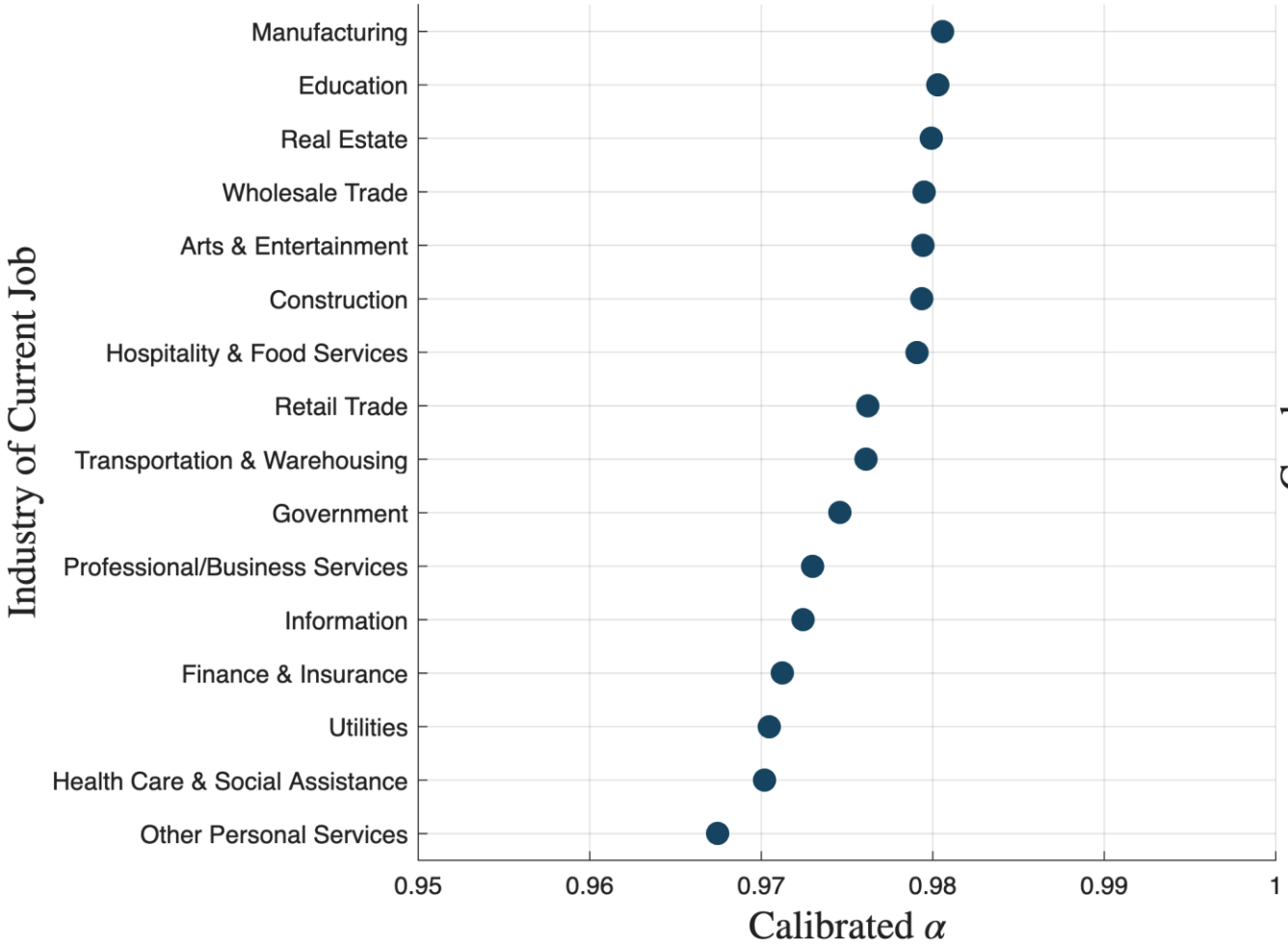
Notes: The figure shows a binned scatter plot (computed using the *binsreg* command by Cattaneo et al., 2024) of self-assessed relative efficiency while WFH by date after controlling for fixed effects for age category (e.g., 30 to 39), sex, education, earnings category (e.g., $20k to $50k) and industry of the current or most recent job. Data are from the SWAA, reweighted to match the CPS by age x sex x education x earnings cells. We omit data for September 2023 due to data quality issues in that month. The vertical axis is scaled so that a value of 1 implies that workers, on average, believe they have 1% higher relative efficiency while WFH.

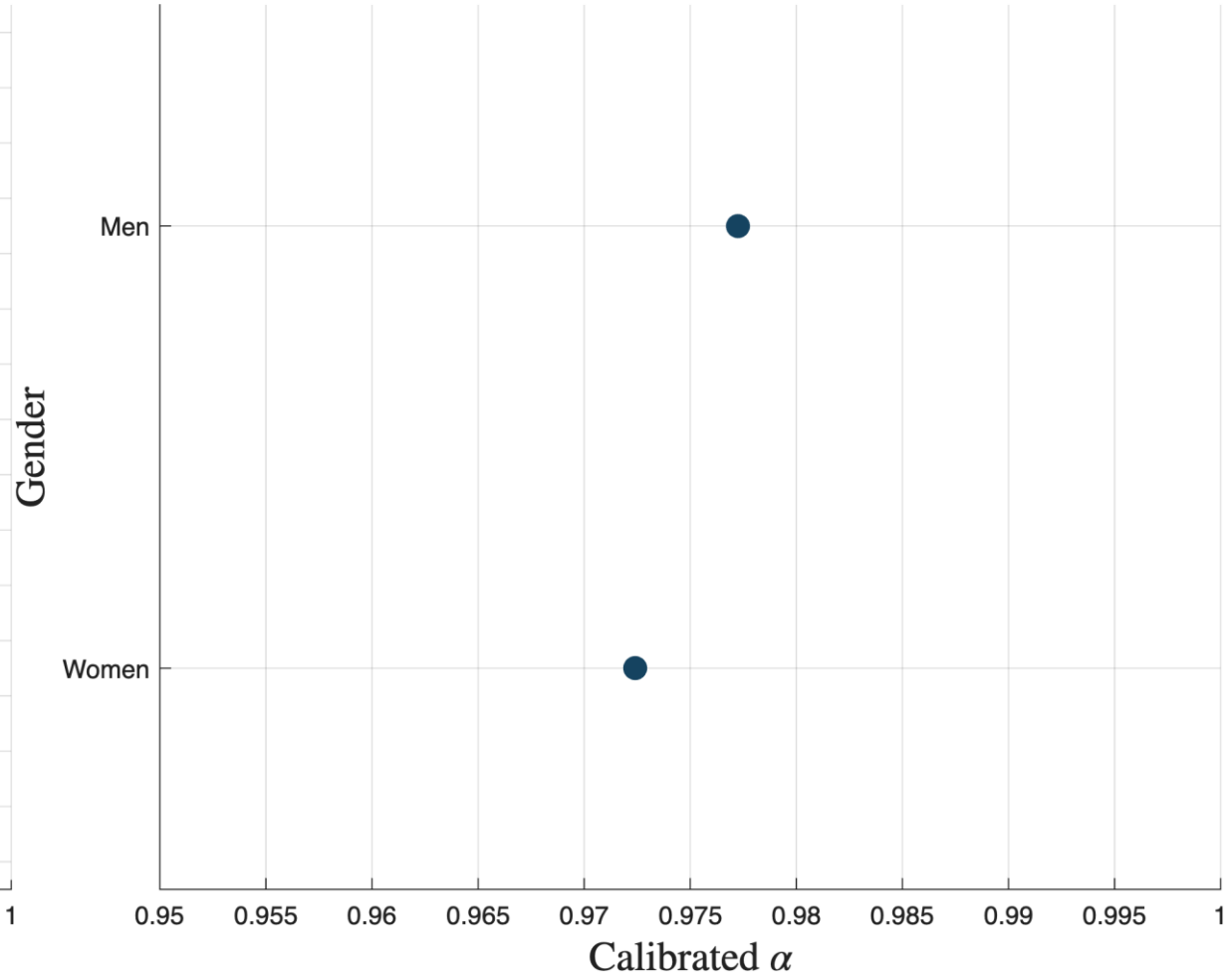
Figure A.10. Setting Alpha to Minimize Squared Deviations Between Self-Assessed and Model-Implied Relative Efficiency in Remote Mode



Notes: We plot the natural logarithm of the objective function for the calibration of alpha $F(\alpha) = \sum_{i \in I} \omega_i \cdot \left(b_i - B_i(\alpha; h_i, \delta_i)\right)^2$ where i indexes workers, b_i is self-assessed relative efficiency while WFH (rescaled so that 0 means the worker cannot WFH at all and 1 means the worker is equally efficient at home and at the worksite), and $B_i(\alpha)$ is the implied productivity shifter in remote mode given by equation (9) in the text. We plot $F(\alpha)$ for α in the vicinity of its unique solution. The data on b_i and the determinants of $B_i(\alpha; h_i, \delta_i)$ come from a sample of SWAA respondents from the **January 2023 to December 2025** waves who worked at least 20 hours during the reference week.

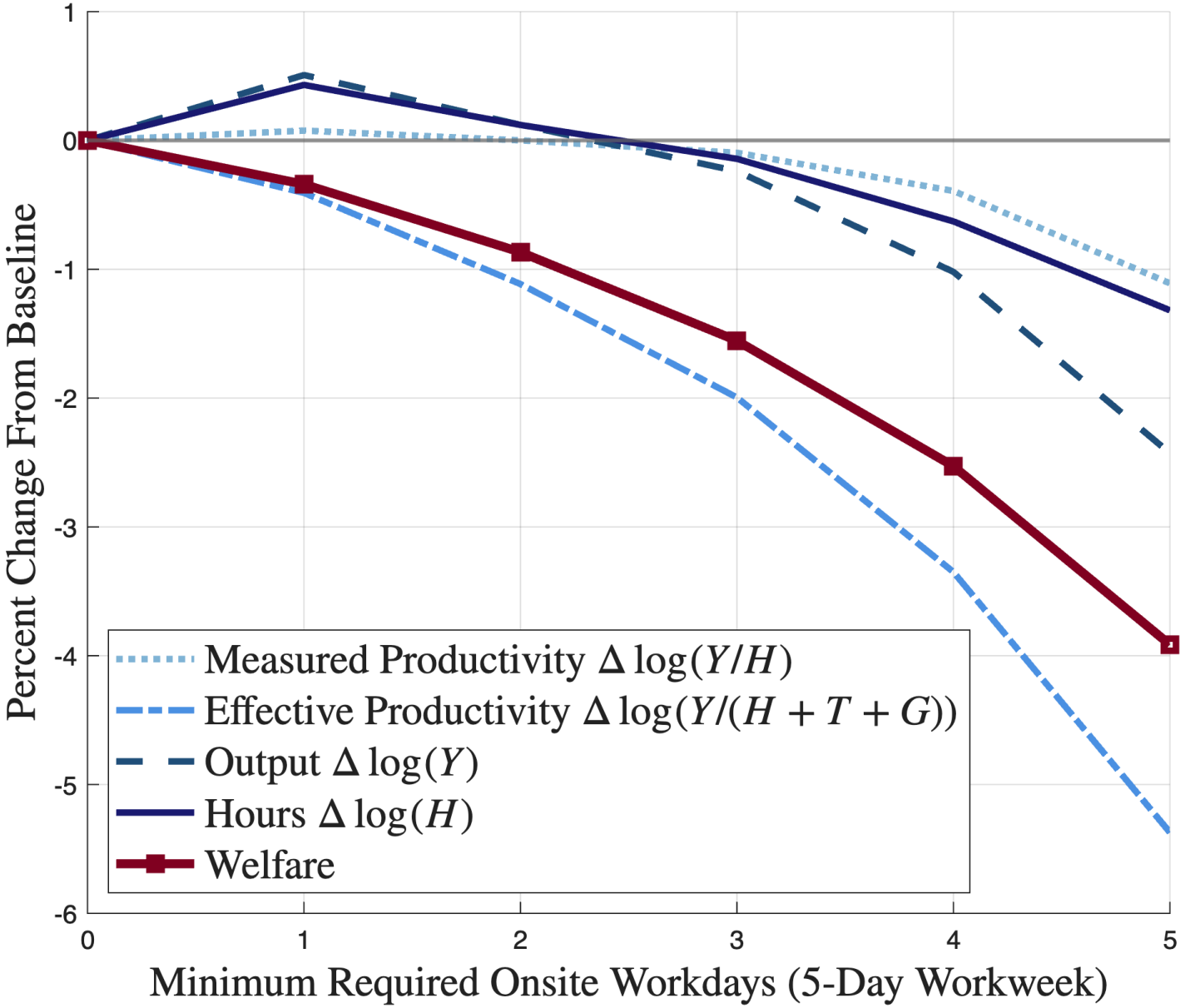
Figure A.11. Calibrating α Separately by Industry and Gender





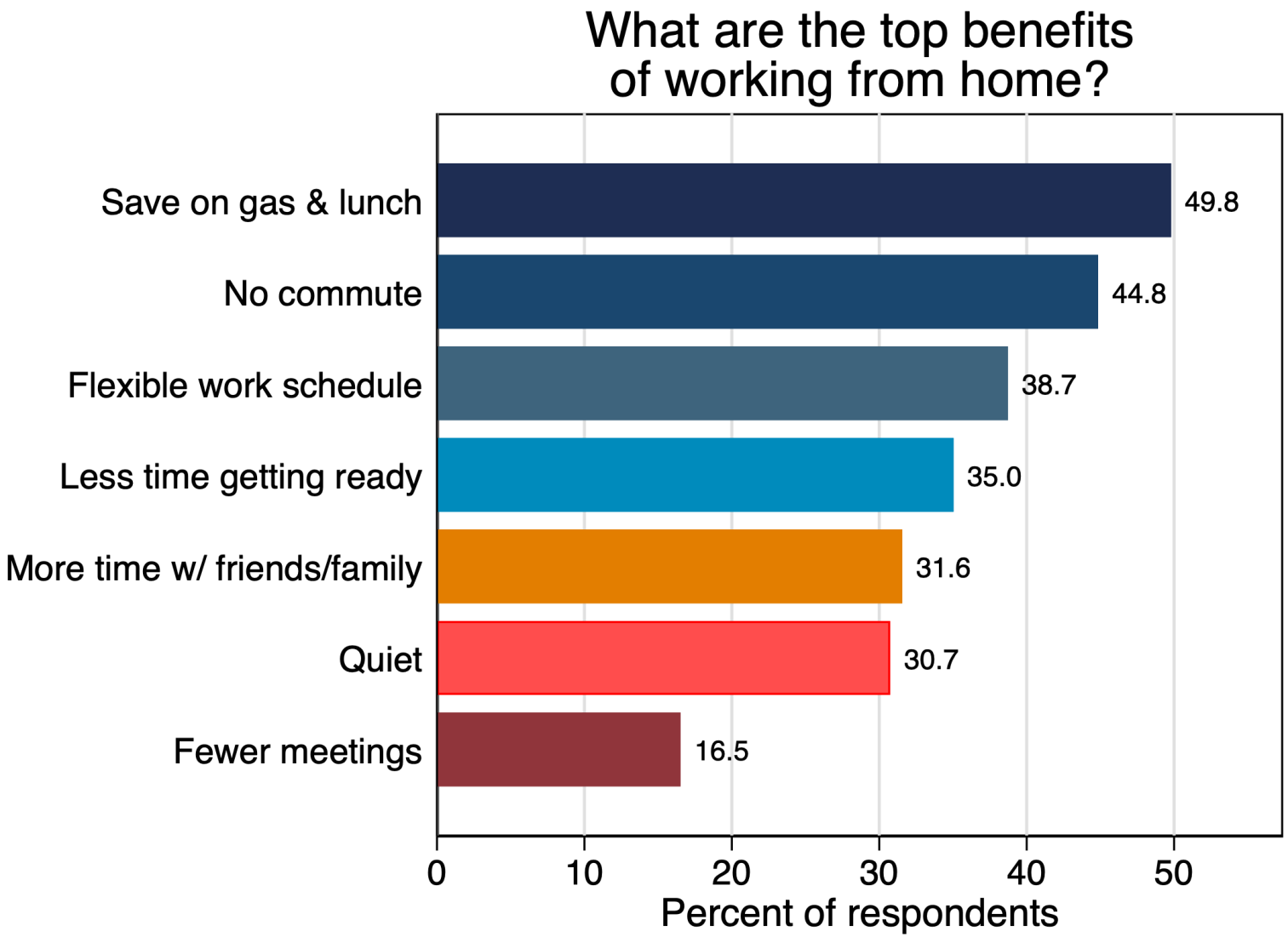
Note: These figures report the calibrated α parameters when we assume different industries (left) or genders (right) have different alpha parameters.

Figure A.12. Requiring a Minimum Number of Onsite Workdays Lowers Effective Productivity and Welfare



Notes: The figure shows how productivity, output and mean consumption-equivalent welfare change relative to baseline when requiring all workers to work a minimum number of days onsite. The x-axis expresses that requirement as 0, 1, 2, 3, 4, or 5 days in a five-day workweek, implemented as maximum allowable WFH rates of 100%, 80%, 60%, 40%, 20%, or 0% of paid workdays. Zero required onsite workdays (i.e., no required curtailment of WFH) reproduces the baseline 2023-25 equilibrium outcomes in the basic model. Moving from 0 to the right on the horizontal scale, we report outcomes as percentage deviations from the baseline.

Figure A.13. What Workers Report as the Top Benefits of Working from Home



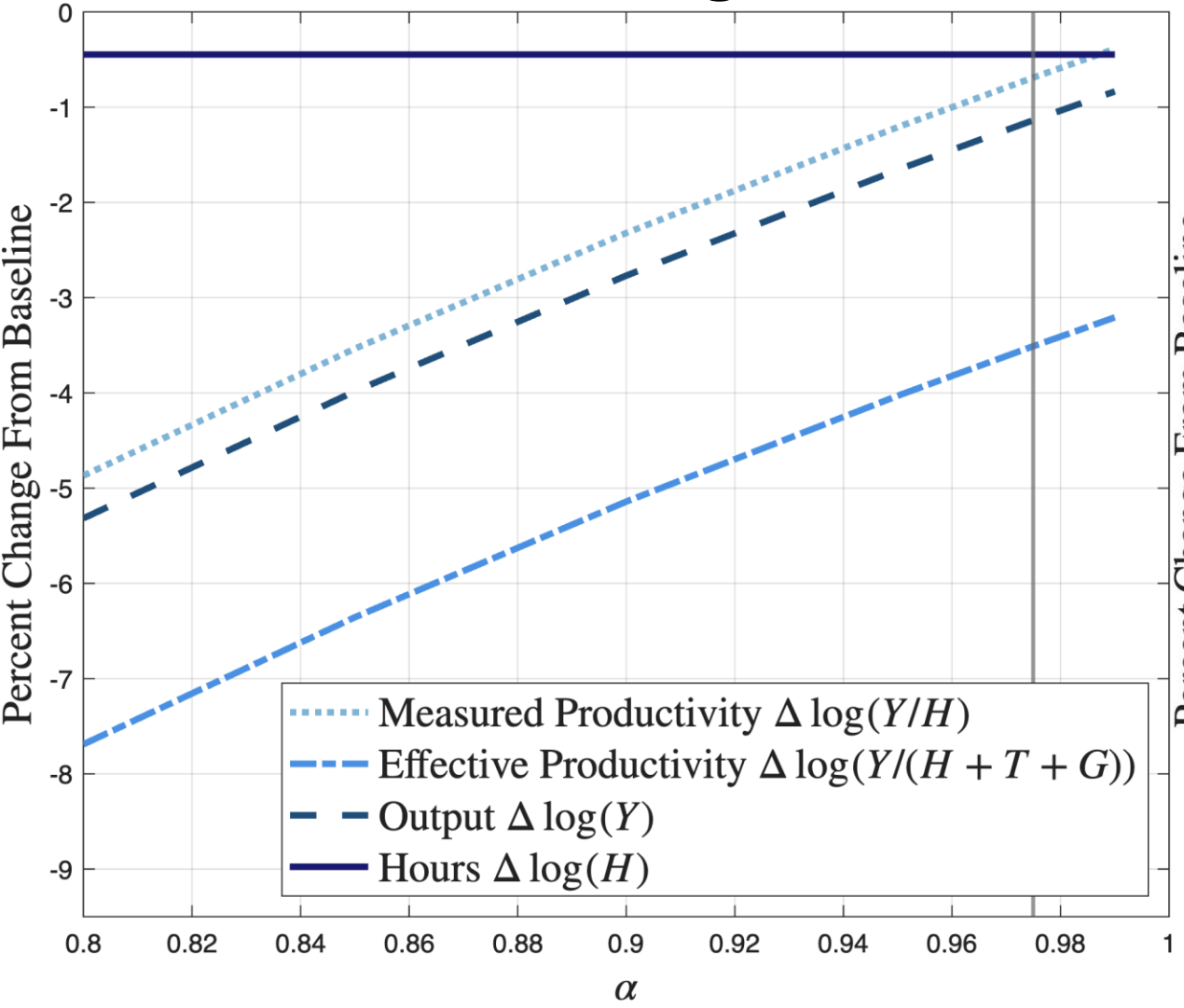
Responses to the Question:

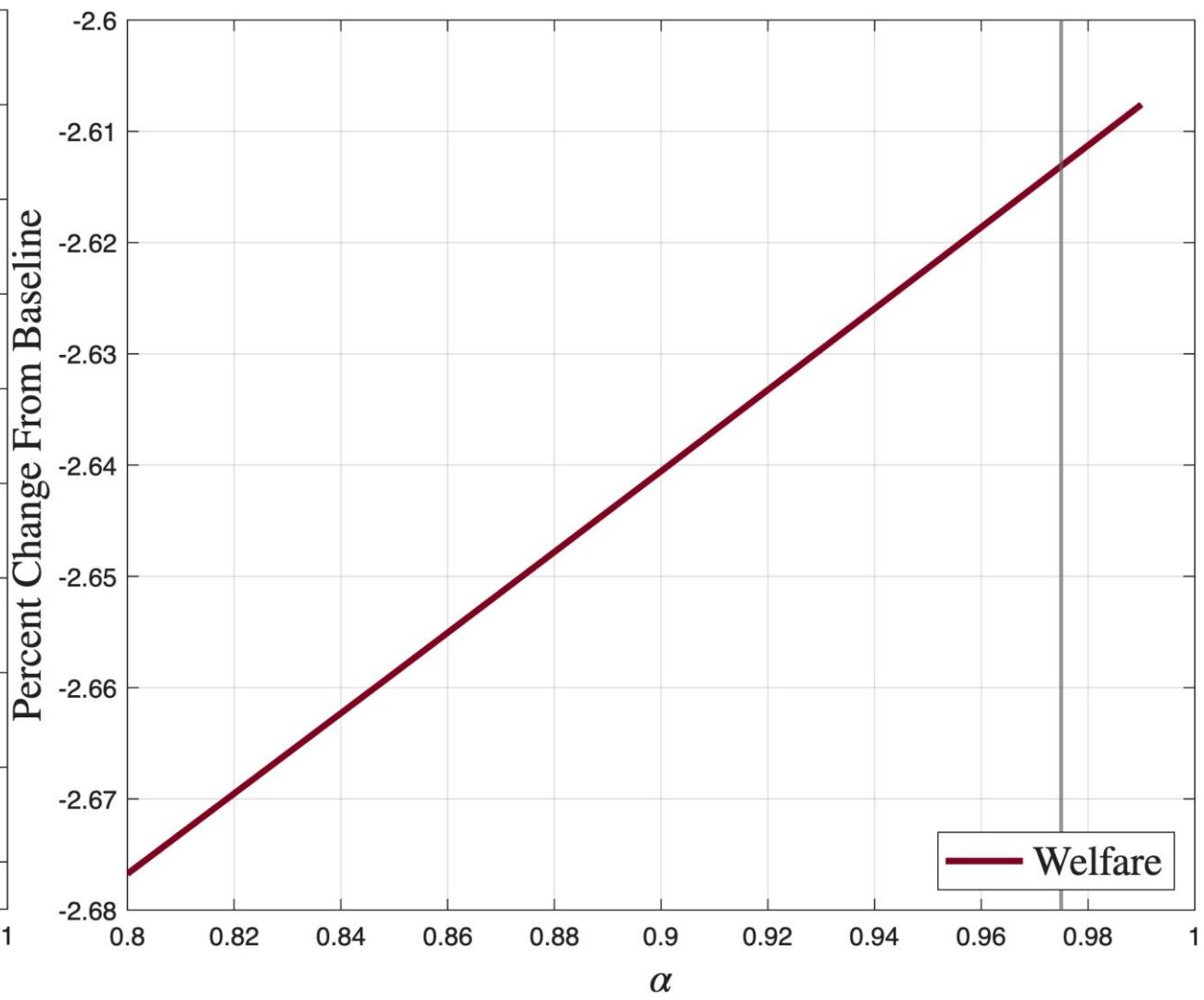
- *What are the* **top benefits** *of* **working from home?** ***Please choose up to three.***

Notes: The figure shows the percent of respondents choosing each top benefit. The sample includes SWAA respondents who worked from home at some point since 2020 and participated in the **June to September 2022, March to September 2023 or March to April 2025** waves. We reweight the SWAA data to match the CPS by age x sex x education x earnings cells.

N = 52,130

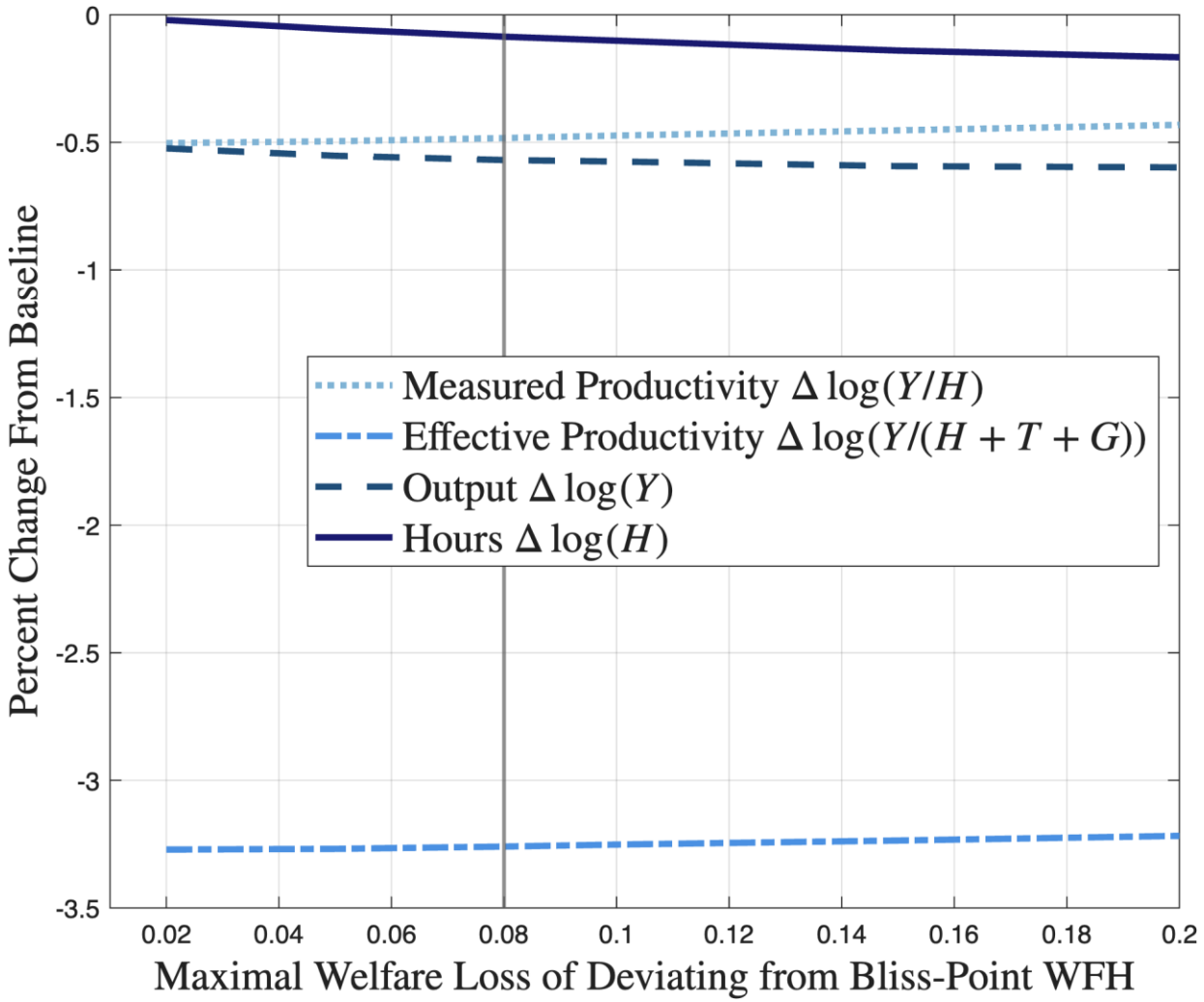
Figure A.14. Productivity, Output, and Welfare Effects of Returning to 2019 Work Arrangements as a Function of α, Using the Basic Model

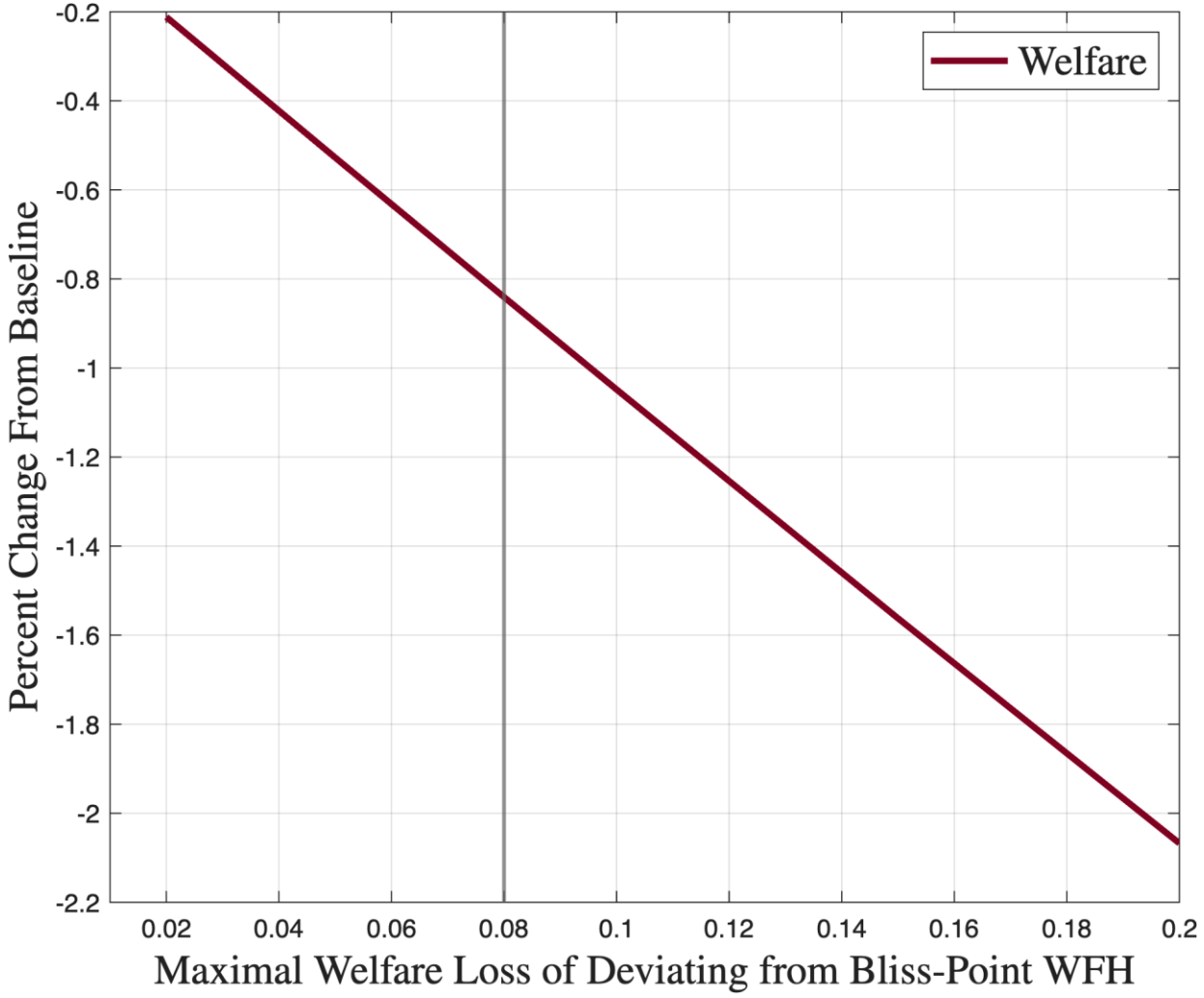




Notes: These figures show how the changes in productivity, output and welfare when imposing the 2019 WFH norms differ across values of α. Each point on the graph recomputes the results in the first row of Table 1 for the value of α shown on the x-axis. The vertical line shows our calibrated value of $\alpha = .975$.

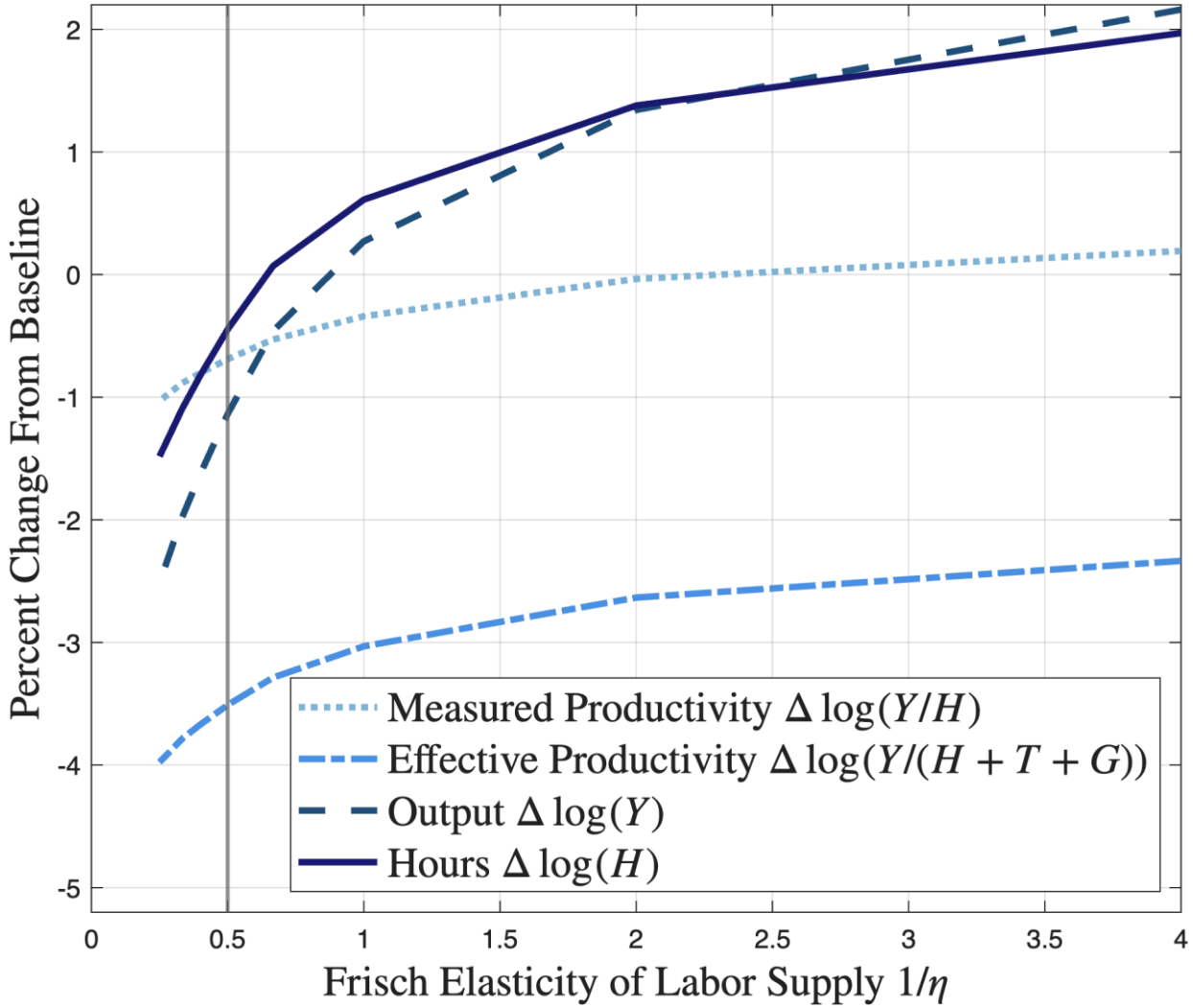
Figure A.15. Effects of Returning to 2019 Work Arrangements as a Function of ψ in the Model with Heterogeneous Preferences Over WFH

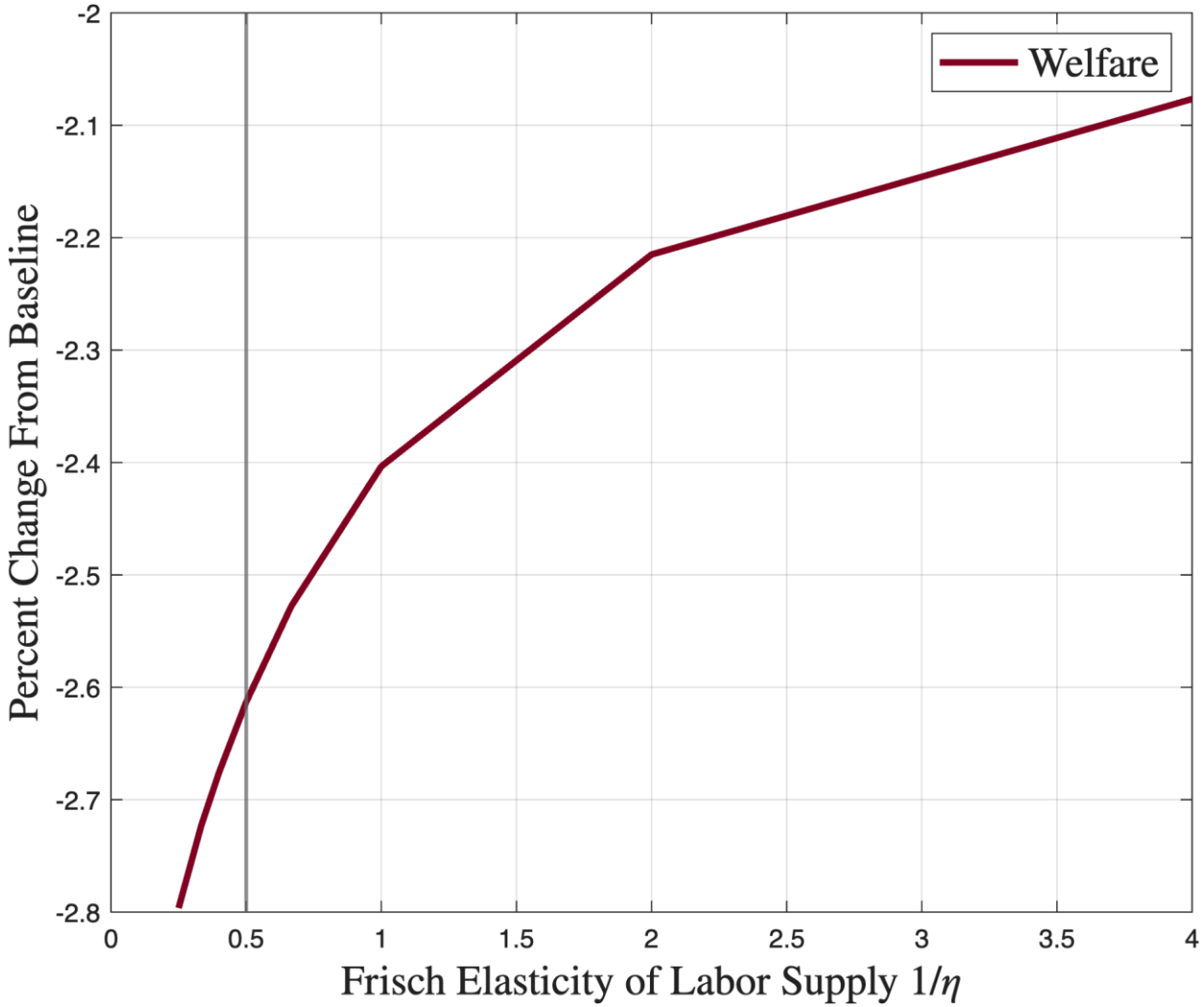




Notes: These figures show how the effects of returning to 2019 work arrangements vary as a function of ψ in the model with heterogeneous preferences over desired WFH rates. Recall that ψ relates to the maximal welfare cost of deviating from the bliss-point WFH rate according to $\psi = -2 \cdot \log(1-x)$, where x is the welfare cost expressed as a proportion of consumption. The vertical line shows our baseline choice of 8% for the maximum welfare cost, which corresponds to ψ=0.17 and reproduces the results from the third row of Table 1.

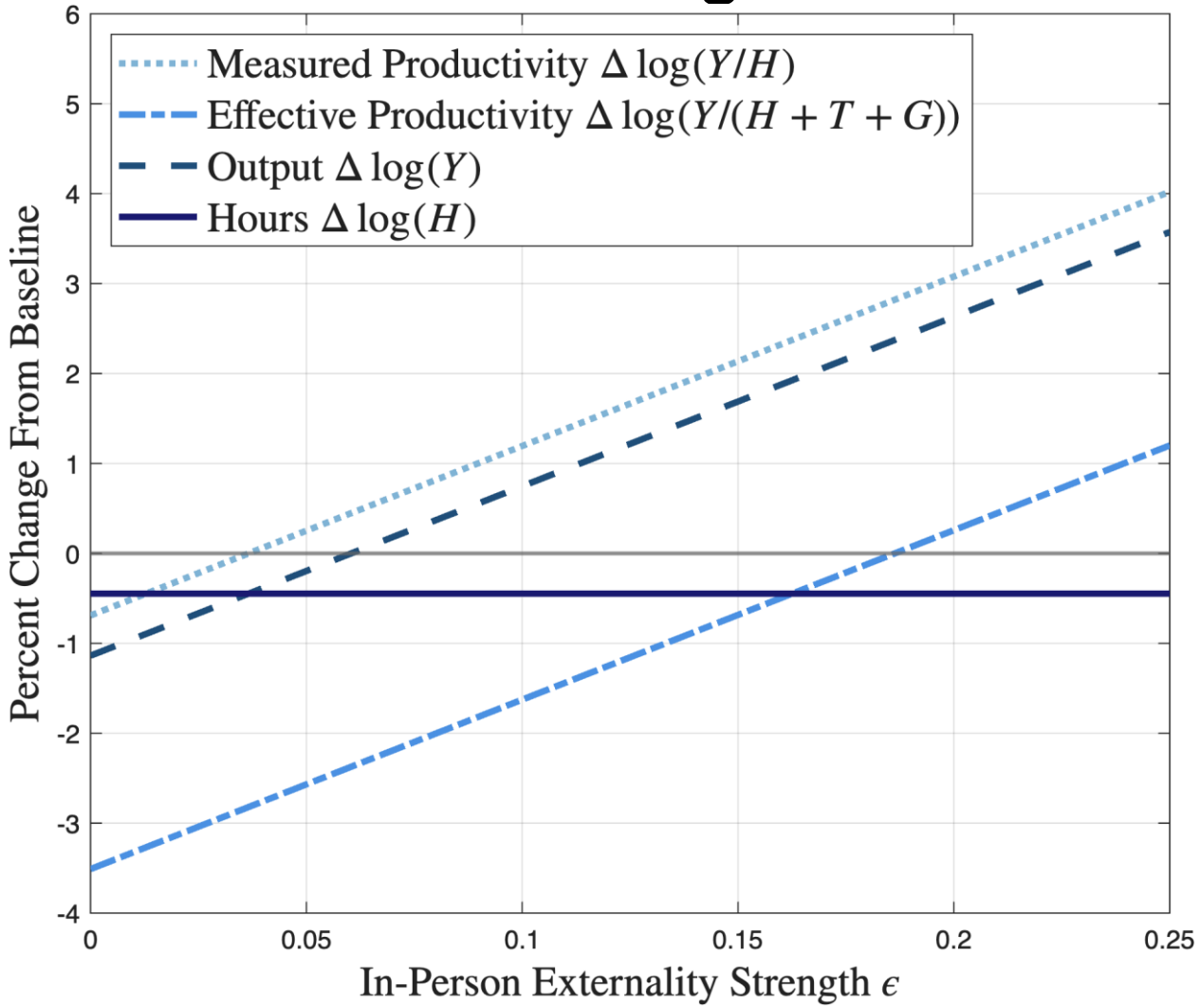
Figure A.16. Productivity, Output, and Welfare Effects of Returning to 2019 Work Arrangements as a Function of $1/\eta$, Using the Basic Model

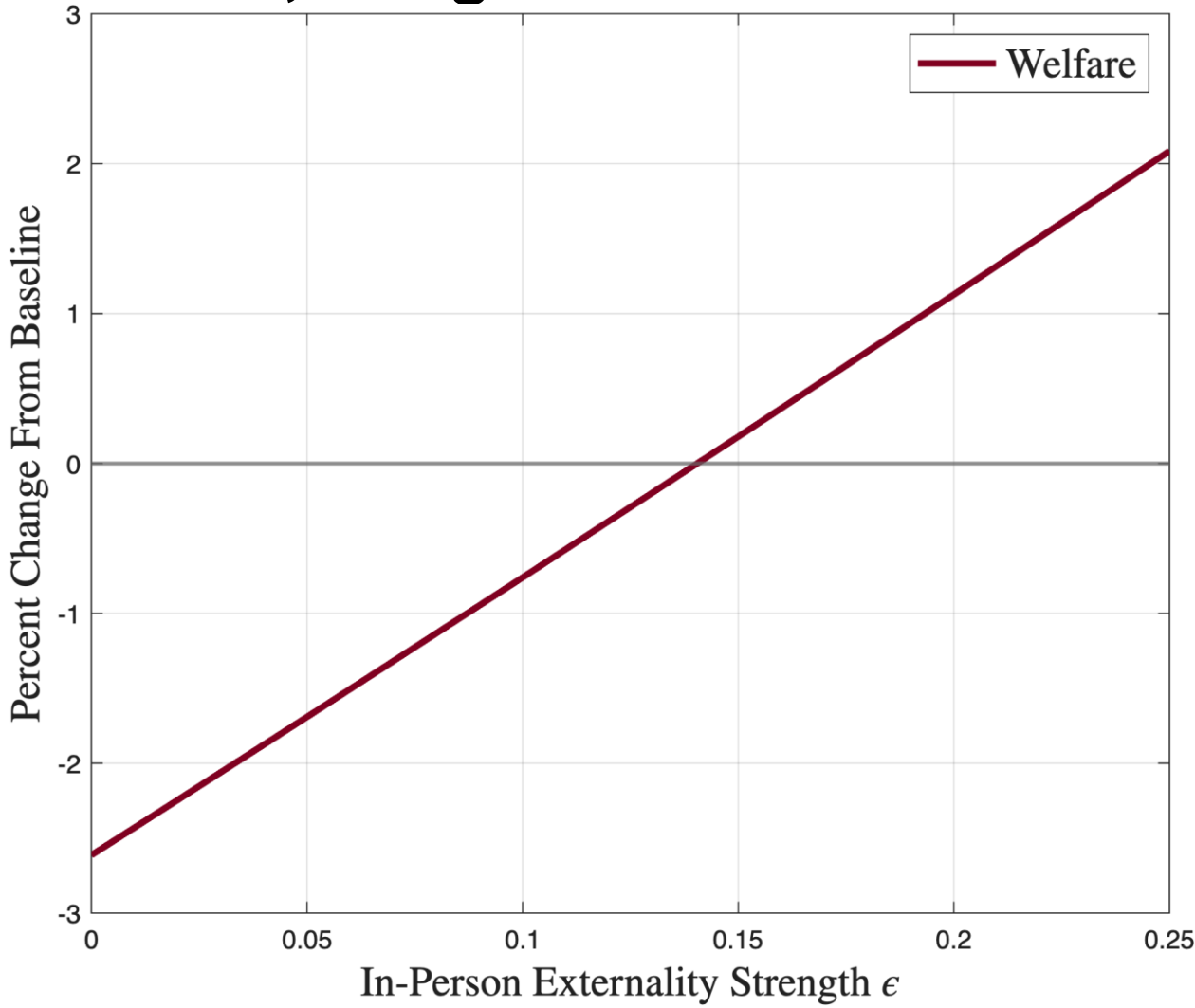




Notes: These figures show how the changes in productivity, output and welfare when imposing the 2019 WFH norms vary with the Frisch elasticity of labor supply $1/\eta$ (for the total of paid work hours, commute time, and extra grooming time on commute days). Each point on the graph recomputes the results in the first row of Table 1 for the value of $1/\eta$ shown on the x-axis. The vertical line shows our baseline value of $1/\eta = .5$.

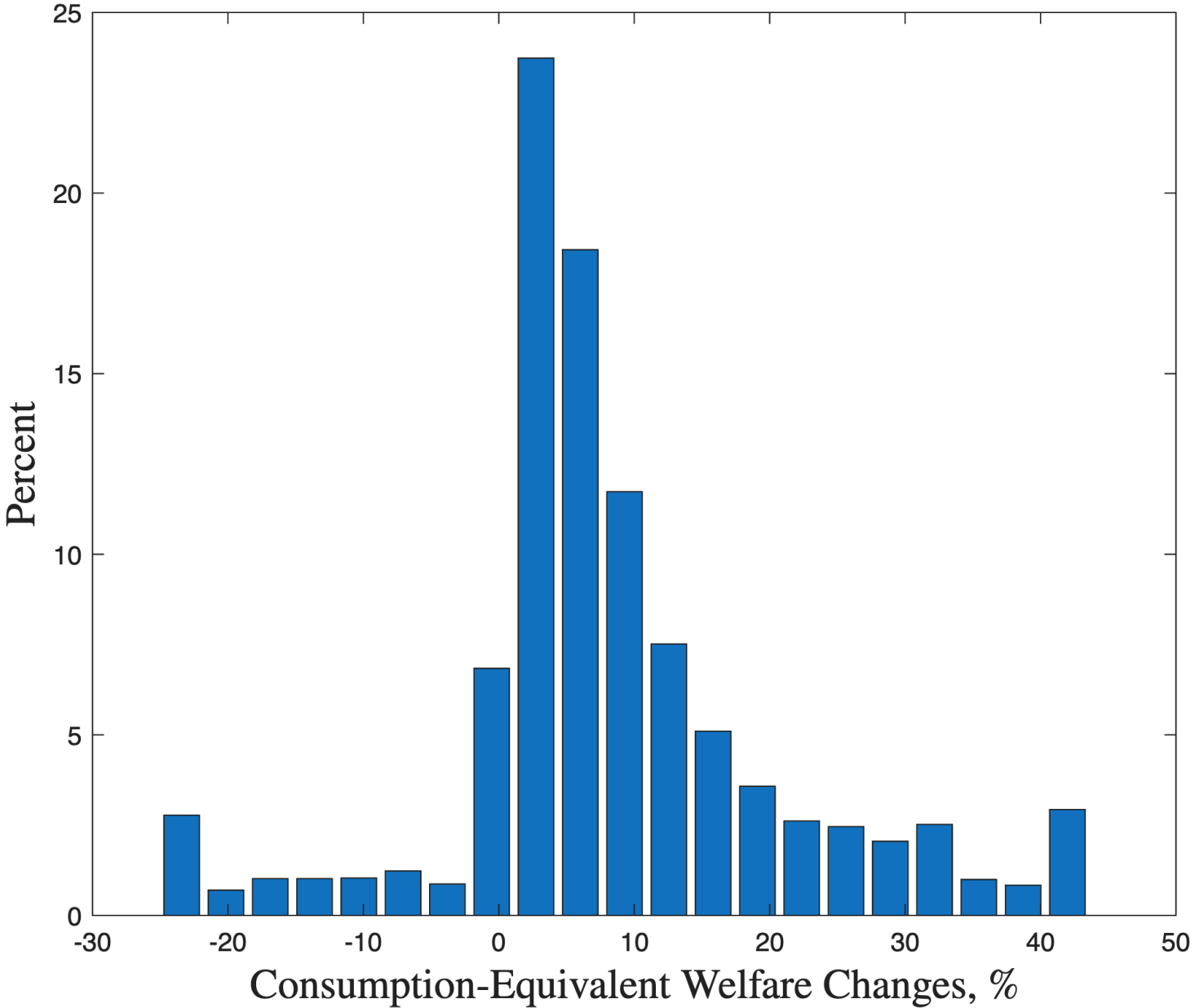
Figure A.17. Productivity, Output, and Welfare Effects of Returning to 2019 Work Arrangements as a Function of ε, Using the Basic Model





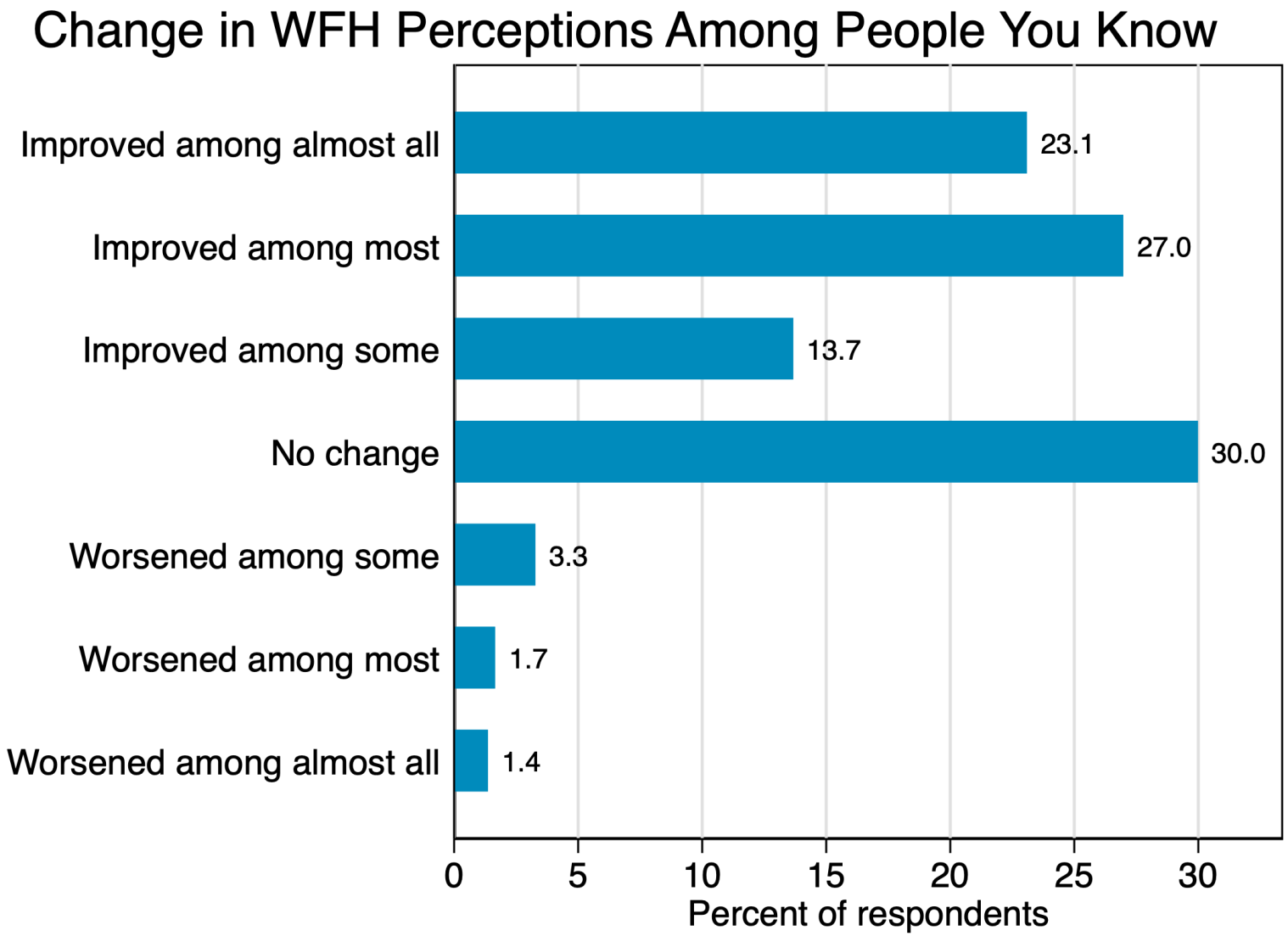
Notes: These figures show how the changes in productivity, output and welfare when imposing the 2019 WFH norms vary with ε, where ε governs the strength of external productivity spillovers from in-person work in our basic model. This version assumes that spillovers depend on the equal-weighted share of labor supplied on-site, but Table 2 considers a version where they depend on the productivity-weighted share. Each point on the graph recomputes the results in the first row of Table 1 for the value of ε shown on the x-axis.

Figure A.18. Experimentation & Learning Raise Average Welfare, With High Cross-Sectional Dispersion in Welfare Changes



Notes: The figure shows a histogram of consumption-equivalent welfare changes for the 28.6% of workers who are directly affected by experimentation and learning. To obtain the individual-level welfare changes, we first compute the 2023-25 baseline equilibrium. We then draw individual-level productivity surprises s_i consistent with the positive relationship between those surprises and 2022 WFH rates in Figure 8 to obtain a vector of implied $\{B_i'\}_{i \in I}$ values that would hold absent experimentation and learning, defining $B'_i = B_i/(1 + s_i)$ where we infer B_i from the baseline calibration. Using the $\{B_i'\}_{i \in I}$ values, we compute the counterfactual equilibrium absent experimentation and learning. We keep all other model parameters at their baseline values, except for capping two-way commute and grooming times at 3.5 hours per day. Welfare falls for workers who WFH in the 2023-25 data after drawing a negative productivity surprise in WFH mode.

Figure A.19. Most Workers Report A Big Reduction in the Stigma Associated with Work from Home



Responses to the Question:

- *Since the COVID pandemic began,* **how have perceptions about working from home (WFH) changed among people you know?**

Notes: The figure shows responses to the above question, with abbreviated versions of the response options shown on the left side. The sample includes SWAA respondents in the July 2020 to October 2021 waves, and March to May 2022 waves.

N = 66,520

Table A.1. How Self-Assessed Relative WFH Productivity b_i and Model-Implied Relative Efficiency B_i Vary with Observables

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent Variable	**Self-Assessed Relative Efficiency of WFH: *100x(b-1)***				**Model-Implied Relative Efficiency of WFH: *100x(B-1)***			
Age: 30-39	0.9**	0.9**	0.9**	0.9**	1.0	0.9	1.0	1.0
	(0.4)	(0.4)	(0.4)	(0.4)	(1.2)	(1.2)	(1.2)	(1.2)
40-49	0.2	0.2	0.4	0.3	-1.8	-1.8	-1.2	-1.2
	(0.4)	(0.4)	(0.4)	(0.4)	(1.2)	(1.2)	(1.2)	(1.2)
50-64	-1.9***	-1.8***	-1.5***	-1.4***	-5.5***	-5.5***	-3.6***	-3.3***
	(0.4)	(0.4)	(0.4)	(0.4)	(1.2)	(1.3)	(1.2)	(1.2)
Education: 1 to 3 Years of College	1.1***	1.1***	0.9**	0.8**	2.6**	2.6**	2.4*	2.5**
	(0.4)	(0.4)	(0.4)	(0.4)	(1.3)	(1.3)	(1.3)	(1.3)
4-Year College Degree	0.9**	0.9**	0.9**	0.9**	7.2***	7.2***	7.8***	7.6***
	(0.4)	(0.4)	(0.4)	(0.4)	(1.2)	(1.2)	(1.2)	(1.2)
Graduate Degree	0.4	0.4	0.8*	0.9**	3.0**	3.0**	5.5***	5.8***
	(0.4)	(0.4)	(0.5)	(0.5)	(1.3)	(1.3)	(1.3)	(1.3)
Sex: Male	-1.5***	-1.5***	-1.6***	-1.4***	2.3***	2.5***	0.6	0.7
	(0.3)	(0.3)	(0.3)	(0.3)	(0.8)	(0.8)	(0.8)	(0.8)
log(Prior-Year Earnings)	2.4***	2.4***	1.9***	1.9***	9.0***	8.8***	6.3***	6.2***
	(0.2)	(0.2)	(0.2)	(0.2)	(0.7)	(0.7)	(0.7)	(0.7)
Two-way Commute Time, Plus Extra Grooming Time	1.0***	1.1***	1.0***	1.0***	4.8***	4.9***	4.3***	4.3***
on In-Person Days (hours)	(0.1)	(0.1)	(0.1)	(0.1)	(0.2)	(0.2)	(0.2)	(0.2)
Survey-Wave FE		Y	Y	Y		Y	Y	Y
Industry of Current Job FE			Y	Y			Y	Y
Occupation FE				Y				Y
Observations	46,236	46,236	46,036	45,944	46,236	46,236	46,036	45,944
R-squared	0.020	0.023	0.042	0.047	0.036	0.039	0.084	0.089

Notes: We regress self-assessed relative WFH efficiency (columns 1 to 4) and model-implied relative efficiency (columns 5 to 8) on individual characteristics. We rescale both dependent variables so that a value of 0 means equal efficiency in the two work modes, while 5 corresponds to 1.05, -5 corresponds to 0.95. See main text for an explanation of how we obtain the individual-level b and B values. All coefficients reflect conditional means relative to the omitted category. The sample includes SWAA respondents from January 2023 to December 2025 who worked at least 20 hours in the reference week and have data on commute times, excluding persons with no WFH experience since 2020. We reweight the SWAA data to match the joint distribution by age, sex, education, and earnings in the CPS. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table A.2. The Quantitative Results Are Similar When Workers Take Work Arrangements as Given -- For Comparison to Table 1 in the Main Text

Counterfactual Work Arrangements	100 × difference between counterfactual and baseline outcomes				Mean Consumption-Equivalent Welfare Change, Percent
	$\Delta \log(Y/H)$	$\Delta \log(Y/(H+T+G))$	$\Delta \log(Y)$	$\Delta \log(\mathrm{H})$	
	Measured Productivity	**Effective Productivity**	**Output**	**Hours**	
A. Basic Model					
(1) Return to 2019	-1.1	-4.1	-3.0	-1.9	-2.9
(2) 2020 Lockdown	0.5	4.2	-20.9	-21.4	-18.9
B. Model with Preference Heterogeneity over WFH					
(3) Return to 2019	-0.5	-3.3	-0.5	0.0	-0.9
(4) 2020 Lockdown	-0.2	3.3	-23.6	-23.4	-21.7

Notes: Negative table entries indicate lower values in the counterfactual equilibrium than in the 2023-2025 baseline equilibrium. Y, H, T, and G are aggregate output, total paid workhours, aggregate commuting time, and aggregated (extra) grooming time, respectively. See Section 5 in the text for a full description of how work arrangements in each counterfactual differ from the baseline equilibrium.

Table A.3. The Quantitative Results Are Similar When We Calibrate α by Industry -- For Comparison to Table 1 in the Main Text

Counterfactual Work Arrangements	100 × difference between counterfactual and baseline outcomes				Mean Consumption-Equivalent Welfare Change, Percent
	$\Delta \log(Y/H)$	$\Delta \log(Y/(H+T+G))$	$\Delta \log(Y)$	$\Delta \log(H)$	
	Measured Productivity	**Effective Productivity**	**Output**	**Hours**	
A. Basic Model					
(1) Return to 2019	-0.7	-3.5	-1.1	-0.4	-2.6
(2) 2020 Lockdown	1.0	4.8	-18.8	-19.8	-18.8
B. Model with Preference Heterogeneity over WFH					
(3) Return to 2019	-0.5	-3.3	-0.6	-0.1	-0.8
(4) 2020 Lockdown	-0.2	3.4	-23.7	-23.5	-21.6

Notes: Negative table entries indicate lower values in the counterfactual equilibrium than in the 2023-2025 baseline equilibrium. Y, H, T, and G are aggregate output, total paid workhours, aggregate commuting time, and aggregated (extra) grooming time, respectively. See Section 5 in the text for a full description of how work arrangements in each counterfactual differ from the baseline equilibrium.

Appendix B. How We Track the Amount of Work from Home in the US Economy

Since 2021 we have posted and regularly updated a version of Figure 1 (see the main text) at www.wfhresearch.com, showing the average share of full paid days in the US economy that are work-from-home days. Since early 2022 we have also posted an Excel file each month with the data series underlying the most recent version of that figure, along with other series that may interest researchers and the broader public.

This appendix summarizes how we use data from the Survey of Working Arrangements and Attitudes (SWAA) to produce the data series plotted in Figure 1, posted on our website and on the Fed's FRED Database at https://fred.stlouisfed.org/series/WFHCOVIDMATQUESTION.

B.1. Measuring Work from Home Since November 2021

The key survey question we use to track WFH rates in the US is shown in Figure A.4. We first fielded this question in the November 2021 wave and have included it in every subsequent SWAA wave. It asks respondents whether they worked each day of the previous week and, if so, where. This question has three key advantages: (1) It asks respondents to make an active choice for whether and where they worked each day of the reference week. (2) It allows respondents to report any number of workdays the prior week (including 6 or 7), instead of presuming a 5-day workweek. (3) Because it requires a choice for each day of the week, it does not bias respondents towards reporting 0 or 5+ total workdays or WFH days.

We use responses to the question shown in Figure A.4 to estimate the percent of full paid days that employed respondents worked from home during the week prior to the survey.

- First, we count the total number of days the respondent either WFH or worked on business premises (i.e., we add the number of rows for which the respondent picked the first or second columns in Figure A.4).
- We count the total number of days they WFH (i.e., we add the number of rows for which they chose the first column).
- For each respondent, the percent of full paid days they WFH equals $100 \times (total\ WFH\ days)/(total\ days\ worked)$.

We then compute an average across employed respondents in each monthly wave, obtaining the time series value for that month. We denote the resulting series by $WFH_{current\ question,t}$.

B.2. Measuring Work From Home Before November 2021

The strategy above, however, does not work for months prior to November 2021 when we did not ask the question shown in Figure A.4. In those months, we rely on other questions about work arrangements.

From May to October 2020 we asked respondents to report their working status and work arrangements categorically:

> ***Currently (this week)*** *what is your working status?*
>
> - *Working on my business premises*
> - *Working from home*
> - *Still employed and paid, but not working*
> - *Unemployed*
> - *Not working and not looking for work*

We compute the WFH rate as the share of respondents who select "working from home" among those selecting either "working from home" or "working on my business premises." (We treat persons "Still employed and paid, but not working" as not working.) We also make minor adjustments for potential misclassification as noted in footnote 10 of Barrero, Bloom, and Davis (2021). In those early months of the pandemic, most people who worked from home did so full time and hybrid arrangements were uncommon, so this coarse approach is simple and captures the key variation in the data.[37]

We compute the work-from-home rate between November 2020 and October 2021 (inclusive) using a regression approach. During those months, we asked three questions about working status and work arrangements. The first question asks:

> ***Currently (this week)*** *what is your work status?*
>
> - *Working, whether on business premises or working from home*
> - *Still employed and paid, but not working*
> - *Unemployed, looking for work*
> - *Unemployed, awaiting recall to my old job*
> - *Not working, and not looking for work*

[37] Based on data from November and December 2020, 85% of respondents worked either fully remote or fully in-person.

For those who work, we ask a second question: *How many full days are you working this week (whether at home or on business premises)?* Response options are 1, 2, …, 5+ days. The third question asks where work happens: *You have indicated that you are working this week. How many* ***full paid working days*** *are you* ***working from home*** *this week?* Response options are: ***None****, all my paid working days were on business premises* and separate options for 1, 2, 3, 4 and 5+ full paid days WFH. We use responses to the second and third questions to compute the percent of full paid workdays that the respondent WFH. Averaging those respondent-level estimates by wave, we obtain a series we denote as $WFH_{old\ question,t}$, covering November 2020 and later months. By 2021, we were concerned about positive bias in $WFH_{old\ question,t}$, perhaps because some respondents reported working 5+ total days during the reference week, and 5+ days working from home without reading the question carefully. These concerns led us to develop the key question shown in Figure A.4, which has been our core measurement tool since late 2021. That said, we continued to ask the questions mentioned in this paragraph that yield $WFH_{old\ question,t}$.

To correct for the potential bias in $WFH_{old\ question,t}$ and produce a consistent series going back to 2020, we use a regression model to impute values for $WFH_{current\ question,t}$ between November 2020 and October 2021, when we did not ask the question shown in Figure A.4. Specifically, we estimate the following regression model at the individual level using the first six months where we have data for both the question shown in Figure A.4 and the questions underlying $WFH_{old\ question,t}$ (i.e., for November 2021 to April 2022):

$$WFH_{current\ question,it} = \alpha + \beta \cdot WFH_{old\ question,it} + \varepsilon.$$

The dependent variable is the percent of full paid days that are WFH days for respondent i in wave t according to the current question from Figure A.4. The independent variable is the corresponding estimate based on the legacy questions that yield $WFH_{old\ question,t}$. We use the estimated regression coefficients, $\hat{\alpha}$ and $\hat{\beta}$, to impute $WFH_{current\ question,it}$ between November 2020 and October 2021:

$$\widehat{WFH}_{current\ question,it} = \hat{\alpha} + \hat{\beta} \cdot WFH_{old\ question,it}.$$

The regression has an in-sample R-squared of 0.53, confirming the predictive power of $WFH_{old\ question,it}$. We obtain the imputed time series value $\widehat{WFH}_{current\ question,t}$ by averaging across respondents in each wave. We also tested specifications where $WFH_{old\ question,it}$ enters quadratically and with separate coefficients by age-sex-education cells, obtaining similar results.

The resulting time series, shown in blue in Figure 1, is posted on FRED, and on the Excel file on our website published on the first tab after the README. The June 2022 and later versions of the Excel file also include data for the legacy time series $WFH_{old\ question,t}$, but we no longer update it.

Figure 1 and published series impute a value for September 2023 using the average for August and October. After examining the September 2023 data, we found it to be unusually low quality and implying a work-from-home rate significantly higher than in adjacent months. We chose not to publish an estimate based on those low-quality data.

Figure 1 shows a value for 2019 using data from that year's American Time Use Survey (ATUS), and a series based on a Census Household Pulse Survey (CHPS) question. To obtain the 2019 value, we examine ATUS data from that year, restricting attention to persons with annual earnings of more than $20,000, which is the earnings threshold for participation in the 2020 waves of our SWAA. We count paid workdays in ATUS as ones in which the individual devotes six or more hours of work to their main job, regardless of work location, and we count WFH days as ones in which the individual works six or more hours on their main job at home. This approach is designed to resemble the SWAA-based measure. The CHPS series is based on a question that asks whether people in the household WFH in the past 7 days, and, if so, whether they did so 1 to 2, 3 to 4, or 5 days that week. Our CHPS series imputes a 30% WFH rate for 1 to 2 days, 70% for 3 to 4 days, and 100% for 5 days. After mid-2024 the Census Bureau stopped posting updated microdata for the CHPS, so we cannot benchmark our series against it in recent months.

Kmetz et al. (2023), Bick et al. (2025) and Buckman et al. (2025) discuss how alternative data sources yield measures of WFH that differ conceptually from ours. Some focus on hours WFH, for example, while others reflect fully remote work. We focus on the share of WFH days among all paid days because we think the shift in work arrangements since 2020 is mostly about the number of workdays that people don't commute to a worksite.

Appendix C. A Theory of How the Pandemic Shifted the WFH Equilibrium

Firms have two available production technologies: a traditional technology (*T*) that involves little or no WFH by staff, and an alternative technology (*R*) with heavy reliance on remote work. Since high levels of WFH were uncommon before COVID-19, we focus on firms that use technology *T* before the pandemic. Firms know their payoff distributions under *T,* but we allow for imperfect, possibly biased, knowledge of payoff distributions under *R.* Each period, firm *i* chooses an action a_i in $\{T, R, M\}$ to maximize the discounted sum of current plus expected future payoffs, where *M* stands for mothballing operations at a per-period payoff of zero.

When operating technology *T* in period *t,* the firm's current payoff x_{it} is distributed $F_i^T(x; p_t)$, where $p_t = \{\text{normal}, \text{pandemic}\}$ and $F_i^T(x; \text{normal}) \leq F_i^T(x; \text{pandemic})$ for all *x.*[38] That is, a pandemic worsens the payoff distribution F^T in the sense of first-order stochastic dominance. Here, p captures the negative effects of social distancing and government orders on the viability of the traditional technology. The first time a firm uses technology *R,* it incurs a one-time cost C_i for upfront investments to enable remote work. Aside from C_i, the firm's current payoff is distributed $F_i^R(x; \gamma_t)$ under *R,* where γ_t is the activity share of firms operating *R* in *t,* and higher values of γ improve F_i^R in the first-order stochastic dominance sense. Thus, $\int x\, dF_i^R(x; \gamma_t) - \int x\, dF_i^T(x; p_t)$ rises with γ for given *p,* and there is a strategic complementarity across firms in the choice of production technology. As a real-world example, WFH becomes more viable for law firms when more of their clients work remotely.

Consider the implications of a pandemic that arrives at $t = 1$ when firms know $F_i^R(x; \gamma_t)$. Let $V_{it}^a(p_t, \gamma_t, \mathbb{C}) \equiv V_{it}^a$ denote the value function associated with action a_{it} under the optimal continuation policy, where $\mathbb{C}$ is an indicator variable that equals 1 if the firm previously operated *R.* Among firms that choose $a_{it} = T$ for $t \leq 0$, a sufficient condition for switching to *R* at $t = 1$ is $\int x\, dF_i^R(x; \gamma_0) - C_i + V_{i1}^R > \int x\, dF_i^T(x; \text{pandemic}) + V_{i1}^T$. The equilibrium share of switchers is governed by the weaker requirements that switchers satisfy $\int x\, dF_i^R(x; \gamma_1) - C_i + V_{i1}^R > \int x\, dF_i^T(x; \text{pandemic}) + V_{i1}^T$. That is, by raising the activity share of the *R* technology to $\gamma_1 > \gamma_0$, the pandemic makes *R* more attractive for each firm. Thus, the pandemic's negative impact on payoffs under *T and* the pandemic-induced increase in remote work both drive the adoption of technology *R* when the pandemic hits.

[38] If p_t is stochastic, we assume that it obeys a first-order Markov process.

Some firms that switch when the pandemic strikes will stick to R after the pandemic ends in period $t = n$, for $n > 1$.[39] Here as well, there are two effects: Having incurred the switching costs, some firms find it optimal to continue with R even if all other firms switch back to T; for these firms, $\int x\, dF_i^R(x;\gamma_0) + V_{in}^R > \int x\, dF_i^T(x;\text{normal}) + V_{in}^T$. Other firms stick to R after the pandemic ends because $\int x\, dF_i^R(x;\gamma_n) + V_{in}^R > \int x\, dF_i^T(x;\text{normal}) + V_{in}^T$, although $\int x\, dF_i^R(x;\gamma_0) + V_{in}^R < \int x\, dF_i^T(x;\text{normal}) + V_{in}^T$. Thus, the strategic complementarity in choice of production technologies amplifies the pandemic-induced switching response at $t = 1$ *and* raises the activity share of firms that operate R after the pandemic ends.[40]

Now consider the situation where firms have imperfect knowledge of their payoff distributions when operating R. Let $\tilde{F}_{it}^R(x;\gamma_t, \boldsymbol{\theta}_{it})$ denote the perceived payoff distribution at t under technology R, where $\boldsymbol{\theta}_{it}$ is a vector that summarizes information and beliefs about the payoff distribution at t. When a firm operates R, its realized payoffs may lead it to update $\boldsymbol{\theta}_{it}$ and revise $\tilde{F}_{it}^R$.[41] As before, the arrival of a pandemic at $t = 1$ causes some firms to switch from $a_{it} = T$ for $t \leq 0$ to $a_{i1} = R$. Firms with sufficiently favorable payoffs under R from $t = 1, 2, \ldots n$ will stick with R after the pandemic ends. Here, stickiness in technology switching does not require $C_i > 0$ or other explicit switching costs. Instead, payoff observations under R lead to revisions in $\tilde{F}_{it}^R$ that, for some firms, are favorable enough for them to prefer R to T after the pandemic ends. That is, some firms discover that remote work is so productive they decide to stick with the practice post-pandemic.

While not necessary for stickiness, overly pessimistic priors about the viability of remote work lead to more stickiness. To see this point, start with the case of unbiased priors. Suppose, for example, that firms know the F^R distributions up to a mean parameter μ_i that differs among firms. They also believe, correctly, that the μ_i are distributed $G(\mu, \sigma)$, where μ is the mean of the μ_i and σ is the standard deviation. Pandemic-induced experimentation and learning lead some firms to discover they have high values of μ_i, so they stick with R after the pandemic ends. We refer to this outcome as a tail effect of experimentation. Now consider the case with overly pessimistic priors.

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[39] This claim requires that some firms be close to the switching margin before the pandemic hits.

[40] This conclusion does not rest on coordination failures of the sort that can arise with strategic complementarities. However, a pandemic could drive a persistent rise in γ even with no switching costs, if strategic complementarities are strong enough to generate multiple equilibria. See Cooper and John (1988) for an analysis of shock amplification and coordination failures in the presence of strategic complementarities in payoff functions.

[41] See Rothschild (1974) on how to formulate $\boldsymbol{\theta}$ in the case of a Bayesian agent with a prior over support points on a multinomial distribution.

In particular, suppose firms believe the μ_i are distributed $G(\tilde{\mu}, \sigma)$, where $\tilde{\mu} < \mu$ and the true distribution remains $G(\mu, \sigma)$. In this case, pandemic-induced experimentation and learning yields even more stickiness through a bias elimination effect.

As we describe in the introduction and Section 6 of the main text, the pandemic created conditions for simultaneous experiments with WFH in networks comprised of firms, customers and suppliers, yielding lessons and know-how that were hard to acquire beforehand. Specifically, firms may find it much easier to learn about $F_i^R(x; \gamma = \text{high})$ when other firms also seek to learn about technology R – a strategic complementarity in experimentation. Conversely, firms may find it infeasible to learn much about $F_i^R(x; \gamma = \text{high})$ when operating in an economy where the traditional technology dominates. This observation helps understand why many firms may have had highly imperfect, possibly biased, views about the viability of WFH before the pandemic.