Online Appendix for:

# Working Remotely?

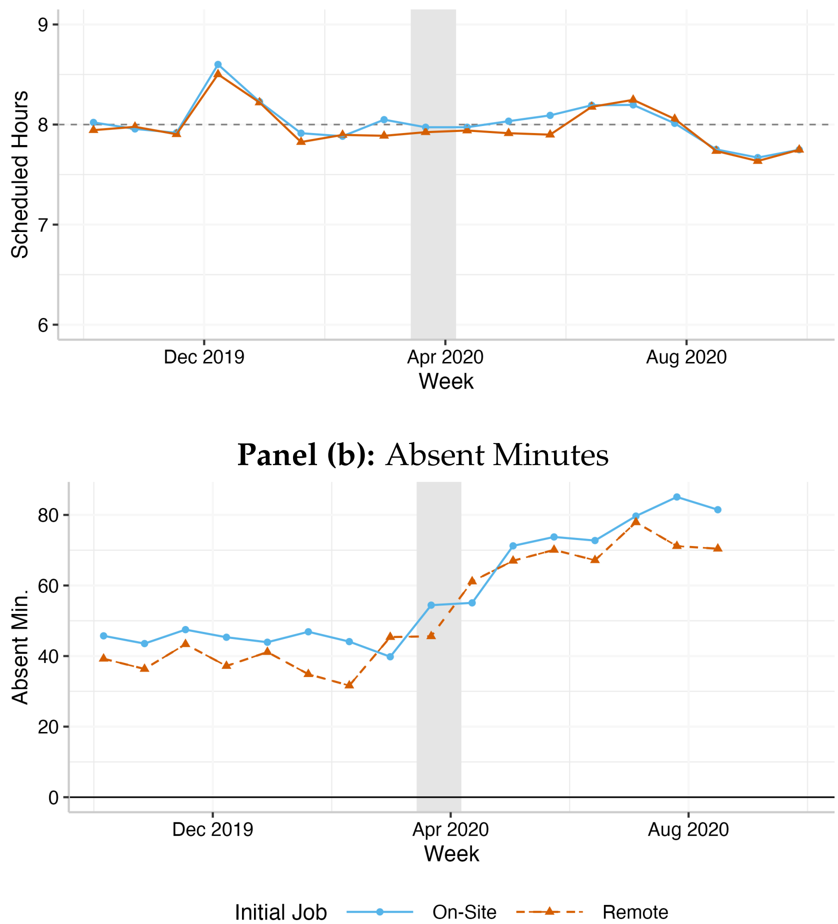
## Selection, Treatment and the Market for Remote Work

Natalia Emanuel · Emma Harrington

February 26, 2024

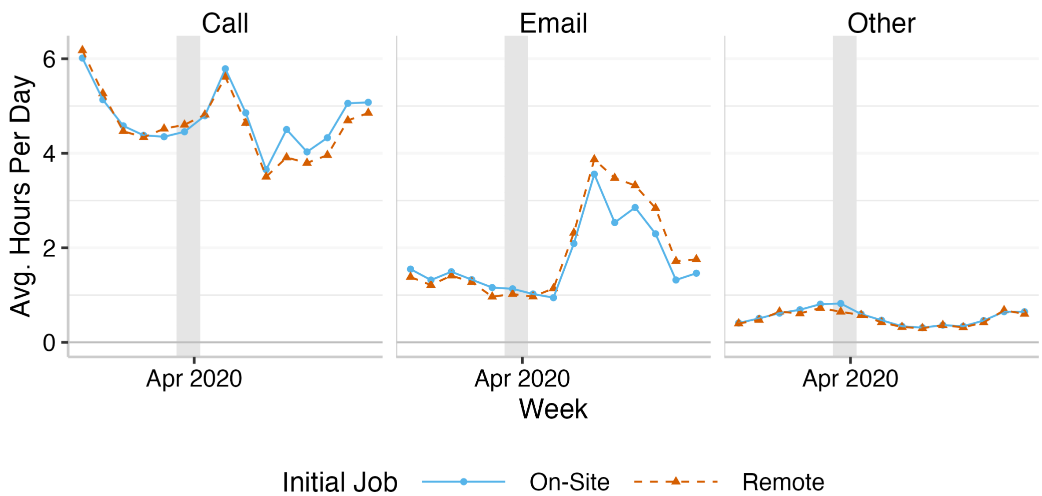
**Figure A.1:** Schedules and Absenteeism for Initially Remote and On-Site Workers Around the Covid-19 Office Closures

**Panel (a):** Scheduled Hours




*Note:* This figure illustrates the patterns of (a) scheduled hours and (b) absenteeism of on-site workers who went remote during the Covid-19 office closures (N=1,592) and workers who were already remote (N=344). The shaded region spans from March 15, 2020 — when on-site workers could start working remotely — to April 6, 2020 — when the offices fully closed. The sample is our primary sample summarized in footnote 23. The data extract that was shared with us on absenteeism ends on August 6th, 2020.

**Figure A.2:** Scheduled Time Per Day for Initially Remote and On-Site Workers Around the Covid-19 Office Closures

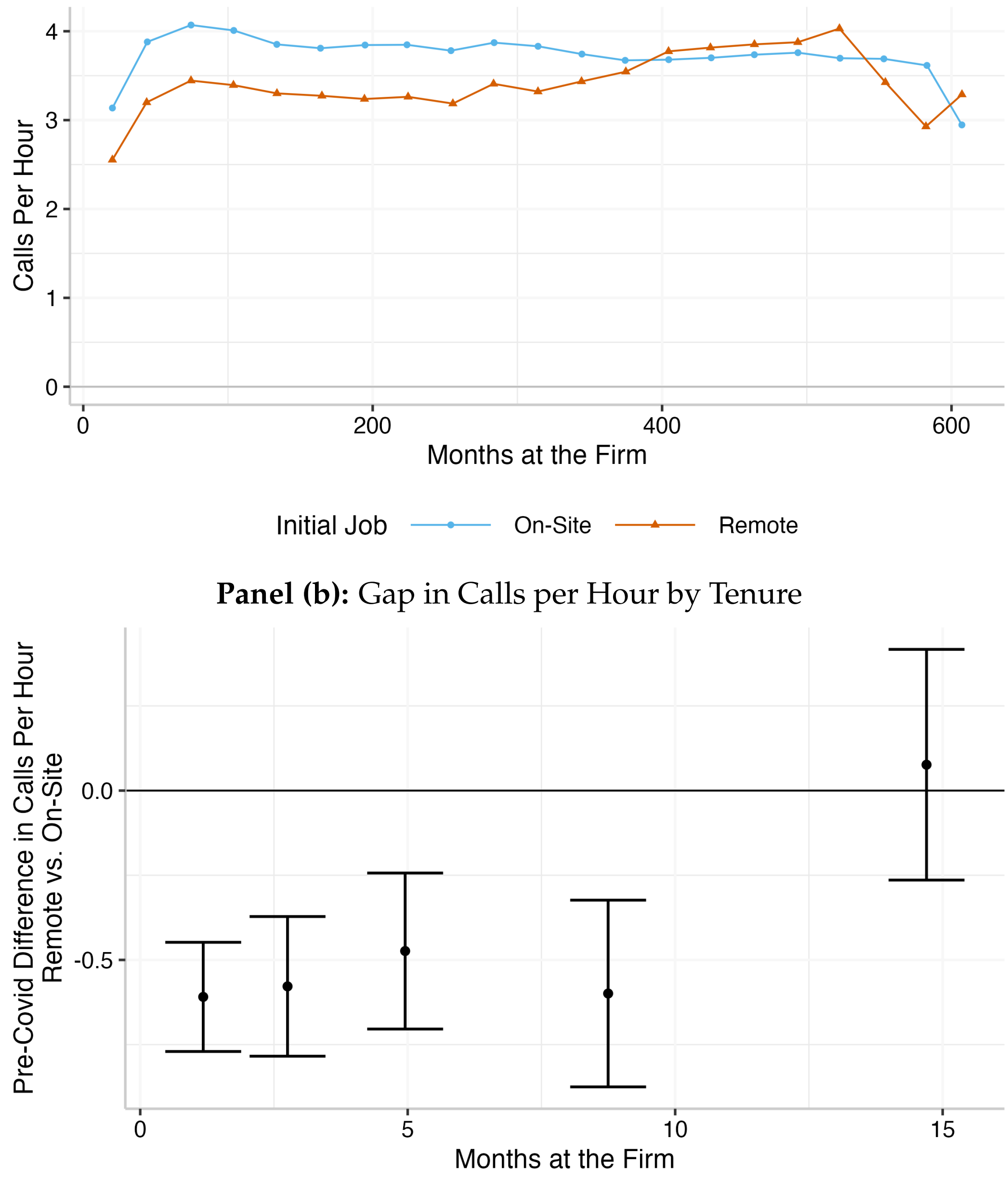



*Note:* This figure illustrates the changes in the scheduled time of on-site workers who went remote during the Covid-19 office closures (N=1,592) and workers who were already remote (N=344). The left plot shows hours scheduled for answering customer calls. The middle plot shows hours scheduled for answering customer emails or instant messages. The right plot shows hours scheduled for other activities, such as training, meetings, and breaks. The shaded region spans from March 15, 2020 — when on-site workers could start working remotely — to April 6, 2020 — when the offices fully closed. The sample is our primary sample summarized in footnote 23.

**Figure A.3:** Pre-pandemic Differences in Performance

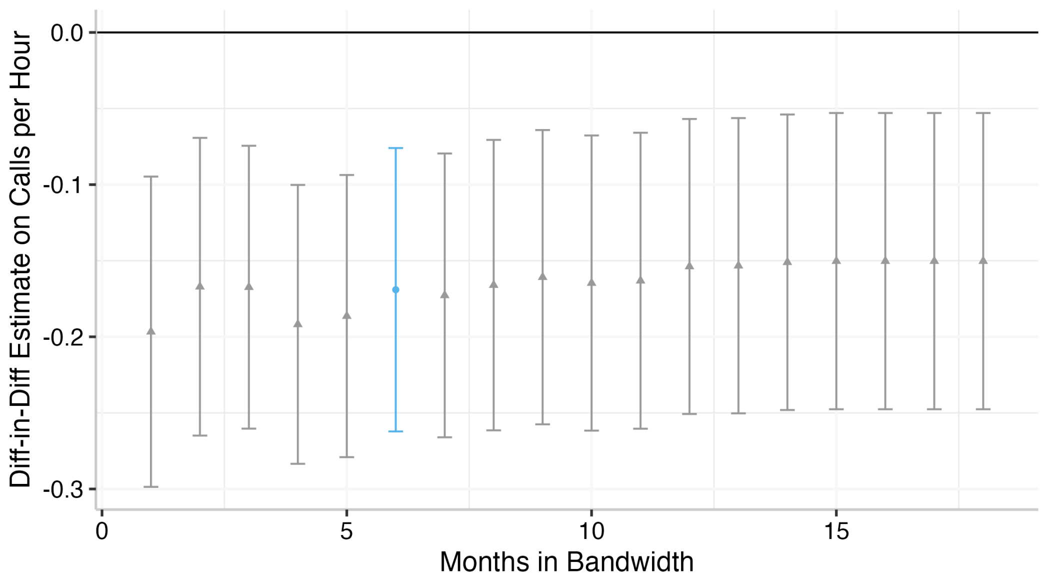
**Panel (a):** Calls per Hour by Tenure

**Panel (b):** Gap in Calls per Hour by Tenure



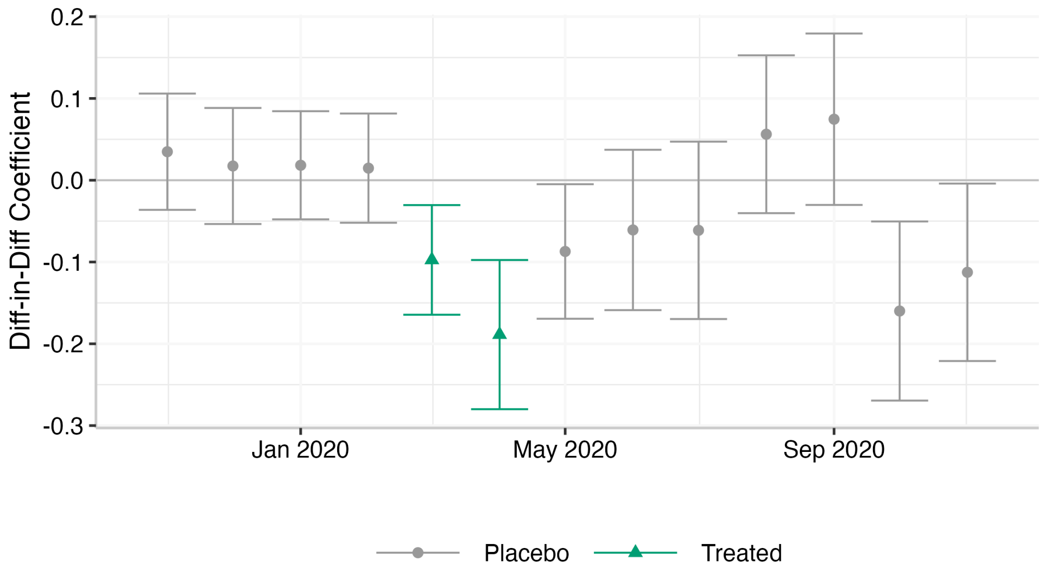

*Note:* This figure illustrates the differences in call quantity for on-site and remote workers as a function of their time at the firm. The sample is our preferred sample summarised in footnote 23. Panel (a) shows raw means of calls per hour for different months of tenure. Panel (b) shows the differences in productivity for different quintiles of firm tenure. The differences condition on the queue of the call, determined by the call-level, time-zone, and date. Error ribbons reflect 95 percent confidence intervals, with standard errors clustered by worker.

**Figure A.4:** Robustness of Diff-in-Diff Estimate to Alternative Bandwidths



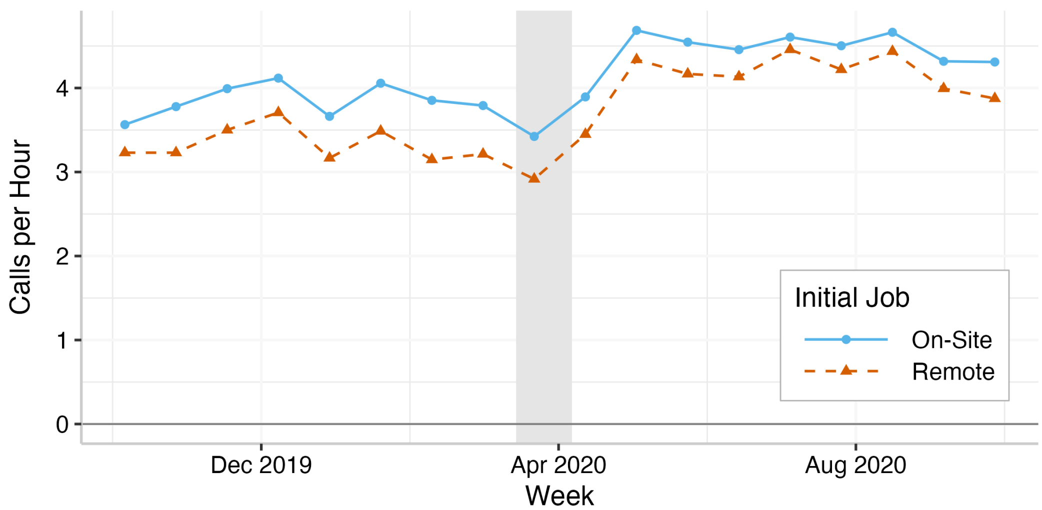

*Notes:* This figure illustrates difference-in-differences estimates that compare the change in calls per hour for on-site and remote hires around the office closures within various bandwidths. The blue circle shows the estimate with our preferred six-month bandwidth. The grey triangles show estimates with alternative bandwidths. All regressions estimate Equation 3 with our preferred controls for worker fixed effects, call-queue fixed effects, and time-varying effects of worker demographics (see Section II.C). The error bars are 95% confidence intervals with standard errors clustered by worker.

**Figure A.5:** Placebo Treatment Dates



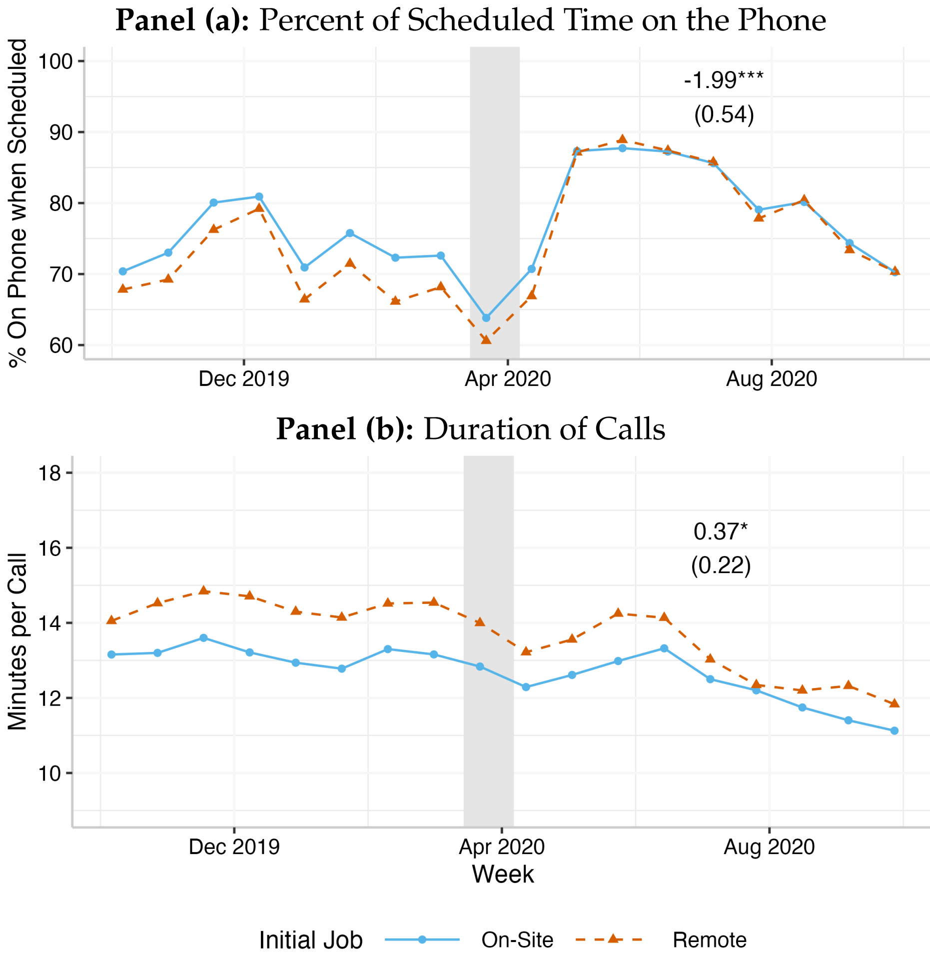

*Notes:* This figure illustrates difference-in-differences estimates that compare the change in calls per hour for on-site and remote hires within two-month bandwidths. The grey circles show periods that do not include the treated window; the green triangles include the treated window. All regressions estimate Equation 3 using our preferred controls for worker fixed effects, call-queue fixed effects, and time-varying effects of worker demographics (see Section II.C). The error bars are 95% confidence intervals with standard errors clustered by worker.

**Figure A.6:** Difference-in-Differences around Covid-19 Office Closures in Locations with $14/hour Pay




*Notes:* This figure illustrates a difference-in-differences design that compares the change in calls per hour for on-site and remote hires, limiting to on-site locations with base-pay of $14 per hour. Each point represents a three-week average for remote and on-site workers, matched on age, gender, and call-queue. The shaded region spans from March 15, 2020 — when on-site workers could start working remotely — to April 6, 2020 — when offices fully closed. Calls per hour is computed as the ratio of the number of calls answered over the number of hours that the worker was scheduled to answer calls that day. The sample limits our preferred sample summarized in footnote 23 to on-site locations with base pay of $14 per hour.

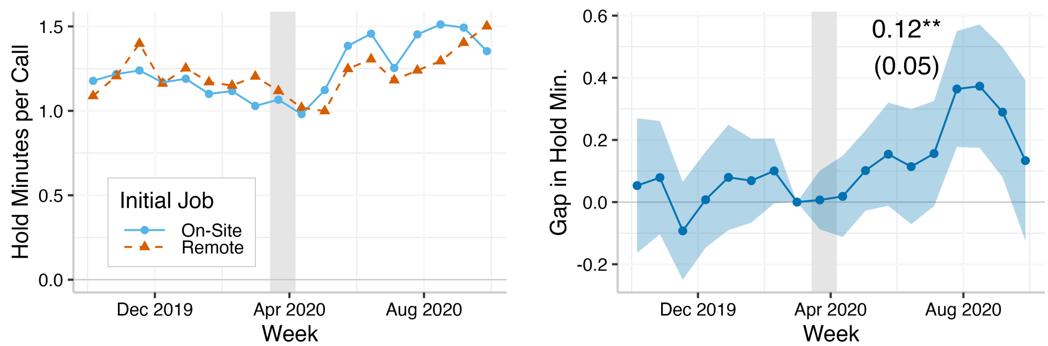
**Figure A.7:** Decomposition of Effects on Calls



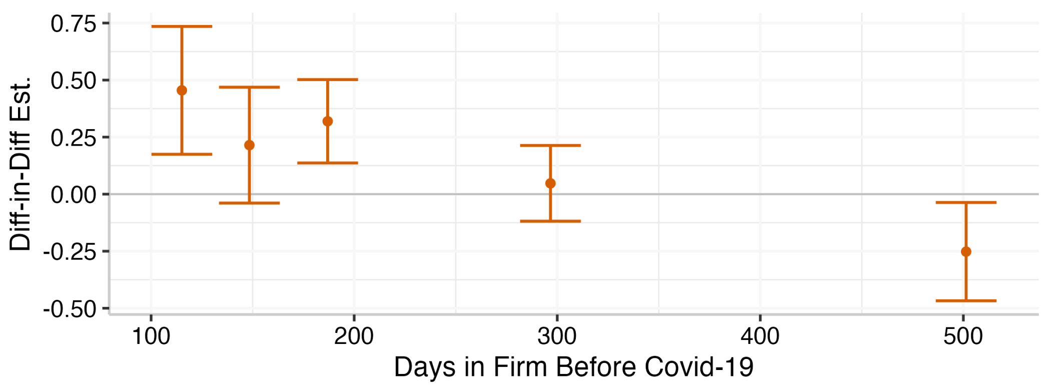

*Note:* This figure decomposes remote work's effect on calls per hour into (a) time spent on the phone and (b) call durations. In Panel (a), the percent of time on the phone is computed as the ratio of a worker's time on the phone to the time that she was scheduled to be taking calls. In Panel (b), the average duration of completed calls is computed as the time that the worker spent on the phone divided by the number of calls that she handled herself (rather than forwarding to another worker). Each panel considers a difference-in-differences design that compares on-site hires who went remote during the Covid-19 office closures (N=1,592) and workers who were already remote (N=344). The shaded region spans from March 15, 2020 — when on-site workers could start working remotely — to April 6, 2020 — when the offices fully closed. Each point represents a three-week average for remote and on-site workers, matched on age, gender, and call-queue. The annotated coefficients indicate the difference-in-differences estimate of the effect of going remote from Equation 3, with a six-month bandwidth excluding the shaded region. The controls are our preferred controls for worker fixed effects, call-queue fixed effects, and time-varying effects of worker demographics (see Section II.C). These coefficients are also reported in Table 3. The sample is our primary sample summarised in footnote 23. Standard errors are clustered by worker. $^{*}$p<0.1; $^{**}$p<0.05; $^{***}$p<0.01.

**Figure A.8:** Challenges in Receiving Coworker Input When Remote

**Panel (a):** Difference-in-Differences in Hold Times



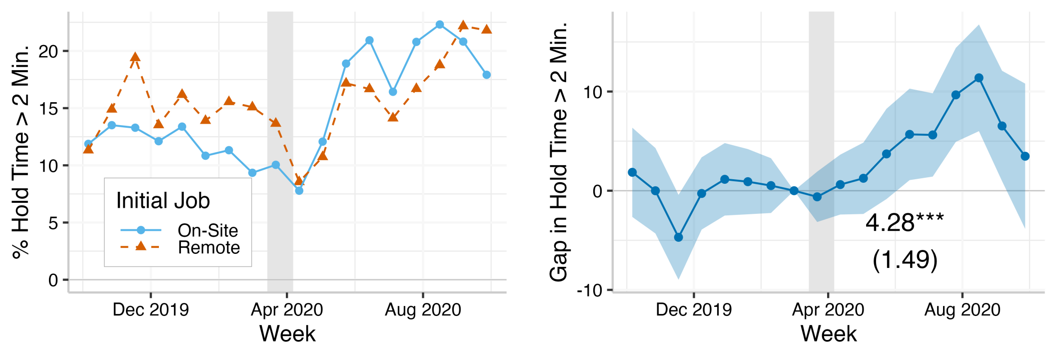

**Panel (b):** Heterogeneous Diff-in-Diff Effects by Worker Tenure



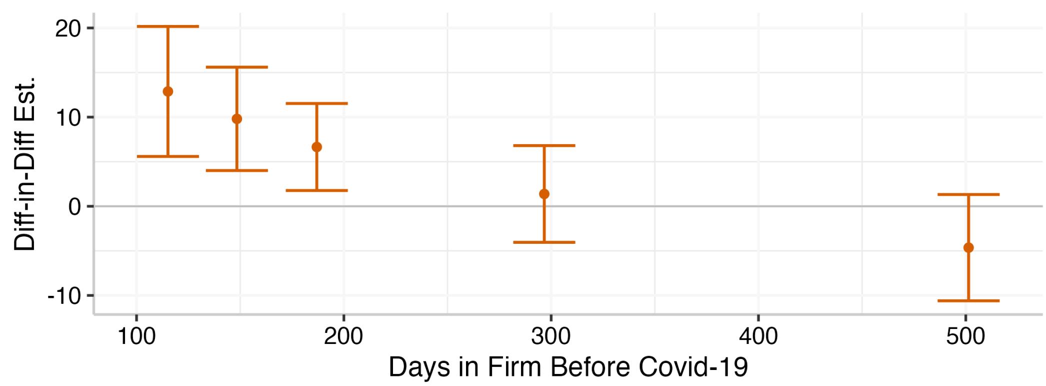

*Note:* This figure investigates remote work's impacts on customer hold times by worker experience. Panel (a) repeats the analysis in Figure 1 for minutes that customers are kept waiting on hold. Panel (b) presents heterogeneity in these difference-in-difference estimates by workers experience at the time that the offices closed for Covid-19. Ribbons and error bars reflect 95% confidence intervals, with standard errors clustered by worker. Figure A.9 shows these patterns for hold times in excess of two minutes. *p<0.1; **p<0.05; ***p<0.01.

**Figure A.9:** Difference-in-Differences in Hold Times Over Two Minutes

**Panel (a):** Difference-in-Differences in Hold Times Over Two Minutes

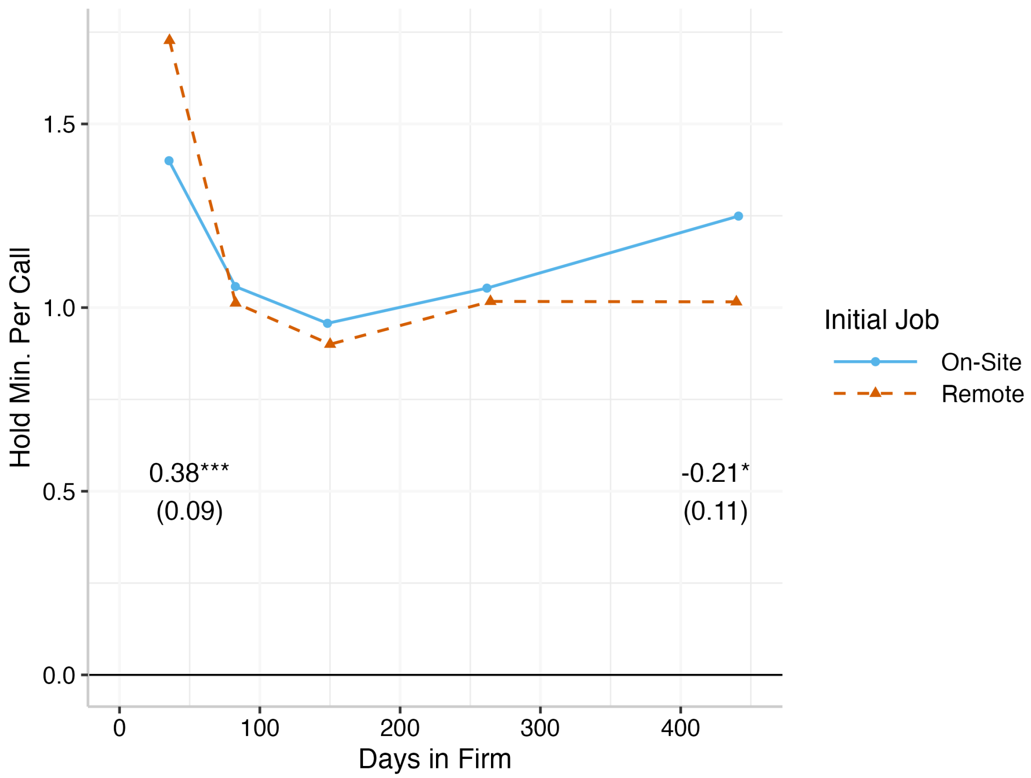



**Panel (b):** Heterogeneous Diff-in-Diff Effects by Worker Tenure




*Note:* This figure investigates remote work's impacts on customer hold times by worker experience, focusing on hold times exceeding two minutes. Panel (a) repeats the analysis in Figure 1 for the share of workers who keep customers waiting on hold for more than two minutes on average. Panel (b) presents heterogeneity in these difference-in-difference estimates by quintiles of workers' experience at the time that the offices closed for Covid-19. Ribbons and error bars reflect 95% confidence intervals, with standard errors clustered by worker. *p<0.1; **p<0.05; ***p<0.01.

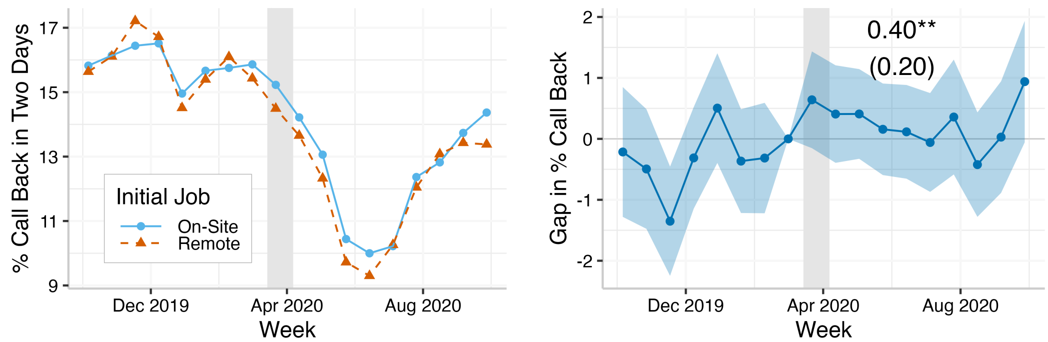
**Figure A.10:** Differences in Hold Times Before the Office Closures



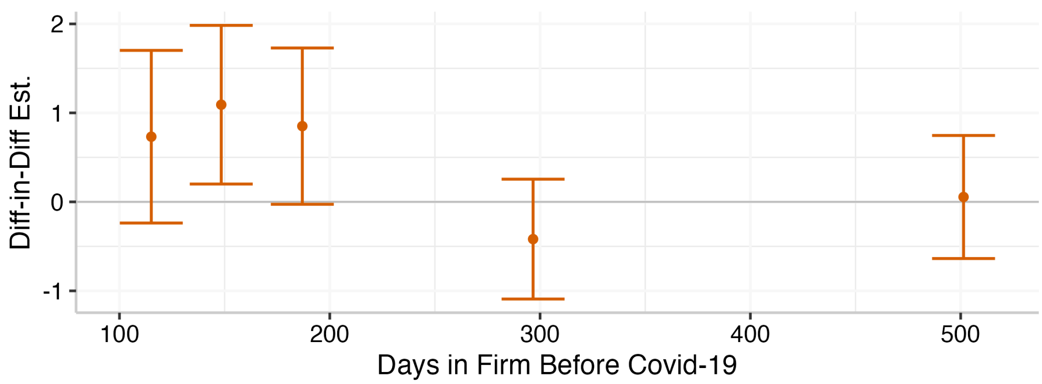

*Note:* This figure shows differences in hold times between remote and on-site workers before the office closures. The annotated coefficients represent differences between remote and on-site workers with call-queue fixed effects for the significant differences for junior and senior workers. Ribbons and error bars reflect 95% confidence intervals, with standard errors clustered by worker. *p<0.1; **p<0.05; ***p<0.01.

**Figure A.11:** Difference-in-Differences in Callback Rates

**Panel (a):** Difference-in-Differences in Callback Rates



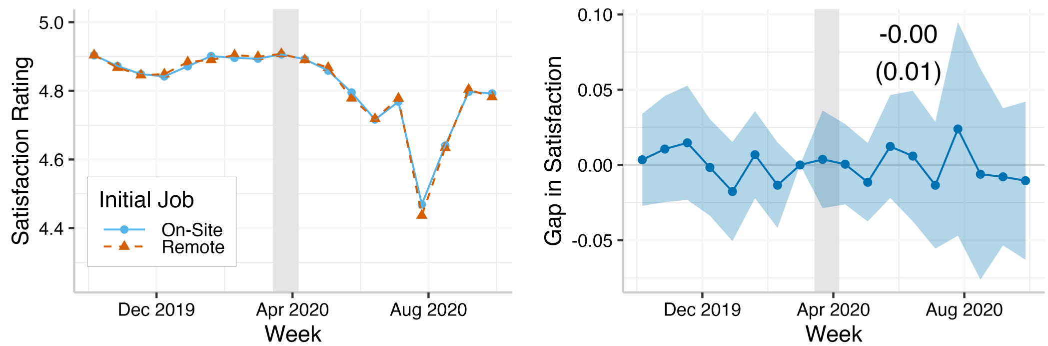

**Panel (b):** Heterogeneous Diff-in-Diff Effects by Worker Tenure



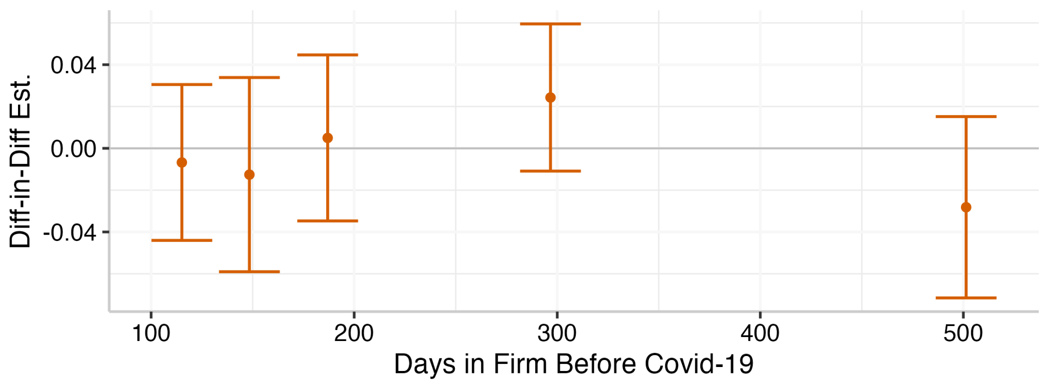

*Note:* This figure investigates remote work's impacts on the rate at which customers call back to the service line within two days, likely with initially unanswered questions. Panel (a) repeats Figure 1 for this quality measure. The difference-in-differences coefficient is also reported in column 4 of Table 3. Panel (b) presents the difference-in-difference estimates separately by quintile of workers' tenure at the firm when the offices closed. Ribbons and error bars reflect 95% confidence intervals, with standard errors clustered by worker. *p<0.1; **p<0.05; ***p<0.01.

## **Figure A.12:** Difference-in-Differences in Satisfaction

**Panel (a):** Average Customer Satisfaction Ratings

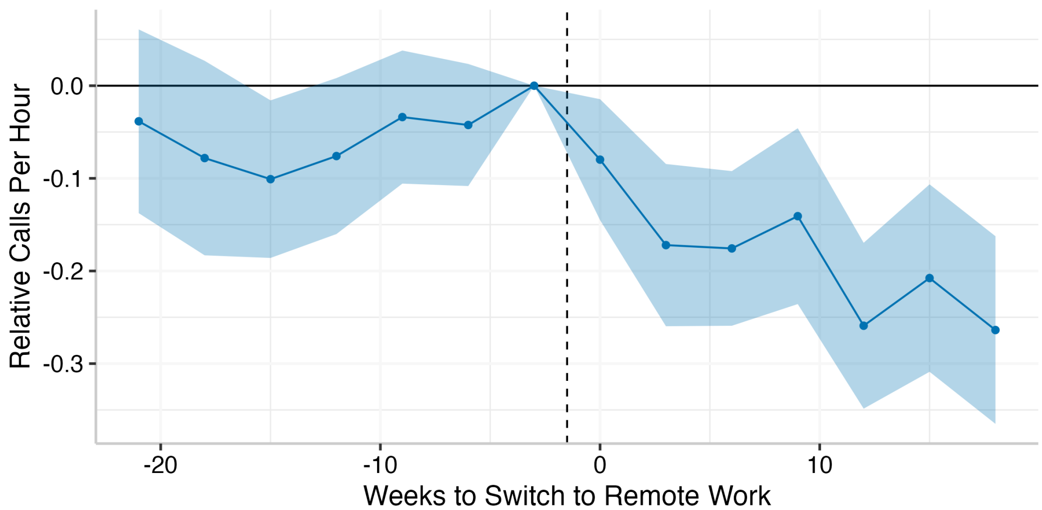



**Panel (b):** Heterogeneous Diff-in-Diff Effects by Worker Tenure




*Note:* This figure investigates remote work's impacts on average customer satisfaction scores on a five-point scale. Panel (a) repeats Figure 1 for this quality measure. The difference-in-differences coefficient is also reported in column 5 of Table 3. Panel (b) presents the difference-in-difference estimates separately by quintile of workers' tenure at the firm when the offices closed. Ribbons and error bars reflect 95% confidence intervals, with standard errors clustered by worker. $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$.

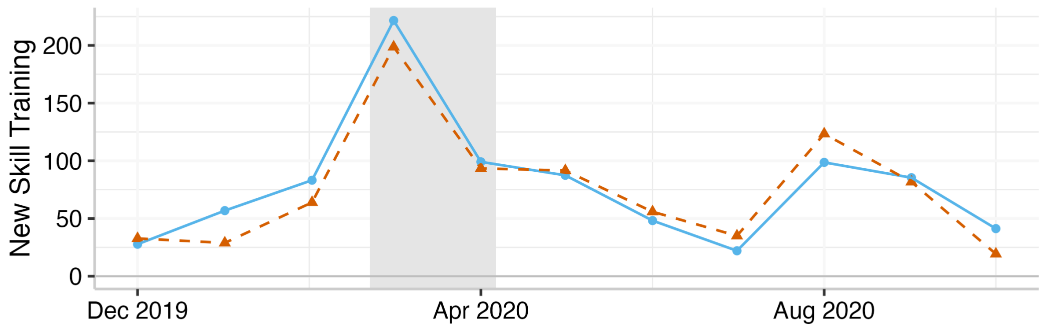
**Figure A.13:** Switches to Remote Work Before Covid-19



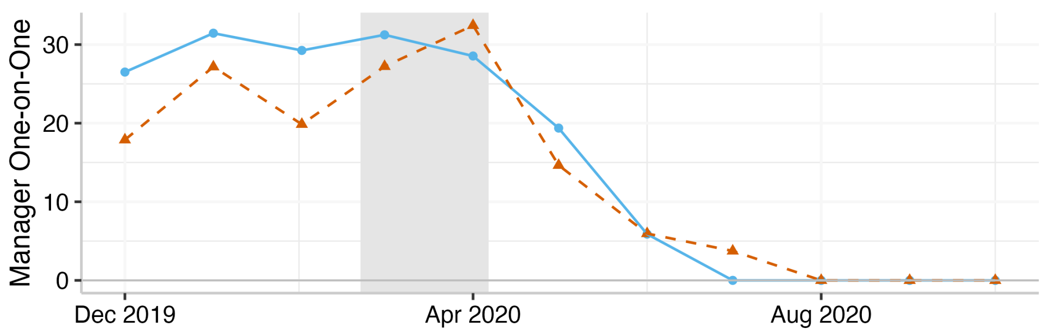

*Note:* This figure illustrates the changes in calls per hour for workers who transitioned from on-site to remote work prior to the pandemic. The figures shows a difference-in-differences design that compares the change in calls handled of on-site workers who were permitted to go remote to that of workers who stayed on-site until the offices closed for Covid-19. Calls per hour is defined as calls answered per hour that the worker is scheduled to answer customers' calls. The figure plots conditional differences relative to the three weeks before the transition to remote work. The controls include worker fixed effects and call-queue fixed effects that specify the date, time-zone, and type of call. We follow the approach of (Dube et al., 2023) to limit the control group to workers who took calls from the same queue but stayed on-site until the pandemic as summarized in footnote 33. The sample excludes workers who handle specialized calls. Ribbons reflect 95% confidence intervals with standard errors clustered by worker.

**Figure A.14:** Remote Work's Career Effects: Time Series

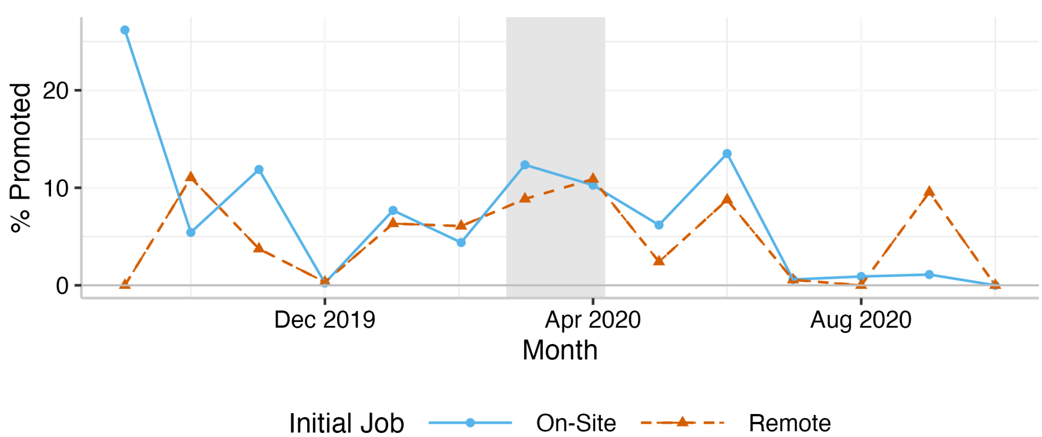
**Panel (a):** Diff-in-Diff in New Skill Training Minutes per Month




**Panel (b):** Diff-in-Diff in Manager One-on-One Meeting Min. per Month

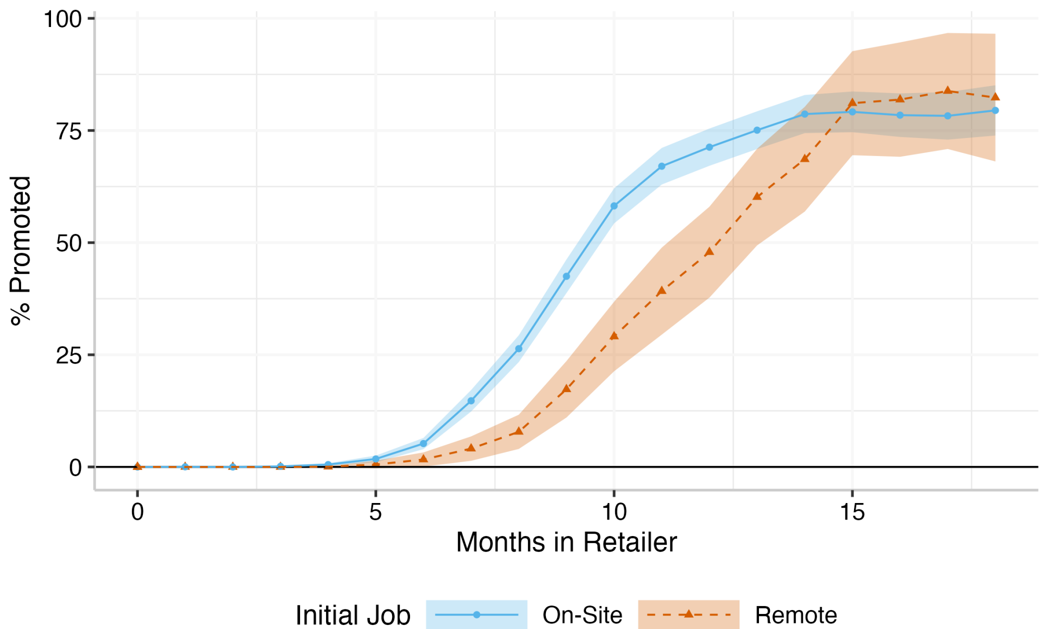



**Panel (c):** Diff-in-Diff in Promotions



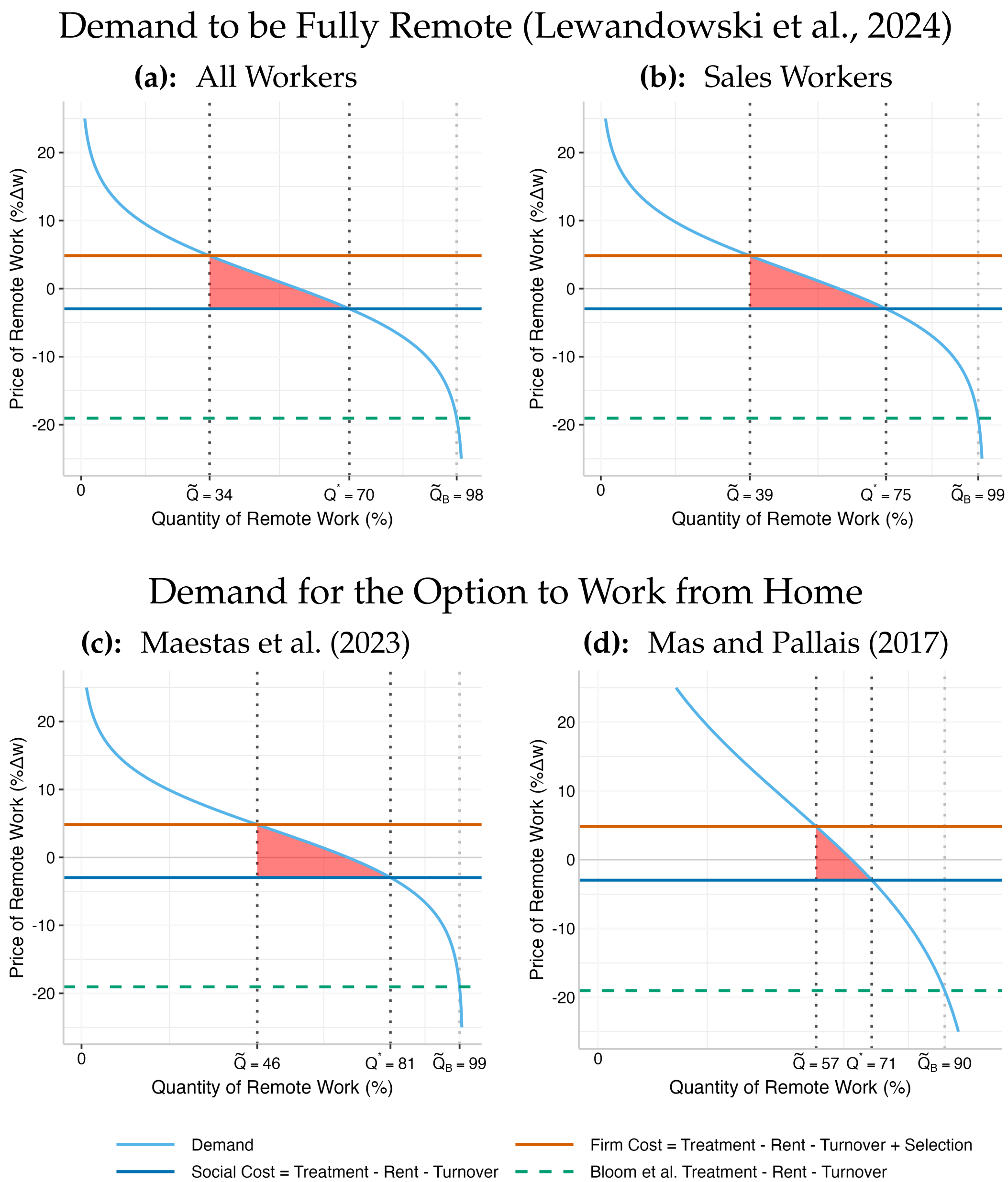

*Note:* This figure investigates remote work's impact on workers' careers. Each panel repeats Figure 1(a). Panel (a) captures time spent per month on training for new skills, and Panel (b) captures time spent attending one-on-one meetings with managers. Panel (c) presents the share of workers who are promoted to higher stakes, customer-service roles each month: these promotions feature pay raises of $2 per hour or 13 percent.

**Figure A.15:** Pre-pandemic Promotion Differences Conditional on Persisting in the Firm



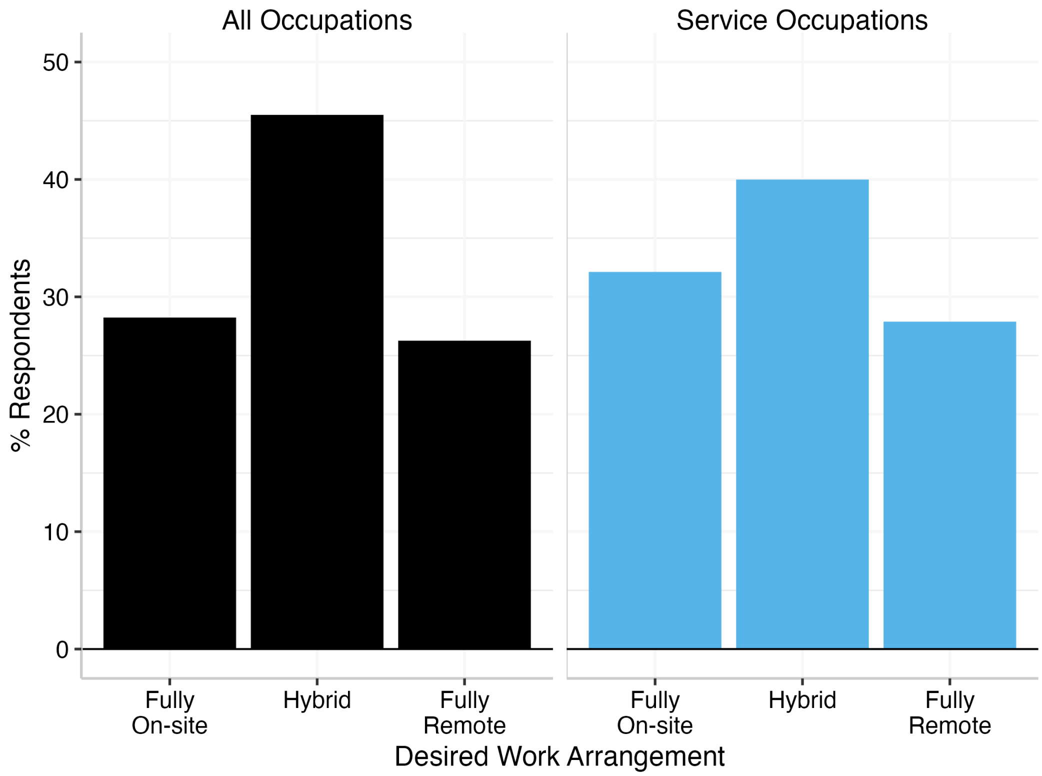

*Note:* This figure illustrates the differences in promotion rates for on-site and remote workers conditional on persisting in the firm. Each point represents the share of workers who have been promoted as a function of the months since their hire date. The sample is limited to workers hired between July 1, 2018 and March 15, 2020. Standard errors are clustered by worker.

**Figure A.16:** Calibration with Alternative Demand Curves




*Note:* This figure replicates Figure 5 with alternative demand curves for remote work. Panels (a)−(b) use data from Lewandowski et al. (2024), who ask a representative sample of Polish workers to choose between hypothetical on-site and fully remote jobs. Panel (a) uses the full sample, while Panel (b) limits to sales workers (ISCO 52). Panels (c)−(d) use data on hypothetical choices between on-site jobs and jobs with the option to work from home in Maestas et al. (2023) and Mas and Pallais (2017). See Section V.B for a summary of the derivation of the demand curve and Appendix B for more details.

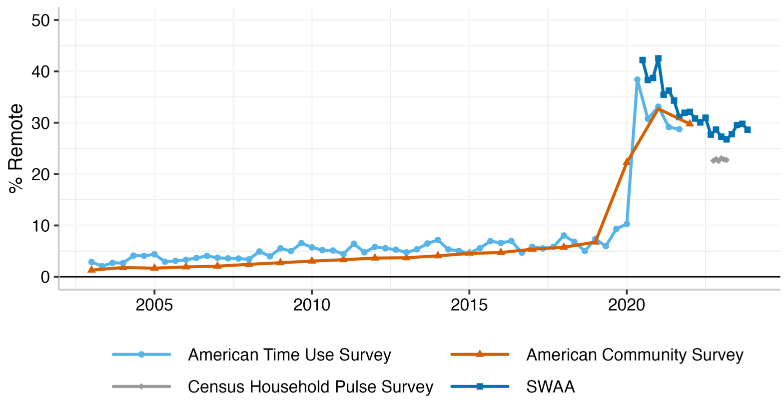
**Figure A.17:** Preferred Work Arrangements in Barrero et al. (2022)



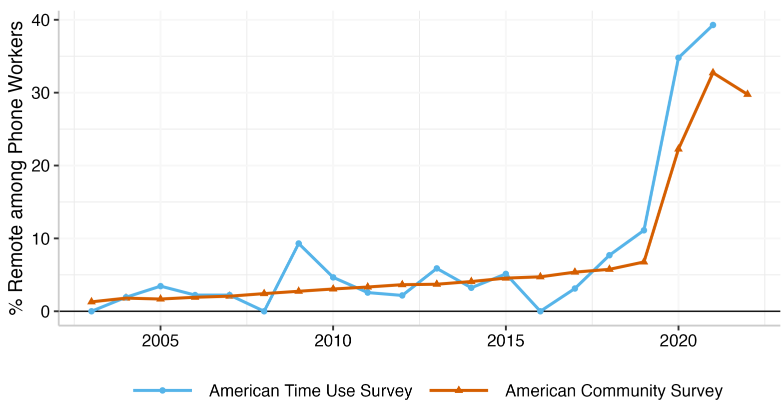

*Notes:* This figure illustrates the percent of respondents who say that they would prefer different post-pandemic working arrangements. We classify those who say that they would prefer to "rarely or never" work from home as preferring fully on-site work and those who say that they would prefer to work from home 5 days per week as preferring fully remote work. We classify workers who report preferring between one and four days of WFH each week as preferring hybrid work. The left plot shows the shares with these preferences among all workers; the right plot focuses on workers in service occupations, who might be more similar to the workers whom we study. Data comes from Barrero et al. (2022), who surveyed 217,381 respondents in total and 22,928 respondents in service occupations between May 2020 and September 2023.

**Figure A.18:** Trends in Remote Works' Prevalence in the US

**Panel (a): All Full-Time Workers**

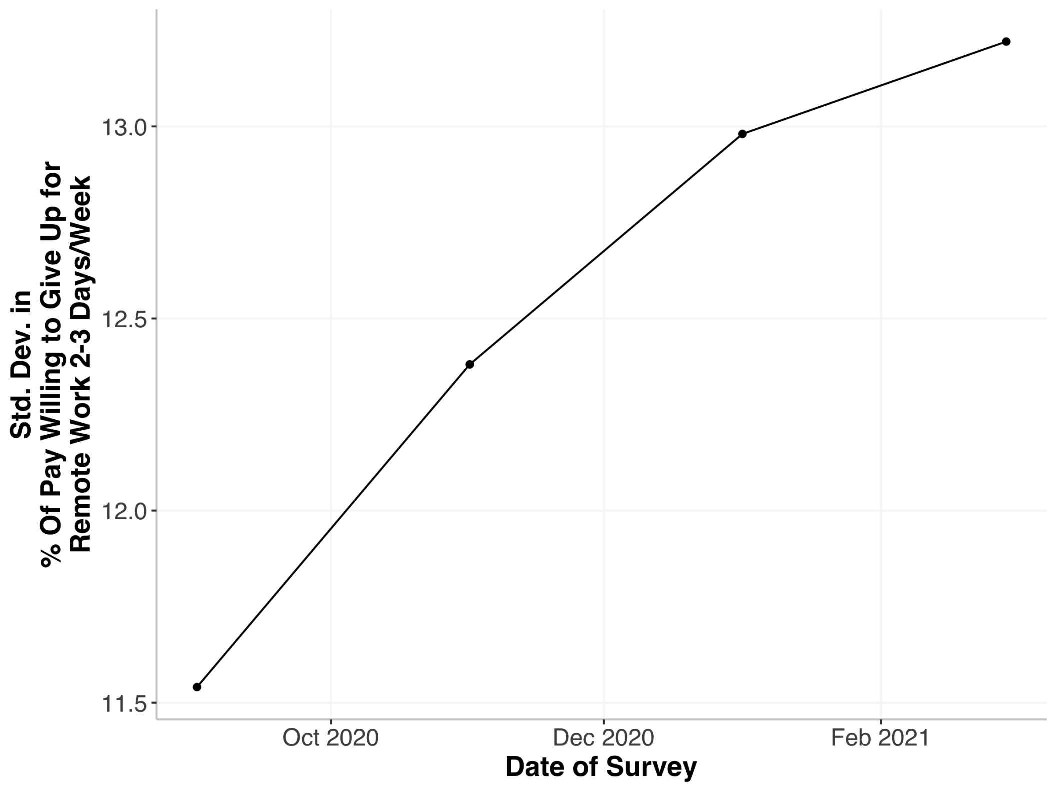



**Panel (b): Full-Time Workers in Phone Occupations**




*Note:* This figure illustrates trends in the prevalence of remote work in the US. All samples are limited to employed workers, ages 18−64 who worked at least 35 hours per week. Panel (a) includes all workers. Panel (b) limits to the subset of phone workers, using Mas and Pallais (2017)'s definition of telemarketers (Census code 4940), bill and account collectors (5100), customer service representatives (5240), and interviewers (except eligibility and loan) (5310) in the surveys in which this is possible. In the American Time Use Survey, remote work is defined as doing all of one's work at home, excluding time-diaries taken on weekends and those with less than 7 hours of work (Flood et al., 2023a). In the American Community Survey, remote work is defined as responding to questions about transportation to work with the possible response of working at home (Ruggles et al., 2022). In the Census Household Pulse Survey (U.S. Census Bureau, 2023) and in the Survey of Workplace Arrangements and Attitudes (SWAA) (Barrero et al., 2022), remote work is defined as the respondent spending all of their paid workdays at home.

**Figure A.19:** The Time-Series of the Variation in Workers' Willingness to Pay for Remote Work Over the Course of the Pandemic




*Notes:* This figure illustrates the time-series change in the variation in workers' stated willingness to pay for remote work over the course of the pandemic, using surveys of Barrero et al. (2022). The x-axis plots the date of the survey. The y-axis plots the standard deviation in the percent of workers' pay that they report being willing to give up to have the option to work at home two to three days per week. Specifically, the question asks respondents: "how much of a pay raise/cut would you value WFH 2 to 3 days per week?" In total, 19,166 individuals were asked this question over the survey waves. Weights are used so that the surveyed individuals match the Current Population Survey. For details on the survey design and reweighting, see Barrero et al. (2022).

## **Table A.1:** Pre-pandemic Productivity Differences

| | Calls per Hour | | | | | | |
|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
| Chose Remote Job | $-0.39^{***}$ | $-0.41^{***}$ | $-0.45^{***}$ | $-0.62^{***}$ | $-0.65^{***}$ | $-0.56^{***}$ | $-0.55^{***}$ |
| | (0.06) | (0.08) | (0.08) | (0.13) | (0.16) | (0.10) | (0.14) |
| Base Pay | | | | $-0.01$ | $-0.01$ | $-0.03$ | $-0.05$ |
| | | | | (0.04) | (0.05) | (0.04) | (0.06) |
| Local Outside Option Pay in MSA | | | | 0.04 | 0.03 | | |
| | | | | (0.03) | (0.03) | | |
| Unemployment Rate in MSA | | | | $0.05^{***}$ | $0.09^{***}$ | | |
| | | | | (0.02) | (0.02) | | |
| Mother | | | | | $-0.01$ | | $-0.05$ |
| | | | | | (0.09) | | (0.11) |
| Father | | | | | $-0.02$ | | 0.11 |
| | | | | | (0.16) | | (0.14) |
| Pre-Mean On-Site | 3.80 | 3.80 | 3.80 | 3.80 | 3.76 | 3.80 | 3.85 |
| Chose Remote in % | -10.38% | -10.91% | -11.95% | -16.31% | -17.18% | -14.72% | -14.35% |
| | (1.66) | (2.15) | (2.14) | (3.34) | (4.35) | (2.70) | (3.61) |
| Age x Gender FE | | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Call Queue FE | | | ✓ | ✓ | ✓ | ✓ | ✓ |
| Propensity Weights | | | | | | ✓ | ✓ |
| # Workers | 1936 | 1936 | 1936 | 1936 | 825 | 1936 | 825 |
| # Remote Workers | 344 | 344 | 344 | 344 | 162 | 344 | 162 |
| # On-site Workers | 1592 | 1592 | 1592 | 1592 | 663 | 1592 | 663 |
| # Days | 116273 | 116273 | 116273 | 116273 | 56150 | 116273 | 56150 |

*Note:* This table presents the differences in calls taken per hour between workers who initially chose on-site jobs and those who initially chose remote jobs in the six months *before* the offices closed. Calls per hour is computed as the ratio of the number of completed calls over the number of hours that the worker was scheduled to answer calls that day. Each specification estimates Equation 4 in the six months before the offices closed. Call queue fixed effects interact the date of the call with the worker's time-zone and call-level (routine, intermediate, or complex) to limit comparisons to workers handling calls randomly routed from the same queue. Pay for customer service representatives in the worker's metropolitan statistical area (MSA) comes from occupational employment statistics (Bureau of Labor Statistics, 2021b). Unemployment information comes from Bureau of Labor Statistics (2021a). Parenting characteristics come from a caregiving survey that the firm fielded in June of 2020 and that we supplemented with a survey run in April of 2021. The last two columns reweight observations based on the inverse likelihood that on-site workers would be on-site and remote workers would be remote based on the local pay in customer service in the MSA and the local unemployment rate. The sample is our preferred sample summarised in footnote 23. Standard errors are clustered by worker. $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$.

**Table A.2:** Pre-pandemic Productivity Differences Limited to $14 per hour Locations

| | Calls per Hour | | | | | | |
|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
| Chose Remote Job | $-0.42^{***}$ | $-0.47^{***}$ | $-0.54^{***}$ | $-0.71^{***}$ | $-0.74^{***}$ | $-0.65^{***}$ | $-0.66^{***}$ |
| | (0.07) | (0.12) | (0.11) | (0.15) | (0.19) | (0.12) | (0.17) |
| Local Outside Option Pay in MSA | | | | 0.04 | 0.03 | | |
| | | | | (0.03) | (0.04) | | |
| Unemployment Rate in MSA | | | | 0.02 | 0.05 | | |
| | | | | (0.03) | (0.03) | | |
| Mother | | | | | $-0.08$ | | $-0.09$ |
| | | | | | (0.11) | | (0.12) |
| Father | | | | | 0.17 | | $0.35^{**}$ |
| | | | | | (0.22) | | (0.17) |
| Pre-Mean On-Site | 3.83 | 3.83 | 3.83 | 3.83 | 3.71 | 3.84 | 3.89 |
| Chose Remote in % | -11.07% | -12.25% | -14.15% | -18.57% | -20.06% | -16.80% | -16.91% |
| | (1.88) | (3.12) | (2.99) | (3.79) | (5.22) | (3.20) | (4.49) |
| Age x Gender FE | | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Call Queue FE | | | ✓ | ✓ | ✓ | ✓ | ✓ |
| Propensity Weights | | | | | | ✓ | ✓ |
| # Workers | 977 | 977 | 977 | 977 | 825 | 977 | 825 |
| # Remote Workers | 344 | 344 | 344 | 344 | 162 | 344 | 162 |
| # On-site Workers | 633 | 633 | 633 | 633 | 663 | 633 | 663 |
| # Days | 62163 | 62163 | 62163 | 62163 | 30678 | 62163 | 30678 |

*Note:* This table replicates Table A.1 for the subsample of on-site locations with base pay of $14 per hour that matches the base pay of remote workers at the firm. Thus, everyone in this sample makes the same wages at entry into the firm. Standard errors are clustered by worker. $^{*}$p<0.1; $^{**}$p<0.05; $^{***}$p<0.01.

**Table A.3:** Adjacent Occupations to Customer Service

| Prior Occupation (Code) | % of Customer Service Workers |
|---|---|
| Customer Service Representatives (5240) | 86.42 |
| Receptionists And Information Clerks (5400) | 1.59 |
| Bookkeeping, Accounting, And Auditing Clerks (5120) | 0.95 |
| Tellers (5160) | 0.57 |
| Couriers And Messengers (5510) | 0.49 |
| Billing And Posting Clerks And Machine Operators (5110) | 0.45 |
| Waiters And Waitresses (4110) | 0.43 |
| Retail Salespersons (4760) | 0.43 |
| Cashiers (4720) | 0.41 |
| Dispatchers (5520) | 0.34 |

*Note:* This table shows the adjacent occupations to customer service. Data comes from the Current Population Survey for 2018 to 2020 (Flood et al., 2023b). The table reports the percent of customer service workers who had been in various occupations in the prior year. These percentages are computed using survey weights. $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$.

# A Model: Microfoundations

This section microfounds the model of the market for remote work in Section V. We show how fewer career opportunities in remote jobs can lead to adverse selection into remote jobs and result in an under-provision of remote jobs.[49]

In our two-period model, workers choose between remote and on-site jobs. Each job features two possible tasks — one low-skill and one high-skill. Workers vary in their tastes for remote work and their productivities. Firms post menus of jobs. All firms have the same, additive production function and operate in competitive markets.[50]

[49] Remote workers could have fewer career opportunities for various reasons. In order to advance, productive workers might need to be noticed, well-connected, or fully tooled-up. If working on-site makes it easier for productive workers to be recognized, build connections, or pick up new skills, then more productive workers will choose to be on-site. Thus, any of these mechanisms would create adverse selection into remote work.

[50] Our stylized model features two-periods and two rungs of the career ladder, which is a good approximation of our empirical context. The insights are qualitatively similar for an

## Table A.4: Turnover Around the Office Closures

| | Turnover | | Fired | | All Quits | | For Personal Reasons | | Other Quits | |
|---|---|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) |
| Initially On-site x Post | 0.24 | 0.13 | 0.03 | 0.005 | 0.20 | 0.13 | 0.19 | 0.20 | 0.02 | $-0.07$ |
| | (0.20) | (0.23) | (0.08) | (0.09) | (0.18) | (0.21) | (0.14) | (0.17) | (0.11) | (0.14) |
| Initially On-site | $0.24^{*}$ | $0.34^{**}$ | 0.001 | 0.05 | $0.25^{*}$ | $0.29^{*}$ | 0.04 | 0.01 | $0.19^{**}$ | $0.28^{***}$ |
| | (0.14) | (0.17) | (0.06) | (0.06) | (0.13) | (0.16) | (0.10) | (0.12) | (0.08) | (0.11) |
| Post | 0.03 | | 0.06 | | $-0.01$ | | 0.003 | | $-0.03$ | |
| | (0.17) | | (0.08) | | (0.16) | | (0.13) | | (0.09) | |
| Dependent Mean | 1.24 | 1.23 | 0.19 | 0.19 | 1.04 | 1.04 | 0.61 | 0.61 | 0.43 | 0.43 |
| Week x Time-Zone x Call Level | | ✓ | | ✓ | | ✓ | | ✓ | | ✓ |
| # Workers | 1,965 | 1,965 | 1,965 | 1,965 | 1,965 | 1,965 | 1,965 | 1,965 | 1,965 | 1,965 |
| # Initially On-site | 1,621 | 1,621 | 1,621 | 1,621 | 1,621 | 1,621 | 1,621 | 1,621 | 1,621 | 1,621 |
| # Already Remote | 344 | 344 | 344 | 344 | 344 | 344 | 344 | 344 | 344 | 344 |
| # Worker Weeks | 67,968 | 67,968 | 67,968 | 67,968 | 67,968 | 67,968 | 67,968 | 67,968 | 67,968 | 67,968 |
| $R^2$ | 0.0003 | 0.02 | 0.0001 | 0.02 | 0.0002 | 0.01 | 0.0002 | 0.01 | 0.0001 | 0.01 |

*Note:* This table presents a difference-in-differences design that compares the change in turnover of on-site workers who went remote during the Covid-19 office closures to that of remote workers who were already working from home. The dependent variable is weekly turnover: the columns $1-2$ include all departures, columns $3-4$ include involuntary firings for performance or behavior, columns $5-6$ include quits, columns $7-8$ include quits for personal reasons (e.g., family move or sickness), and columns $9-10$ include quits for other reasons. Each specification estimates Equation 3 in a six month bandwidth, excluding the period from March 15, 2020 when on-site workers were allowed to work from home and April 6, 2020 when the offices closed. The sample is our preferred sample summarised in footnote 23 but includes individuals who never took calls in six months before and after the office closures. Standard errors are clustered by worker. $^{*}$p<0.1; $^{**}$p<0.05; $^{***}$p<0.01.

**Table A.5:** Difference-in-Differences Around Covid-19 Office Closures without Donut around Closure Period

| | Calls per Hour | | | | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Initially On-Site x Post | $-0.18^{***}$ | $-0.12^{*}$ | $-0.14^{*}$ | $-0.14^{**}$ | $-0.14^{**}$ | $-0.20^{***}$ |
| | (0.06) | (0.06) | (0.08) | (0.05) | (0.05) | (0.07) |
| Initially On-Site | $0.39^{***}$ | $0.45^{***}$ | $0.45^{***}$ | | | |
| | (0.06) | (0.06) | (0.08) | | | |
| Post | $0.62^{***}$ | | | | | |
| | (0.06) | | | | | |
| County Covid Cases/10K | | | | | 0.02 | 0.01 |
| | | | | | (0.01) | (0.02) |
| County Covid Deaths/100K | | | | | $-0.02$ | $-0.05$ |
| | | | | | (0.05) | (0.06) |
| Mother x Post | | | | | | $-0.04$ |
| | | | | | | (0.06) |
| Father x Post | | | | | | $-0.12$ |
| | | | | | | (0.12) |
| Pre Dependent Mean On-Site | 3.80 | 3.80 | 3.80 | 3.80 | 3.80 | 3.80 |
| Initially On-Site x Post in % | -4.65% | -3.24% | -3.74% | -3.67% | -3.65% | -5.28% |
| | (1.65) | (1.69) | (1.99) | (1.44) | (1.43) | (1.76) |
| Age x Gender x Post FE | | ✓ | ✓ | ✓ | ✓ | ✓ |
| Call Queue FE | | | ✓ | ✓ | ✓ | ✓ |
| Worker FE | | | | ✓ | ✓ | ✓ |
| # Workers | 1,965 | 1,965 | 1,965 | 1,965 | 1,965 | 840 |
| # Initially On-site | 1,621 | 1,621 | 1,621 | 1,621 | 1,621 | 678 |
| # Already Remote | 344 | 344 | 344 | 344 | 162 | |
| # Worker Days | 242,365 | 242,365 | 242,365 | 242,365 | 242,365 | 136,493 |

*Note:* This table presents a difference-in-differences design that compares the change in productivity of on-site workers who went remote during the Covid-19 office closures to that of remote workers who were already working from home. The dependent variable is calls answered per hour that the worker is scheduled to answer customers' calls. Each specification estimates Equation 3 in a six month bandwidth. The post period is defined as starting on March 15, 2020 when on-site workers were allowed to work from home. The queue fixed effects specify the date, time-zone, and call-type (see Section II.C). Covid-19 cases and deaths in columns 4 and 5 come from NYT (2021). Parenting characteristics in column 5 come from a caregiving survey that the firm fielded in June of 2020 and that we supplemented in April of 2021. The sample is our preferred sample summarised in footnote 23. Standard errors are clustered by worker. $^{*}$p<0.1; $^{**}$p<0.05; $^{***}$p<0.01.

**Table A.6:** Difference-in-Difference Around Covid-19 Office Closures in Locations with \$14/hour Pay

| | Calls per Hour | | | | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Initially On-Site x Post | $-0.16^{**}$ | $-0.11$ | $-0.19$ | $-0.23^{***}$ | $-0.23^{***}$ | $-0.28^{***}$ |
| | (0.08) | (0.08) | (0.12) | (0.08) | (0.08) | (0.11) |
| Initially On-Site | $0.42^{***}$ | $0.46^{***}$ | $0.54^{***}$ | | | |
| | (0.07) | (0.08) | (0.11) | | | |
| Post | $0.79^{***}$ | | | | | |
| | (0.06) | | | | | |
| County Covid Cases/10K | | | | | 0.01 | 0.01 |
| | | | | | (0.02) | (0.02) |
| Mother x Post | | | | | | $-0.01$ |
| | | | | | | (0.09) |
| Father x Post | | | | | | $-0.24$ |
| | | | | | | (0.18) |
| Pre Dependent Mean On-Site | 3.83 | 3.83 | 3.83 | 3.83 | 3.83 | 3.83 |
| Initially On-Site x Post in % | -4.3% | -2.9% | -4.8% | -5.9% | -6% | -7.2% |
| | (2.00) | (2.10) | (3.00) | (2.20) | (2.20) | (2.70) |
| Age x Gender x Post FE | | ✓ | ✓ | ✓ | ✓ | ✓ |
| Call Queue FE | | | ✓ | ✓ | ✓ | ✓ |
| Worker FE | | | | ✓ | ✓ | ✓ |
| # Workers | 994 | 994 | 994 | 994 | 994 | 428 |
| # Initially On-site | 650 | 650 | 650 | 650 | 650 | 266 |
| # Already Remote | 344 | 344 | 344 | 344 | 344 | 162 |
| # Worker Days | 113,864 | 113,864 | 113,864 | 113,864 | 113,864 | 64,366 |
| $R^2$ | 0.06 | 0.11 | 0.21 | 0.48 | 0.48 | 0.50 |

*Note:* This table replicates Table 2 but limits to on-site locations with \$14 per hour base pay: in this sample, all workers have the same base pay upon entry into the firm. Standard errors are clustered by worker. $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$.

**Table A.7:** Difference-in-Difference Around Covid-19 Office Closures with Schedule Controls

| | Calls per Hour | | | | |
|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) |
| Initially On-Site x Post | $-0.16^{**}$ | $-0.15^{**}$ | $-0.14^{**}$ | $-0.15^{**}$ | $-0.14^{**}$ |
| | (0.07) | (0.07) | (0.07) | (0.07) | (0.07) |
| Initially On-Site x Post in % | -4.1% | -4.0% | -3.7% | -3.8% | -3.6% |
| | (1.8) | (1.8) | (1.7) | (1.7) | (1.7) |
| Preferred | ✓ | ✓ | ✓ | ✓ | ✓ |
| Call Min. FE | | ✓ | ✓ | ✓ | ✓ |
| Email Min. FE | | | ✓ | ✓ | ✓ |
| Meeting Min. FE | | | | ✓ | ✓ |
| Other Min. FE | | | | | ✓ |
| # Workers | 1,646 | 1,646 | 1,646 | 1,646 | 1,646 |
| # Worker Days | 172,352 | 172,352 | 172,352 | 172,352 | 172,352 |
| $R^2$ | 0.44 | 0.45 | 0.46 | 0.46 | 0.46 |

*Note:* This table presents a difference-in-difference design that compares the change in productivity of on-site workers who went remote during the Covid-19 office closures to that of remote workers who were already working from home. The dependent variable is calls answered per hour that the worker is scheduled to answer customers' calls. Each specification estimates Equation 3 in a six month bandwidth excluding the period from March 15, 2020, when on-site workers could work from home, to April 6, 2020, when remote work was required. The preferred set of controls include worked fixed effects, call-queue fixed effects, and time-varying demographic effects (see Section II.C). Standard errors are clustered by worker. $^{*}$p<0.1; $^{**}$p<0.05; $^{***}$p<0.01.

**Table A.8:** Difference-in-Differences Around Covid-19 Office Closures with Geographic Controls

| | Calls per Hour | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Initially On-Site x Post | $-0.15^{**}$ | $-0.15^{**}$ | $-0.13^{**}$ | $-0.15^{**}$ |
| | (0.06) | (0.06) | (0.06) | (0.06) |
| Covid-19 Cases/10K | | 0.02 | 0.02 | 0.02 |
| | | (0.01) | (0.01) | (0.01) |
| Covid-19 Deaths/100K | | $-0.03$ | $-0.03$ | $-0.03$ |
| | | (0.05) | (0.05) | (0.05) |
| % In Customer Service | | | $0.37^{***}$ | $0.44^{***}$ |
| | | | (0.13) | (0.17) |
| % Unemployed | | | | $-0.03^{**}$ |
| | | | | (0.01) |
| Initially On-Site x Post in % | -3.9% | -3.9% | -3.9% | -3.4% |
| | (1.60) | (1.60) | (1.60) | (1.60) |
| Preferred | ✓ | ✓ | ✓ | ✓ |
| # Workers | 1,965 | 1,965 | 1,965 | 1,965 |
| # Initially On-site | 1,621 | 1,621 | 1,621 | 1,621 |
| # Already Remote | 344 | 344 | 344 | 344 |
| # Worker Days | 224,447 | 224,447 | 224,447 | 224,447 |
| $R^2$ | 0.44 | 0.44 | 0.44 | 0.44 |

*Note:* This table presents a difference-in-difference design that compares the change in productivity of on-site workers who went remote during the Covid-19 office closures to that of remote workers who were already working from home. The dependent variable is calls answered per hour that the worker is scheduled to answer customers' calls. Each specification estimates Equation 3 in a six month bandwidth in a six month bandwidth excluding the period from March 15, 2020 when on-site workers could work from home to April 6, 2020, when remote work was required. The preferred set of controls include worked fixed effect, age-by-gender-by-post fixed effects to allow for different pandemic shocks for different demographic groups, and call-queue fixed effects that specify the date, time-zone, and call-type (see Section II.C). Covid-19 cases and deaths come from NYT (2021). Controls for the share of employment in customer service in the metropolital statistical area (MSA) comes from Bureau of Labor Statistics (2021b). The unemployment rate in the MSA comes from Bureau of Labor Statistics (2021a). Standard errors are clustered by worker. $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$.

**Table A.9:** Difference-in-Differences with Pre-Covid Switchers Control Group

| | Calls per Hour | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Initially On-Site x Post | $-0.20^{***}$ | $-0.20^{***}$ | $-0.11$ | $-0.11$ |
| | (0.07) | (0.07) | (0.07) | (0.09) |
| County Covid Cases/10K | | $-0.01$ | $-0.01$ | $-0.001$ |
| | | (0.02) | (0.02) | (0.02) |
| Mother x Post | | | | $-0.01$ |
| | | | | (0.06) |
| Father x Post | | | | 0.04 |
| | | | | (0.13) |
| Pre Dependent Mean On-Site | 3.8 | 3.8 | 3.8 | 3.8 |
| Initially On-Site x Post in % | -5.3% | -5.3% | -3% | -2.8% |
| | (1.90) | (1.90) | (2.00) | (2.50) |
| Age x Gender x Post FE | ✓ | ✓ | ✓ | ✓ |
| Call Queue FE | ✓ | ✓ | ✓ | ✓ |
| Worker FE | ✓ | ✓ | ✓ | ✓ |
| Hired Location x Post FE | | | ✓ | ✓ |
| # Workers | 2,091 | 2,091 | 2,091 | 886 |
| # Initially On-site | 1,859 | 1,859 | 1,859 | 780 |
| # Already Remote | 232 | 232 | 232 | 106 |
| # Worker Days | 238,113 | 238,113 | 238,113 | 134,374 |
| $R^2$ | 0.46 | 0.46 | 0.47 | 0.46 |

*Note:* This table presents difference-in-differences designs that compare the change in productivity metrics of initially on-site workers who went remote because of the pandemic office closures to workers who voluntarily chose to go remote before the pandemic. We include time varying controls for age and gender, call-queue fixed effects, and worker fixed effects. Column 3 adds in the area the worker was hired and Column 4 the Covid-19 case rate. Standard errors are clustered at the worker level. $^{*}$p<0.1; $^{**}$p<0.05; $^{***}$p<0.01.

**Table A.10:** Difference-in-Difference Around Covid-19 Office Closures with Subsamples with Complete Metrics

| | Calls/Scheduled Hour | | % Call Back in 2 Days | | Call Without Call Back/Hour | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Initially On-Site x Post | $-0.15^{**}$ | $-0.17^{***}$ | $0.35^{*}$ | $0.35^{*}$ | $-0.13^{**}$ | $-0.15^{***}$ |
| | (0.06) | (0.06) | (0.20) | (0.19) | (0.05) | (0.05) |
| Sample: Time-Use | ✓ | | ✓ | | ✓ | |
| Sample: Satisfaction | | ✓ | | ✓ | | ✓ |
| Pre Mean On-Site | 3.8 | 3.9 | 15.8 | 15.8 | 3.2 | 3.3 |
| Initially On-Site x Post in % | -4% | -4.4% | 2.2% | 2.2% | -4.1% | -4.5% |
| | (1.6) | (1.5) | (1.3) | (1.2) | (1.70) | (1.6) |
| Preferred Controls | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| # Workers | 1,965 | 1,954 | 1,965 | 1,954 | 1,965 | 1,954 |
| # Initially On-site | 1,621 | 1,610 | 1,621 | 1,610 | 1,621 | 1,610 |
| # Already Remote | 344 | 344 | 344 | 344 | 344 | 344 |
| # Worker Days | 216,671 | 189,285 | 216,671 | 189,285 | 216,671 | 189,285 |
| $R^2$ | 0.45 | 0.48 | 0.13 | 0.17 | 0.42 | 0.45 |

*Note:* This table presents a difference-in-differences design that compares the change in productivity of on-site workers who went remote during the Covid-19 office closures to that of already-remote workers. The table considers the robustness of the results to using subsamples with complete data on worker time-use in call-time and hold-time in the odd columns and subsamples with complete data on customer satisfaction in the even columns. The first two columns consider calls per hour, the second two consider two-day call-back rates (that indicate initial questions went unanswered), and the last two columns consider calls without call-backs per hour. Standard errors are clustered by worker. $^{*}$p<0.1; $^{**}$p<0.05; $^{***}$p<0.01.

**Table A.11:** Difference-in-Differences By a Continuous Measure of Worker Experience

| | Calls / Hour | % On Phone | Min. / Call | Hold Min. / Call | % Call Back (2 Day) | Satisfaction Rating | Call Without Call Back / Hour |
|---|---|---|---|---|---|---|---|
| | | Decomposition | | Call Quality | | | |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
| Initially On-Site x Post | $-0.17^{***}$ | $-2.02^{***}$ | $0.45^{**}$ | $0.14^{***}$ | $0.46^{**}$ | $-0.002$ | $-0.15^{***}$ |
| | (0.06) | (0.52) | (0.21) | (0.05) | (0.20) | (0.01) | (0.05) |
| Tenure (Z-Score) x Initially On-Site x Post | 0.09 | 0.46 | $-0.49^{**}$ | $-0.18^{***}$ | $-0.41^{**}$ | $-0.003$ | 0.09 |
| | (0.06) | (0.69) | (0.23) | (0.05) | (0.18) | (0.01) | (0.05) |
| Pre Mean On-Site | 3.8 | 74.3 | 13.2 | 1.1 | 15.9 | 4.9 | 3.2 |
| Percentage Effects | | | | | | | |
| Initially On-Site x Post | -4.4% | -2.7% | 3.4% | 12.5% | 2.9% | -0.05% | -4.58% |
| | (1.6) | (0.7) | (1.6) | (4.7) | (1.3) | (0.20) | (1.60) |
| Tenure (Z) x Initially On-Site x Post | 2.5% | 0.6% | -3.7% | -16% | -2.6% | -0.05% | 2.7% |
| | (1.6) | (0.9) | (1.7) | (4.3) | (1.1) | (0.20) | (1.70) |
| Preferred Controls | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| # Workers | 1,965 | 1,965 | 1,965 | 1,965 | 1,965 | 1,954 | 1,965 |
| # Worker Days | 224,447 | 216,671 | 216,671 | 216,671 | 224,447 | 189,285 | 224,447 |
| $R^2$ | 0.44 | 0.63 | 0.38 | 0.18 | 0.13 | 0.09 | 0.42 |

*Note:* This table analyzes the heterogeneous effects of remote work by workers' tenure at the firm. Each specification estimates the difference-in-differences design in Equation 3, fully interacted with tenure. In column 1, the dependent variable is calls answered per hour that the worker is scheduled to answer customers' calls. The next three columns consider three metrics of call quality: (2) minutes that customers are kept waiting on hold; (3) the rate at which customers call back to the service line within two days, likely with unanswered questions; (4) average customer satisfaction scores on a five-point scale. The final column considers an alternative measure of productivity that considers the number of customer calls that do not lead to a call back that the worker answers each hour. Call-queue fixed effects account for the date, time-zone, and call-level to compare workers handling calls randomly routed from the same queue. Standard errors are clustered by worker. $^{*}$p<0.1; $^{**}$p<0.05; $^{***}$p<0.01.

## **Table A.12:** Heterogeneous Effects by Parenting

| | Calls / Hour | Hold Min. / Call | % Call Back (2 Day) | Satisfaction Rating | Call Without Call Back / Hour |
|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) |
| Initially On-Site x Post | $-0.23^{**}$ | 0.13 | 0.50 | 0.004 | $-0.21^{**}$ |
| | (0.12) | (0.09) | (0.35) | (0.02) | (0.10) |
| Parent x Initially On-Site x Post | 0.03 | 0.03 | $-0.22$ | 0.01 | 0.04 |
| | (0.15) | (0.12) | (0.43) | (0.02) | (0.13) |
| Pre Mean On-Site, Parent | 3.9 | 1.0 | 15.5 | 4.9 | 3.3 |
| Pre Mean On-Site, Non-Parent | 3.8 | 1.0 | 15.7 | 4.9 | 3.2 |
| Percentage Effects | | | | | |
| **Parent:** Initially On-Site x Post | -6% | 12.9% | 3.2% | 0.08% | -6.23% |
| | (2.9) | (8.4) | (2.2) | (0.40) | (2.90) |
| **Non-Parent:** Initially On-Site x Post | -5.2% | 16% | 1.8% | 0.27% | -5.18% |
| | (2.6) | (9.1) | (1.9) | (0.30) | (2.70) |
| Parent x Post FE | ✓ | ✓ | ✓ | ✓ | ✓ |
| Worker FE | ✓ | ✓ | ✓ | ✓ | ✓ |
| Age x Gender x Post FE | ✓ | ✓ | ✓ | ✓ | ✓ |
| Call Queue FE | ✓ | ✓ | ✓ | ✓ | ✓ |
| # Workers | 840 | 840 | 840 | 838 | 840 |
| # Initially On-site | 678 | 678 | 678 | 676 | 678 |
| # Already Remote | 162 | 162 | 162 | 162 | 162 |
| # Worker Days | 126,603 | 121,167 | 126,603 | 107,687 | 126,603 |
| $R^2$ | 0.45 | 0.16 | 0.15 | 0.11 | 0.43 |

*Notes:* This table presents difference-in-differences designs that compare the change in calls answered of on-site workers who went remote during the Covid-19 office closures to that of already remote workers, interacted with whether the individual is a parent. Parental responsibilities come from a June 2020 survey that we supplemented in April 2021. Each specification estimates Equation 4, with our preferred set of controls for worker fixed effects, demographics (age by gender by post period fixed effects), and call-queue fixed effects (date by time-zone by call-level). Standard errors are clustered by worker. $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$.

**Table A.13:** Heterogeneous Effects by Private Workspace

| | Calls / Hour | Hold Min. / Call | % Call Back (2 Day) | Satisfaction Rating | Call Without Call Back / Hour |
|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) |
| Initially On-Site x Post | $-0.43^{**}$ | $0.45^{***}$ | $1.10^{*}$ | $-0.02$ | $-0.39^{***}$ |
| | (0.17) | (0.15) | (0.62) | (0.02) | (0.14) |
| No Private Workspace x Initially On-Site x Post | 0.24 | 0.34 | $-0.40$ | $-0.04$ | 0.24 |
| | (0.23) | (0.27) | (1.49) | (0.04) | (0.18) |
| Pre Mean On-Site | 3.8 | 1.0 | 16.0 | 4.9 | 3.2 |
| Worker FE | ✓ | ✓ | ✓ | ✓ | ✓ |
| Age x Gender x Post FE | ✓ | ✓ | ✓ | ✓ | ✓ |
| Call Queue FE | ✓ | ✓ | ✓ | ✓ | ✓ |
| # Workers | 234 | 234 | 234 | 233 | 234 |
| # Initially On-site | 194 | 194 | 194 | 193 | 194 |
| # Already Remote | 40 | 40 | 40 | 40 | 40 |
| # Worker Days | 37,644 | 35,885 | 37,644 | 32,267 | 37,644 |
| $R^2$ | 0.50 | 0.30 | 0.22 | 0.19 | 0.48 |

*Notes:* This table presents difference-in-differences designs that compare the change in calls answered of on-site workers who went remote during the Covid-19 office closures to that of already remote workers, interacted with whether the individual had a private workspace. Information on workspaces come from a survey that we conducted of workers in April 2021. Respondents were asked where they had typically worked in the previous week. We define a private workspace as an office or bedroom as opposed to a living room or kitchen. Each specification estimates Equation 4, with our preferred set of controls for worker fixed effects, demographics (age by gender by post period fixed effects), and call-queue fixed effects (date by time-zone by call-level). Standard errors are clustered by worker. $^{*}$p<0.1; $^{**}$p<0.05; $^{***}$p<0.01.

## Table A.14: Difference-in-Differences By Gender

| | Calls / Hour | Hold Min. / Call | % Call Back (2 Day) | Satisfaction Rating | Call Without Call Back / Hour |
|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) |
| Initially On-Site x Post | $-0.14^{**}$ | $0.13^{**}$ | $0.37^{*}$ | $-0.001$ | $-0.12^{**}$ |
| | (0.06) | (0.06) | (0.21) | (0.01) | (0.06) |
| Male x Initially On-Site x Post | $-0.08$ | $-0.10$ | 0.24 | $-0.01$ | $-0.08$ |
| | (0.17) | (0.19) | (0.62) | (0.02) | (0.15) |
| Pre Mean On-Site, Female | 3.8 | 1.1 | 15.9 | 4.9 | 3.2 |
| Pre Mean On-Site, Male | 3.7 | 1.2 | 15.7 | 4.9 | 3.1 |
| Percentage Effects | | | | | |
| **Female:** Initially On-Site x Post | -3.5% | 12.1% | 2.3% | -0.02% | -3.62% |
| | (1.7) | (5.1) | (1.3) | (0.20) | (1.70) |
| **Male:** Initially On-Site x Post | -5.9% | 3% | 3.9% | -0.15% | -6.2% |
| | (4.4) | (15.1) | (3.8) | (0.40) | (4.60) |
| Worker FE | ✓ | ✓ | ✓ | ✓ | ✓ |
| Age x Gender x Post FE | ✓ | ✓ | ✓ | ✓ | ✓ |
| Call Queue FE | ✓ | ✓ | ✓ | ✓ | ✓ |
| # Workers | 1,965 | 1,965 | 1,965 | 1,954 | 1,965 |
| # Worker Days | 224,447 | 216,671 | 224,447 | 189,285 | 224,447 |
| $R^2$ | 0.44 | 0.18 | 0.13 | 0.09 | 0.42 |

*Note:* This table analyzes the heterogeneous effects of remote work by workers' self-reported gender. Each specification estimates the difference-in-differences design in Equation 3, fully interacted with gender. In Column 1, the dependent variable is calls answered per hour that the worker is scheduled to answer customers' calls. The next three columns consider three metrics of call quality: (2) minutes that customers are kept waiting on hold; (3) the rate at which customers call back to the service line within two days, likely with unanswered questions; (4) average customer satisfaction scores on a five-point scale. The final column considers an alternative measure of productivity that considers the number of customer calls that do not lead to a call back that the worker answers each hour. Call-queue fixed effects account for the date, time-zone, and call-level to compare workers handling calls randomly routed from the same queue. Standard errors are clustered by worker. $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$.

**Table A.15:** Remote Work and Investments in Workers

**Panel (a):** New Skill Training Min. Per Month

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| Initially On-Site x Post | $-16.43^{*}$ | $-16.88^{**}$ | $-22.80^{***}$ | $-19.12^{**}$ | $-23.46^{**}$ |
| | (8.60) | (8.39) | (8.30) | (8.37) | (9.56) |
| Initially On-Site | $14.95^{***}$ | $14.35^{***}$ | $21.30^{***}$ | $17.84^{***}$ | $19.48^{***}$ |
| | (3.13) | (2.64) | (5.90) | (4.86) | (4.84) |
| Post | $14.35^{*}$ | $27.22^{***}$ | | | |
| | (7.73) | (7.66) | | | |
| R2 | 0.000 | 0.001 | 0.09 | 0.15 | 0.15 |
| Pre Mean On-Site | 72.7 | 72.7 | 72.7 | 72.7 | 72.7 |
| Percentage Effect | | | | | |
| Initially On-Site x Post | -22.6% | -23.2% | -31.3% | -26.3% | -32.3% |
| Initially On-Site | 20.6% | 19.7% | 29.3% | 24.5% | 26.8% |

**Panel (b):** Manager One-on-One Min. Per Month

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| Initially On-Site x Post | $-8.29^{***}$ | $-9.54^{***}$ | $-10.98^{***}$ | $-10.23^{***}$ | $-10.52^{***}$ |
| | (2.69) | (2.03) | (2.52) | (1.93) | (2.00) |
| Initially On-Site | $8.63^{***}$ | $7.86^{***}$ | $9.92^{***}$ | $9.20^{***}$ | $9.47^{***}$ |
| | (2.20) | (1.52) | (2.09) | (1.76) | (1.82) |
| Post | $-11.73^{***}$ | $4.08^{**}$ | | | |
| | (2.40) | (1.85) | | | |
| R2 | 0.003 | 0.016 | 0.13 | 0.23 | 0.23 |
| Pre Mean On-Site | 30.0 | 30.0 | 30.0 | 30.0 | 30.0 |
| Percentage Effect | | | | | |
| Initially On-Site x Post | -27.6% | -31.8% | -36.6% | -34.1% | -35.1% |
| Initially On-Site | 28.8% | 26.2% | 33.1% | 30.7% | 31.6% |
| Quartic in Worker Tenure | | ✓ | ✓ | | |
| Date x Hire Month FE | | | | ✓ | ✓ |
| Call-Queue FE | | | ✓ | ✓ | ✓ |
| Age by Gender by Post FE | | | | | ✓ |
| # Workers | 1,965 | 1,965 | 1,965 | 1,965 | 1,965 |

*Note:* This table investigates remote work's impact on workers' careers. Each specification estimates the difference-in-differences design in Equation 3, excluding the period when on-site workers could start working from home on March 15, 2020 and when the offices closed entirely on April 6, 2020. Panel (a) captures time spent per month on training for new skills, and Panel (b) captures time spent attending one-on-one meetings with managers. The sample is the primary sample summarised in footnote 23. Call-queue fixed effects account for the date, time-zone, and call-level to compare workers who handle calls randomly routed from the same queue. Standard errors are clustered by worker. $^{*}$p<0.1; $^{**}$p<0.05; $^{***}$p<0.01.

**Table A.16:** Effect of Remote Work on Promotions

| | % Promoted Each Month | | | | |
|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) |
| Initially On-Site x Post | $-0.59$ | $-1.44$ | $-3.08^{*}$ | $-4.14^{***}$ | $-4.03^{**}$ |
| | (1.42) | (1.43) | (1.58) | (1.46) | (1.59) |
| Initially On-Site | 0.55 | $2.12^{***}$ | $2.27^{**}$ | $3.27^{***}$ | $3.27^{***}$ |
| | (0.77) | (0.76) | (0.91) | (0.89) | (0.95) |
| Post | 0.73 | $-5.89^{***}$ | | | |
| | (1.27) | (1.33) | | | |
| Pre Mean On-Site | 6.1 | 6.1 | 6.1 | 6.1 | 6.1 |
| Percentage Effect | | | | | |
| Initially On-Site x Post | -9.6% | -23.4% | -50.2% | -67.5% | -65.7% |
| | (23.2) | (23.3) | (25.8) | (23.9) | (25.9) |
| Initially On-Site | 8.9% | 34.6% | 37% | 53.4% | 53.3% |
| | (12.6) | (12.5) | (14.8) | (14.6) | (15.5) |
| Quartic in Worker Tenure | | ✓ | ✓ | | |
| Date x Hire Month FE | | | | ✓ | ✓ |
| Call-Queue FE | | | ✓ | ✓ | ✓ |
| Age by Gender by Post FE | | | | | ✓ |
| # Workers | 1,745 | 1,745 | 1,745 | 1,745 | 1,745 |
| # Initially On-Site | 1,425 | 1,425 | 1,425 | 1,425 | 1,425 |
| # Initially Remote | 320 | 320 | 320 | 320 | 320 |
| # Worker Days | 278,031 | 278,031 | 278,031 | 278,031 | 278,031 |
| $R^2$ | 0.0000 | 0.002 | 0.16 | 0.28 | 0.28 |

*Note:* This table investigates remote work's impact on workers' promotion rates. Each specification estimates the difference-in-differences design in Equation 3, excluding the period when on-site workers could start working from home on March 15, 2020 and when the offices closed entirely on April 6, 2020. The sample is the primary sample summarised in footnote 23, which is further limited to workers who have either not yet been promoted or just been promoted. Promotions to higher-stakes customer-service roles involve a pay raise of \$2 per hour or 13 percent of base pay. Call-queue fixed effects account for the date, time-zone, and call-level. Standard errors are clustered by worker. $^{*}$p<0.1; $^{**}$p<0.05; $^{***}$p<0.01.

**Table A.17:** Productivity Differences When All Workers are Remote Due to Covid-19 in Locations with $14/hour Pay

| | Calls per Hour | | | | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Remote Hire | $-0.26^{***}$ | $-0.35^{***}$ | $-0.36^{***}$ | $-0.36^{***}$ | $-0.37^{***}$ | $-0.34^{**}$ |
| | (0.08) | (0.09) | (0.11) | (0.11) | (0.12) | (0.15) |
| County Covid Cases/10K | | | | 0.005 | 0.01 | 0.01 |
| | | | | (0.03) | (0.03) | (0.03) |
| Local Outside Option Pay in MSA | | | | | 0.01 | $-0.0002$ |
| | | | | | (0.03) | (0.04) |
| Mother | | | | | | 0.003 |
| | | | | | | (0.12) |
| Father | | | | | | 0.01 |
| | | | | | | (0.21) |
| Dependent Mean On-Site Hire | 4.45 | 4.45 | 4.45 | 4.45 | 4.45 | 4.45 |
| Remote Hire in % | -5.9% | -7.8% | -8% | -8% | -8.4% | -7.4% |
| | (1.8) | (2.0) | (2.4) | (2.4) | (2.7) | (3.3) |
| Age x Gender FE | | ✓ | ✓ | ✓ | ✓ | ✓ |
| Call Queue FE | | | ✓ | ✓ | ✓ | ✓ |
| # Workers | 714 | 714 | 714 | 714 | 714 | 397 |
| # Initially On-site | 452 | 452 | 452 | 452 | 452 | 246 |
| # Already Remote | 262 | 262 | 262 | 262 | 262 | 151 |
| # Worker Days | 51,701 | 51,701 | 51,701 | 51,701 | 51,701 | 33,688 |
| $R^2$ | 0.01 | 0.07 | 0.16 | 0.16 | 0.16 | 0.19 |

*Notes:* This table presents the differences in calls taken per hour between workers who initially chose on-site jobs and those who initially chose remote jobs in the six months after the offices closed in locations with hourly pay of $14/hour. Each specification estimates Equation 4. Calls per hour is computed as the ratio of the number of completed calls over the number of hours that the worker was scheduled to answer calls that day (as opposed to, e.g., attending meetings or answering customer emails). Call queue fixed effects interact the date of the call with the worker's time-zone and call-level (routine, intermediate, or complex) to limit comparisons to workers handling calls randomly routed from the same queue. Covid-19 cases come from NYT (2021). Pay for customer service representatives in the worker's metropolitan statistical area comes from occupational employment statistics (Bureau of Labor Statistics, 2021b). Parenting characteristics come from a caregiving survey that the firm fielded in June of 2020. The sample is limited to workers hired between July 2018 and March 15, 2020. Standard errors are clustered by worker. $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$.

**Table A.18:** Productivity Differences When All Workers are Remote Due to Covid-19 with Schedule Controls

| | Calls per Hour | | | | |
|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) |
| Initially Remote | $-0.30^{***}$ | $-0.29^{***}$ | $-0.29^{***}$ | $-0.29^{***}$ | $-0.28^{***}$ |
| | (0.08) | (0.08) | (0.08) | (0.08) | (0.08) |
| Initially Remote in % | -6.75% | -6.55% | -6.5% | -6.49% | -6.45% |
| | (1.81) | (1.91) | (1.90) | (1.90) | (1.90) |
| Preferred | ✓ | ✓ | ✓ | ✓ | ✓ |
| Call Min. FE | | ✓ | ✓ | ✓ | ✓ |
| Email Min. FE | | | ✓ | ✓ | ✓ |
| Meeting Min. FE | | | | | ✓ |
| Other Min. FE | | | | | |
| # Workers | 1,436 | 1,436 | 1,436 | 1,436 | 1,436 |
| # Worker Days | 108,174 | 101,019 | 101,019 | 101,019 | 101,019 |
| $R^2$ | 0.13 | 0.15 | 0.16 | 0.16 | 0.17 |

*Notes:* This table presents the differences in calls taken per hour between workers who initially chose on-site jobs and those who initially chose remote jobs in the six months after the offices closed. Each specification estimates Equation 4. Controls for minutes scheduled for calls, emails, meetings, and other tasks account for fatigue effects. Calls per hour is computed as the ratio of the number of completed calls over the number of hours that the worker was scheduled to answer calls that day (as opposed to, e.g., attending meetings or answering customer emails). Our preferred controls include call queue fixed effects that interact the date of the call with the worker's time-zone and call-level (routine, intermediate, or complex) to limit comparisons to workers handling calls randomly routed from the same queue. The sample is limited to workers hired between July 2018 and March 15, 2020. Standard errors are clustered by worker. $^{*}$p<0.1; $^{**}$p<0.05; $^{***}$p<0.01.

**Table A.19:** Productivity Differences When All Workers are Remote Due to Covid-19 with Geographic Controls

| | Calls per Hour | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Remote Hire | $-0.30^{***}$ | $-0.31^{***}$ | $-0.26^{***}$ | $-0.18^{*}$ |
| | (0.08) | (0.08) | (0.09) | (0.10) |
| Covid-19 Cases/10K | | 0.01 | 0.02 | 0.02 |
| | | (0.02) | (0.02) | (0.02) |
| Covid-19 Deaths/100K | | 0.07 | 0.05 | 0.10 |
| | | (0.09) | (0.09) | (0.09) |
| % In Customer Service | | | $-0.07$ | $-0.10^{*}$ |
| | | | (0.06) | (0.06) |
| % Unemployed | | | | $-0.03$ |
| | | | | (0.02) |
| Remote Hire in % | -6.75% | -7.01% | -5.91% | -4.2% |
| | (1.81) | (1.81) | (2.01) | (2.35) |
| Preferred | ✓ | ✓ | ✓ | ✓ |
| # Workers | 1,436 | 1,436 | 1,436 | 1,436 |
| # Worker Days | 108,174 | 101,019 | 101,019 | 101,019 |
| $R^2$ | 0.13 | 0.13 | 0.13 | 0.13 |

*Notes:* This table presents the differences in calls taken per hour between workers who initially chose on-site jobs and those who initially chose remote jobs once everyone was remote due to the offices closures of Covid-19. Each specification estimates Equation 4 in the six months after the office closures. Calls per hour is computed as the ratio of the number of completed calls over the number of hours that the worker was scheduled to answer calls that day (as opposed to, e.g., answering customer emails). Call queue fixed effects interact the date of the call with the worker's time-zone and call-level (routine, intermediate, or complex) to limit comparisons to workers handling calls randomly routed from the same queue. Covid-19 cases and deaths come from NYT (2021). The share of employment in customer service representatives in the worker's metropolitan statistical area (MSA) comes from occupational employment statistics (Bureau of Labor Statistics, 2021b). Unemployment rates in MSAs come from the Bureau of Labor Statistics (2021a). The sample is our primary sample summarized in footnote 33. Standard errors are clustered by worker. $^{*}$p<0.1; $^{**}$p<0.05; $^{***}$p<0.01.

**Table A.20:** Customer Satisfaction Score Differences When All Workers are Remote Due to Covid-19

| | Satisfaction Rating (out of 5) | | | | | | |
|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
| Remote Hire | 0.003 | 0.007 | 0.012 | 0.013 | 0.012 | 0.013 | 0.012 |
| | (0.009) | (0.010) | (0.011) | (0.011) | (0.013) | (0.013) | (0.017) |
| County Covid Cases/10K | | | | −0.002 | −0.002 | −0.002 | −0.003 |
| | | | | (0.004) | (0.004) | (0.004) | (0.005) |
| Base Pay | | | | | −0.001 | −0.0001 | 0.001 |
| | | | | | (0.005) | (0.005) | (0.006) |
| Local Outside Option Pay in MSA | | | | | | −0.001 | −0.001 |
| | | | | | | (0.003) | (0.004) |
| Mother | | | | | | | 0.007 |
| | | | | | | | (0.011) |
| Father | | | | | | | −0.014 |
| | | | | | | | (0.019) |
| Dependent Mean Initially On-Site | 4.77 | 4.77 | 4.77 | 4.77 | 4.77 | 4.77 | 4.77 |
| Remote Hire in % | 0.06% | 0.15% | 0.26% | 0.27% | 0.26% | 0.28% | 0.25% |
| | (0.20) | (0.21) | (0.24) | (0.24) | (0.28) | (0.28) | (0.36) |
| Age x Gender x Post FE | | ✓ | ✓ | ✓ | ✓ | ✓ | |
| Call Queue FE | | | ✓ | ✓ | ✓ | ✓ | ✓ |
| # Workers | 1,429 | 1,429 | 1,429 | 1,429 | 1,429 | 1,429 | 785 |
| # Initially On-site | 1,168 | 1,168 | 1,168 | 1,168 | 1,168 | 1,168 | 634 |
| # Already Remote | 261 | 261 | 261 | 261 | 261 | 261 | 151 |
| # Worker Days | 89,143 | 89,143 | 89,143 | 89,143 | 89,143 | 89,143 | 58,678 |
| $R^2$ | 0.00000 | 0.003 | 0.076 | 0.076 | 0.076 | 0.076 | 0.090 |

*Notes:* This table presents the differences in customer satisfaction scores between workers who initially chose on-site jobs and those who initially chose remote jobs once everyone was remote due to the offices closures of Covid-19. Each specification estimates Equation 4 in the six months after the office closures. Call queue fixed effects interact the date of the call with the worker's time-zone and call-level (routine, intermediate, or complex) to limit comparisons to workers handling calls randomly routed from the same queue. Covid-19 cases come from NYT (2021). Pay for customer service representatives in the worker's metropolitan statistical area comes from occupational employment statistics (Bureau of Labor Statistics, 2021b). Parenting characteristics come from a caregiving survey that the firm fielded in June of 2020. The sample is our primary sample summarized in footnote 33. Standard errors are clustered by worker. $^{*}$p<0.1; $^{**}$p<0.05; $^{***}$p<0.01.

**Table A.21:** Hold Time Differences When All Workers are Remote Due to Covid-19

| | Hold Min./Call | | | | | | |
|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
| Remote Hire | $-0.16^{***}$ | $-0.02$ | $-0.02$ | $-0.02$ | $-0.05$ | $-0.04$ | $-0.10$ |
| | (0.05) | (0.05) | (0.06) | (0.06) | (0.07) | (0.08) | (0.09) |
| County Covid Cases/10K | | | | $-0.01$ | $-0.01$ | $-0.01$ | 0.01 |
| | | | | (0.02) | (0.02) | (0.02) | (0.02) |
| Base Pay | | | | | $-0.03$ | $-0.02$ | $-0.04$ |
| | | | | | (0.03) | (0.03) | (0.04) |
| Local Outside Option Pay in MSA | | | | | | $-0.004$ | 0.004 |
| | | | | | | (0.02) | (0.02) |
| Mother | | | | | | | 0.02 |
| | | | | | | | (0.06) |
| Father | | | | | | | $-0.06$ |
| | | | | | | | (0.14) |
| Dependent Mean Initially On-Site | 1.32 | 1.32 | 1.32 | 1.32 | 1.32 | 1.32 | 1.32 |
| Remote Hire in % | -12.1% | -1.26% | -1.89% | -1.66% | -3.75% | -3.1% | -8.44% |
| | (4.16) | (4.11) | (4.54) | (4.46) | (5.09) | (5.95) | (7.64) |
| Age x Gender x Post FE | | ✓ | ✓ | ✓ | ✓ | ✓ | |
| Call Queue FE | | | ✓ | ✓ | ✓ | ✓ | ✓ |
| # Workers | 1,436 | 1,436 | 1,436 | 1,436 | 1,436 | 1,436 | 785 |
| # Initially On-site | 1,174 | 1,174 | 1,174 | 1,174 | 1,174 | 1,174 | 634 |
| # Already Remote | 262 | 262 | 262 | 262 | 262 | 262 | 151 |
| # Worker Days | 100,414 | 100,414 | 100,414 | 100,414 | 100,414 | 100,414 | 65,025 |
| $R^2$ | 0.001 | 0.04 | 0.12 | 0.12 | 0.12 | 0.12 | 0.12 |

*Notes:* This table presents the differences in minutes that customers spent on hold between workers who initially chose on-site jobs and those who initially chose remote jobs once everyone was remote due to the offices closures of Covid-19. Each specification estimates Equation 4 in the six months after the office closures. Call queue fixed effects interact the date of the call with the worker's time-zone and call-level (routine, intermediate, or complex) to limit comparisons to workers handling calls randomly routed from the same queue. Covid-19 cases come from NYT (2021). Pay for customer service representatives in the worker's metropolitan statistical area comes from occupational employment statistics (Bureau of Labor Statistics, 2021b). Parenting characteristics come from a caregiving survey that the firm fielded in June of 2020. The sample is our primary sample summarized in footnote 33. $^{*}$p<0.1; $^{**}$p<0.05; $^{***}$p<0.01.

## **Table A.22:** Differences in Call Back Rates When All Workers are Remote Due to Covid-19

| | Percent who Call Back in Two Days | | | | | | |
|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
| Remote Hire | $-0.36^{**}$ | $-0.47^{**}$ | $-0.62^{***}$ | $-0.64^{***}$ | $-0.72^{***}$ | $-0.60^{**}$ | $-0.35$ |
| | (0.18) | (0.19) | (0.20) | (0.20) | (0.23) | (0.27) | (0.31) |
| County Covid Cases/10K | | | | 0.10 | 0.10 | 0.09 | 0.02 |
| | | | | (0.06) | (0.06) | (0.06) | (0.07) |
| Base Pay | | | | | $-0.07$ | $-0.03$ | 0.02 |
| | | | | | (0.09) | (0.10) | (0.11) |
| Local Outside Option Pay in MSA | | | | | | $-0.07$ | $-0.06$ |
| | | | | | | (0.07) | (0.08) |
| Mother | | | | | | | 0.28 |
| | | | | | | | (0.19) |
| Father | | | | | | | $0.56^{*}$ |
| | | | | | | | (0.33) |
| Dependent Mean Initially On-Site | 12.19 | 12.19 | 12.19 | 12.19 | 12.19 | 12.19 | 12.19 |
| Remote Hire in % | -2.99% | -3.88% | -5.06% | -5.29% | -5.91% | -4.9% | -2.88% |
| | (1.46) | (1.56) | (1.68) | (1.67) | (1.85) | (2.23) | (2.60) |
| Age x Gender x Post FE | | ✓ | ✓ | ✓ | ✓ | ✓ | |
| Call Queue FE | | | ✓ | ✓ | ✓ | ✓ | ✓ |
| # Workers | 1,436 | 1,436 | 1,436 | 1,436 | 1,436 | 1,436 | 785 |
| # Initially On-site | 1,174 | 1,174 | 1,174 | 1,174 | 1,174 | 1,174 | 634 |
| # Already Remote | 262 | 262 | 262 | 262 | 262 | 262 | 151 |
| # Worker Days | 108,174 | 108,174 | 108,174 | 108,174 | 108,174 | 108,174 | 70,453 |
| $R^2$ | 0.0002 | 0.01 | 0.08 | 0.08 | 0.08 | 0.08 | 0.10 |

*Notes:* This table considers the percent of calls that result in a callback within two days, which often indicates the initial question went unanswered. The table compares the callback rate of workers who initially chose on-site jobs and those who initially chose remote jobs once everyone was remote due to the offices closures of Covid-19. Each specification estimates Equation 4 in the six months after the office closures. Call queue fixed effects interact the date of the call with the worker's time-zone and call-level (routine, intermediate, or complex) to limit comparisons to workers handling calls randomly routed from the same queue. Covid-19 cases come from NYT (2021). Pay for customer service representatives in the worker's metropolitan statistical area comes from occupational employment statistics (Bureau of Labor Statistics, 2021b). Parenting characteristics come from a caregiving survey that the firm fielded in June of 2020. The sample is our primary sample summarized in footnote 33. Standard errors are clustered by worker. $^{*}$p<0.1; $^{**}$p<0.05; $^{***}$p<0.01.

**Table A.23:** Differences in Call Transfer Rates When All Workers are Remote Due to Covid-19

| | Call Transfer Rate | | | | | | |
|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
| Initially Remote | 3.68*** | 4.54*** | 3.98*** | 3.91*** | 2.92*** | 2.25** | 1.86* |
| | (0.75) | (0.75) | (0.83) | (0.83) | (0.87) | (0.89) | (1.07) |
| County Covid Cases/10K | | | | 0.27 | 0.24 | 0.11 | 0.12 |
| | | | | (0.22) | (0.22) | (0.20) | (0.23) |
| Base Pay | | | | | −0.97*** | −0.68* | −1.11** |
| | | | | | (0.35) | (0.39) | (0.44) |
| Local Outside Option Pay in MSA | | | | | | −0.24 | −0.42* |
| | | | | | | (0.22) | (0.24) |
| Unemployment Rate in MSA | | | | | | 0.54*** | 0.53*** |
| | | | | | | (0.16) | (0.19) |
| Mother | | | | | | | 0.63 |
| | | | | | | | (0.72) |
| Father | | | | | | | 1.07 |
| | | | | | | | (1.33) |
| Pre Dependent Mean On-Site | 20.8 | 20.8 | 20.8 | 20.8 | 20.8 | 20.8 | 20.8 |
| Initially Remote in % | 17.6% | 21.8% | 19.1% | 18.8% | 14% | 10.8% | 9.1% |
| | (3.6) | (3.6) | (4.0) | (4.0) | (4.2) | (4.3) | (5.2) |
| Age x Gender x Post FE | | ✓ | ✓ | ✓ | ✓ | ✓ | |
| Call Queue FE | | | ✓ | ✓ | ✓ | ✓ | ✓ |
| # Workers | 1,436 | 1,436 | 1,436 | 1,436 | 1,436 | 1,436 | 785 |
| # Initially On-site | 1,174 | 1,174 | 1,174 | 1,174 | 1,174 | 1,174 | 634 |
| # Already Remote | 262 | 262 | 262 | 262 | 262 | 262 | 151 |
| # Worker Days | 108,174 | 108,174 | 108,174 | 108,174 | 108,174 | 108,174 | 70,453 |
| $R^2$ | 0.01 | 0.04 | 0.14 | 0.14 | 0.14 | 0.14 | 0.17 |

*Notes:* This table considers the percent of incoming calls that workers transfer to other workers. The table compares the transfer rate of workers who initially chose on-site jobs and those who initially chose remote jobs once everyone was remote due to the offices closures of Covid-19. Each specification estimates Equation 4 in the six months after the office closures. Call queue fixed effects interact the date of the call with the worker's time-zone and call-level (routine, intermediate, or complex) to limit comparisons to workers handling calls randomly routed from the same queue. Covid-19 cases come from NYT (2021). Pay for customer service representatives in the worker's metropolitan statistical area comes from occupational employment statistics (Bureau of Labor Statistics, 2021b). Parenting characteristics come from a caregiving survey that the firm fielded in June of 2020. The sample is our primary sample summarized in footnote 33. Standard errors are clustered by worker. *p<0.1; **p<0.05; ***p<0.01.

## **Table A.24:** Differences in Calls without Call Backs per Hour When All Workers are Remote Due to Covid-19

| | Calls with No Call Back per Hour | | | | | | |
|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
| Remote Hire | $-0.16^{***}$ | $-0.26^{***}$ | $-0.24^{***}$ | $-0.24^{***}$ | $-0.19^{**}$ | $-0.24^{***}$ | $-0.18^{*}$ |
| | (0.06) | (0.06) | (0.07) | (0.07) | (0.08) | (0.09) | (0.11) |
| County Covid Cases/10K | | | | 0.01 | 0.01 | 0.02 | 0.02 |
| | | | | (0.02) | (0.02) | (0.02) | (0.02) |
| Base Pay | | | | | 0.05 | 0.03 | 0.06 |
| | | | | | (0.03) | (0.04) | (0.05) |
| Local Outside Option Pay in MSA | | | | | | 0.03 | 0.03 |
| | | | | | | (0.02) | (0.03) |
| Mother | | | | | | | 0.05 |
| | | | | | | | (0.07) |
| Father | | | | | | | $-0.06$ |
| | | | | | | | (0.13) |
| Dependent Mean Initially On-Site | 3.86 | 3.86 | 3.86 | 3.86 | 3.86 | 3.86 | 3.86 |
| Remote Hire in % | -4.17% | -6.62% | -6.12% | -6.19% | -4.8% | -6.16% | -4.63% |
| | (1.60) | (1.63) | (1.80) | (1.79) | (2.02) | (2.31) | (2.74) |
| Age x Gender x Post FE | | ✓ | ✓ | ✓ | ✓ | ✓ | |
| Call Queue FE | | | ✓ | ✓ | ✓ | ✓ | ✓ |
| # Workers | 1,436 | 1,436 | 1,436 | 1,436 | 1,436 | 1,436 | 785 |
| # Initially On-site | 1,174 | 1,174 | 1,174 | 1,174 | 1,174 | 1,174 | 634 |
| # Already Remote | 262 | 262 | 262 | 262 | 262 | 262 | 151 |
| # Worker Days | 108,174 | 108,174 | 108,174 | 108,174 | 108,174 | 108,174 | 70,453 |
| $R^2$ | 0.002 | 0.03 | 0.13 | 0.13 | 0.13 | 0.13 | 0.15 |

*Notes:* This table considers the number of calls that workers handle per hour, limiting to calls that do not result in a callback within two days. The table compares the number of these calls of workers who initially chose on-site jobs and those who initially chose remote jobs once everyone was remote due to the offices closures of Covid-19. Each specification estimates Equation 4 in the six months after the office closures. Call queue fixed effects interact the date of the call with the worker's time-zone and call-level (routine, intermediate, or complex) to limit comparisons to workers handling calls randomly routed from the same queue. Covid-19 cases come from NYT (2021). Pay for customer service representatives in the worker's metropolitan statistical area comes from occupational employment statistics (Bureau of Labor Statistics, 2021b). Parenting characteristics come from a caregiving survey that the firm fielded in June of 2020. The sample is our primary sample summarized in footnote 33. Standard errors are clustered by worker. $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$.

**Table A.25:** Heterogeneity in Differences in Call Rates When All Workers are Remote Due to Covid-19

| | Calls/Working Hour | | | Calls Without Call Back/Working Hour | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Initially Remote | −0.41** | −0.23* | −0.29*** | −0.33* | −0.17 | −0.23*** |
| | (0.20) | (0.13) | (0.08) | (0.17) | (0.12) | (0.07) |
| Initially Remote x Female | 0.13 | | | 0.10 | | |
| | (0.21) | | | (0.18) | | |
| Initially Remote x Parent | | −0.03 | | | −0.06 | |
| | | (0.17) | | | (0.15) | |
| Initially Remote x Tenure (Z-Score) | | | 0.04 | | | 0.04 |
| | | | (0.08) | | | (0.07) |
| Preferred Controls | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Pre Mean On-Site, Control | 3.7 | 3.8 | 3.8 | 3.1 | 3.2 | 3.2 |
| Pre Mean On-Site, Focal Group | 3.8 | 4.0 | 3.8 | 3.2 | 3.3 | 3.2 |
| # Control Workers | 363 | 215 | 501 | 363 | 215 | 501 |
| # Focal Workers | 811 | 324 | 673 | 811 | 324 | 673 |
| $R^2$ | 0.13 | 0.15 | 0.13 | 0.13 | 0.15 | 0.13 |

*Notes:* This table considers heterogeneity in the differences in productivity between remote and on-site hires by gender identity, parenthood status, tenure before the offices closed for the pandemic. The first three columns consider calls handled per work hour; the next three consider calls per hour that do not result in a call back within two days. Each specification estimates Equation 4 with interactions for the focal characteristic in the six months after the office closures. Call queue fixed effects interact the date of the call with the worker's time-zone and call-level (routine, intermediate, or complex) to limit comparisons to workers handling calls randomly routed from the same queue. Covid-19 cases come from NYT (2021). Pay for customer service representatives in the worker's metropolitan statistical area comes from occupational employment statistics (Bureau of Labor Statistics, 2021b). Parenting characteristics come from a caregiving survey that the firm fielded in June of 2020. The sample is our primary sample summarized in footnote 33. Standard errors are clustered by worker. $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$.

In period zero, each firm posts a menu of one-period contracts.[51] Each worker chooses a contract after privately learning the probability that she will be a high-performer. During the first period of work, firms learn some workers are high-performers and some are poor-performers, while remaining uncertain about others. Those revealed to be high-performers are promoted, while those revealed to be poor-performers are demoted. Firms are more likely to learn about — or act upon — the productivity of on-site workers than remote workers.

### I.A The Firm's Problem

Each firm's production function is as follows. In the low-skill task ($T = L$), a poor-performer ($\Theta_i = L$) produces $y$, while a high-performer ($\Theta_i = H$) produces $y + a$ where $a > 0$. When assigned the high-skill task, a high-performer's output increases by $A$ and a poor-performer's output decreases by $C$. Working remotely changes output by $\tau$, the treatment effect of remote work. The per-period output $Y$ of worker $i$ in job $j \in \{\text{r} \equiv \text{remote}, \text{o} \equiv \text{on-site}\}$ doing task $T$ is:

$$Y_{ijT} = y + a \cdot \mathbb{1}[\Theta_i = \text{H}] + \begin{cases} -C & \Theta_i = L,\ T = H \\ A & \Theta_i = H,\ T = H \end{cases} + \tau \cdot \mathbb{1}[j = \text{remote}], \quad (7)$$

where $C$ is assumed to be sufficiently high that the firm only assigns workers the high-skill task when they are known to be high-performers.

infinite period problem with a continuous choice of what share of time to spend working remotely.

[51] We assume that firms cannot sort workers by varying the bonus for high productivity. This constraint could reflect fairness concerns or risk aversion.

Initially, firms do not know individual workers' productivities and can only infer likely productivity from workers' choices to be remote or on-site. Once workers' productivity is revealed, workers are paid their marginal product since we assume that the signals are public and markets are competitive. The average cost of hiring a remote worker instead of an on-site one equals the difference in average products in the first period:

$$\text{AC} = \mathbb{E}_{\text{o}}[Y_{ioL}] - \mathbb{E}_{\text{r}}[Y_{irL}] = -\tau + a(\Pr(\Theta_i = H \mid o) - \Pr(\Theta_i = H \mid r)) \quad (8)$$

The first term reflects the treatment effect of remote work; the second term reflects the self-selection of high-performers into on-site jobs.

### I.B The Worker's Problem

Workers vary in their productivities and tastes. Worker $i$'s productivity is either high or low, $\Theta_i \in \{H, L\}$. When choosing her first job, she privately knows her probability, $\theta_i \sim \text{Uniform}[0,1]$, of being a high-performer. Each worker has an idiosyncratic taste for remote work, $\nu_i = \bar{\nu} + \mathcal{s}\epsilon_i$ where $\epsilon_i \sim \mathscr{L}(0,1)$ is logistic and orthogonal to productivity.[52]

We assume that workers make fixed cost investments in their work arrangement that make switching prohibitively costly in the second period.[53]

[52] This might reflect, for example, the length of the worker's potential commute or her childcare responsibilities.

[53] Workers might buy a car to commute or build a home office for working remotely.

Workers choose their job to maximize:

$$U(\theta_i, \nu_i) = \max_{j \in \{\mathrm{r,o}\}} \begin{cases} w_{\mathrm{r}} + (1+\delta)\nu_i + \delta \mathbb{E}[w \mid \theta_i, r] & \text{if remote} \\ w_{\mathrm{o}} + \delta \mathbb{E}[w \mid \theta_i, o] & \text{if on-site} \end{cases}, \tag{9}$$

yielding a threshold rule for choosing remote work of:

$$w_o - w_r \leq \nu_i(1+\delta) + \delta(\mathbb{E}[w \mid \theta_i, r] - \mathbb{E}[w \mid \theta_i, o]). \tag{10}$$

The worker weighs the first-period change in income against her tastes and her likely second-period income, which is discounted according to $\delta$.[54]

When predicting her future income, the worker considers two possibilities. One, with probability, $p_j$, her productivity is revealed and she earns her marginal product. This is more likely in on-site jobs than remote ones ($p_o > p_r$). Two, with probability, $1 - p_j$, her type remains unknown and her wage remains constant, so:[55]

$$\mathbb{E}[w \mid \theta_i, j] = w_j + p_j(\mathbb{E}[\mathrm{MP}_j \mid \theta_i] - w_j). \tag{11}$$

A worker who privately knows she is likely to be a high-performer (high $\theta_i$) expects her marginal product to exceed the pooled wage ($\mathbb{E}[\mathrm{MP}_j \mid \theta_i] > w_j$). Thus, for her, working remotely is costly because it obscures her productivity. By contrast, a worker who privately knows he is likely to be a poor-performer (low $\theta_i$) expects his marginal product to fall short of the pooled wage ($\mathbb{E}[\mathrm{MP}_j \mid \theta_i] < w_j$). Thus, for him, working remotely hides his low-

[54]In reality, the gains from promotion may also include social validation.

[55]The probability $p_j$ is a feature of the job and not of the worker. Thus, nothing can be inferred about productivity if it is not fully revealed.

productivity and allows him to pool with more productive types.

Remote work's career consequences reduce the demand for remote work among workers who know they are likely high-performers. This downward shift is the source of the selection problem: at any given wage penalty — or price of remote work — a lower share of workers who are likely high-performers choose remote work.

Workers' idiosyncratic tastes mean their choice to be remote is not fully revealing of their private information about their productivity. Particularly, some workers choose to be remote despite positive signals about their likely productivity because of strong tastes for remote work, while others choose on-site jobs despite negative signals about their likely productivity because of strong tastes for the office. The more variable tastes are (higher $\mathscr{s}$), the more likely these outliers will be and the noisier workers' choices will be as signals of latent productivity.

By contrast, the more career concerns weigh in workers' choices, the rarer these outliers will be and the more informative choices will be about likely productivity. The weight on career concerns depends on the answer to two questions. The first is "how much does choosing a remote job affect the probability of being identified as high- or low-productivity?" The answer is $p_o - p_r$. The second is "how much does it matter to be revealed as high- versus low-productivity?" The answer is $\frac{\delta}{1+\delta}(A + a)$, which reflects (a) the returns to productivity in the low-skill task ($a$), (b) the productivity increase from assigning a high-productivity worker, a high-skill task ($A$), and (c) worker's discounting of second period income ($\delta$).

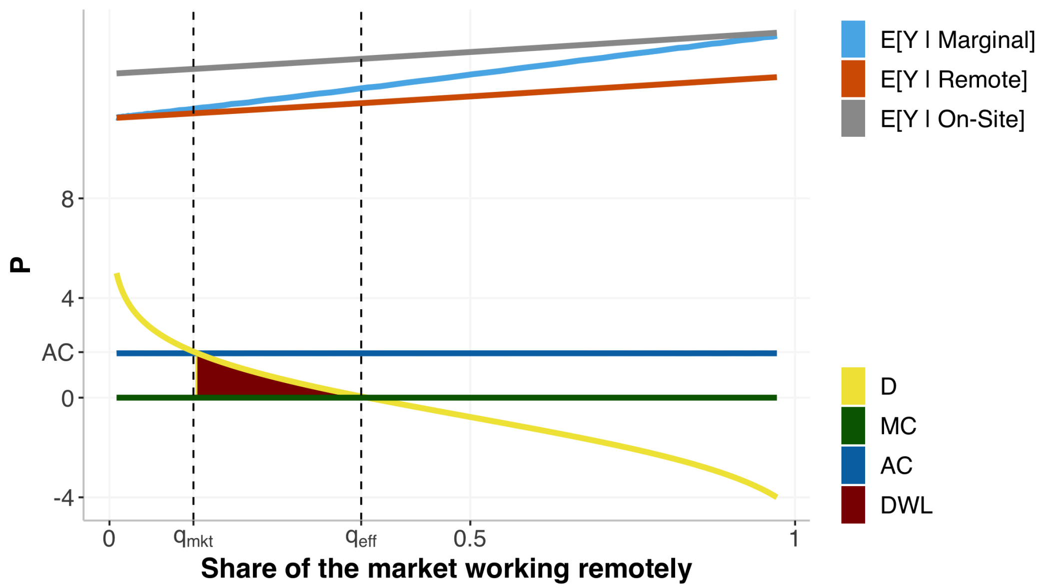
The link between a worker's latent productivity and her demand for remote work is the source of the selection problem. Selection is more acute when career concerns loom large relative to variation in tastes.

### I.C The Market Equilibrium

Figure A.20 illustrates the market for remote work. The x-axis plots the share of workers who are working remotely and the y-axis plots the wage penalty — or price of remote work. In equilibrium, the price of remote work equals the average cost of hiring a remote worker instead of an on-site one in the navy line. Even when the marginal cost of switching a given worker from on-site to remote work is zero as pictured in the green line, it can still be costly for a firm to hire a remote worker instead of an on-site one.

**Deriving the Average Product in Remote and On-Site Work.** The sorting of workers into remote and on-site jobs depends on workers' demand for remote work that reflect both tastes and likely productivity. Consider the pool of workers who choose a remote job even at a high price (e.g., \$4/hour in Figure A.20). A worker who is likely to perform well (high $\theta_i$) knows that she is likely to miss a potential promotion and unlikely to avoid a demotion by taking a remote job. Thus, she will only choose a remote job is if she has an extreme taste for remote work. By contrast, a worker who is less likely to perform well knows that he is less likely to miss out on a promotion and more likely to avoid a demotion by taking a remote job. Thus, he requires a less extreme taste to opt into remote work. Since tastes in the tails are less likely, a worker who is likely to do well will be less likely to opt into the remote job than a worker who expects to do poorly. As the price of remote work falls, workers who know they are likely to be high-productivity

**Figure A.20:** Selection Market for Remote Work




*Note:* This figure plots the market for remote work under selection into on-site and remote jobs assuming there is no treatment effect of remote work on productivity. The x-axis represents the share of the market working remotely. The y-axis represents the price or wage penalty of remote work. The yellow curve plots the demand curve for remote work or the share of the market that would work remotely at any given price. Since the expected ability of workers on the margin of remote work, $\mathbb{E}[Y \mid \text{Marginal}]$, rises with the share of the market working remotely, the marginal product in remote work, drawn in light blue, is increasing. The average product in the remote job, $\mathbb{E}[Y \mid \text{Remote}]$, drawn in orange, integrates the light blue line from left to right to average over the output of marginal and inframarginal remote workers. The average product in the on-site job, $\mathbb{E}[Y \mid \text{On-Site}]$, drawn in grey, integrates the light blue line from right to left to average over marginal and inframarginal on-site workers. The differences in average product between the on-site workers (in grey) and the remote workers (in orange) produces the average cost, AC, of remote work to the firm in navy blue. This will be the equilibrium price of remote work in the market. The intersection with the demand curve in yellow will determine the equilibrium share of the market working remotely. By contrast, the efficient price of remote work would be zero, which would induce a higher share of the market to work remotely.

need less extreme tastes to choose remote work: hence, the share of high-productivity workers on the margins of remote work rises. This causes the marginal product curve — illustrated by the light blue line of Figure A.20 — to have a positive slope. While the marginal remote work becomes more productive, the gap in the average productivity of remote workers and on-site workers does not change because two margins of selection are changing simultaneously.

The average output of remote workers increases as more workers work remotely. At each point, the pool of remote workers include both marginal workers and inframarginal remote workers, who choose remote work even when the wage penalty is higher. Thus, the average output of remote workers (in orange) integrates the light blue line from left to right (or 0 to $q$) in Figure A.20. If we approximate the marginal product as $\mathrm{MP_j}(q) \approx m_0 + m_1 q + \tau \mathbb{1}[j = \text{remote}]$, then:

$$\mathrm{AP_r}(q) = \mathbb{E}[Y \mid \text{Remote}, q] = \frac{1}{q}\int_0^q m_0 + m_1 q + \tau dq = m_0 + \frac{1}{2}m_1 q + \tau. \quad (12)$$

Since the marginal product is rising, workers on the margin of remote work (in light blue) are always more productive than the average remote worker (in orange). In equations, $\mathrm{AP_r}(q) - \mathrm{MP_r}(q) = -\frac{1}{2}m_1 q < 0$. Thus, marginal workers pool with *less* productive workers when they opt into remote work.

At the same time, the average output of on-site workers increases as more workers work remotely and a more selected set of workers work on-site. At each point, the pool of on-site workers includes both marginal workers and inframarginal on-site workers, who only choose remote work when the wage penalty is lower. Thus, the average output of on-site workers (in grey) integrates the light blue line from right to left (or 1 to $q$) in Figure A.20:

$$\mathrm{AP_o}(q) = \mathbb{E}[Y \mid \text{On-Site}, q] = \frac{1}{1-q} \int_q^1 m_0 + m_1 q dq = m_0 + \frac{1}{2} m_1 (1+q). \tag{13}$$

Since the marginal product is rising, those on the margin of on-site work (in light blue) are always *less* productive than the average on-site worker (in grey). In equations, $\mathrm{AP_o}(q) - \mathrm{MP_o}(q) = \frac{1}{2} m_1 (1-q) > 0$. Thus, choosing on-site work means marginal workers pool with *more* productive workers.

In sum, as the wage penalty — or price — of remote work falls, remote jobs become less adversely selected in keeping with classic selection models. At the same time, those who remain on-site become more advantageously selected. Thus, the average product in both remote and on-site jobs rise as the price of remote work falls. As a result, the difference in average products — or the average cost of hiring a remote worker in navy — remains constant at:

$$\mathrm{AC}(q) = \mathrm{AP_o}(q) - \mathrm{AP_r}(q) = \frac{1}{2} m_1 - \tau. \tag{14}$$

where $m_1$ summarises the link between workers' willingness to work remotely and their productivity: the tighter this link is, the greater the average cost of hiring a remote work instead of an on-site one. Starting from equation 8, this cost can be shown to be:

$$\mathrm{AC} \approx -\tau + a \frac{(p_\mathrm{o} - p_\mathrm{r}) \frac{\delta}{1+\delta} (A + a)}{\mathscr{s}} \mathrm{Var}(\theta_i). \tag{15}$$

Workers' self-selection into jobs based on their private information about their productivity drives a wedge between the marginal and average costs of remote work. The wedge is larger when there are greater returns to high-productivity in the low-skill task ($a$) and when more workers self-select into jobs based on their latent productivity. Workers self-select more on productivity when they have more private information about productivity, $\text{Var}(\theta_i)$, and when remote work is more determinative of their second-period income. Remote work affects second period income more when (i) there is a greater gap in the probability that productivity is revealed in the two jobs, $p_o - p_r$, and (ii) there is a greater discounted return to being observably high- rather than low-productivity, $\frac{\delta}{1+\delta}(A + a)$. Workers self-select less on productivity when there is more taste variation, $\mathscr{s}$, which can cause latently high-performers to choose remote jobs and latently poor-performers to choose on-site jobs.

Since the average cost determines the equilibrium price of remote work, the market quantity, $q_{\text{mkt}}$, is found at its intersection with the demand curve in Figure 5.

The market does not arrive at the efficient equilibrium because firms price at the average rather than the marginal cost of remote work, leading to deadweight losses in the red Harberger triangle in Figure 5.[56]

This inefficient equilibrium, however, is not set in stone. Instead, it is a function of the technologies for evaluating remote workers, which determine $p_o - p_r$, and the distribution of tastes for remote work, which determines $\mathscr{s}$.

[56]In addition, workers' demand for remote work also deviates from the marginal social benefit because the revelation of productivity changes the attribution of credit as well as the assignment of tasks. These private gains lead to excessive sorting by productivity and depress the demand for remote work around the equilibrium quantity. Thus, the Harberger triangle is a conservative estimate of the deadweight losses from asymmetric information.

If firms become better able to evaluate remote workers, then the average cost of remote work will fall towards the marginal cost $\left(\frac{\partial \text{AC}}{\partial (p_{\text{r}} - p_{\text{o}})} < 0\right)$. If firms have learned how to better assess the productivity of remote workers during the pandemic, Covid-19 could lead to a more efficient equilibrium.

If tastes become more variable, the average cost of remote work falls towards the marginal cost $\left(\frac{\partial \text{AC}}{\partial \mathcal{s}} < 0\right)$. During Covid-19, tastes may have become more variable as many workers experienced full-time remote work for the first time. By forcing all workers to learn about their tastes, Covid-19 may have pushed the market into a new equilibrium where workers are more certain of their tastes, tastes are more heterogeneous, and choices to be remote are less indicative of low-productivity.[57]

In the model, greater informational frictions in remote work make remote work (i) unattractive for latently high-productivity workers who want their productivity revealed and (ii) attractive for latently low-productivity workers who want their productivity hidden. Thus, the model's central empirical prediction is that remote workers will be adversely selected. Adverse selection leads to the model's central welfare implication that remote work will be under-provided.

## B ESTIMATING THE DEMAND FOR REMOTE WORK

To calibrate our model, we draw on existing literature that estimates workers' demand for remote jobs. Section II.A describes the data and settings

[57]Covid-19 may have also made remote work more attractive if workers bore fixed costs of setting up home offices or learning new technologies. These changes would increase both the efficient and market quantity of remote work so would not eliminate the market failure.

of the studies. Section II.B focuses on how each study measures participant inattention, and Section II.C shows how inattention enters the choice model. Section II.D describes the results.

### II.A Data & Setting of the Studies

We consider three papers that all ask workers to make hypothetical choices between jobs that vary in their pay and whether they allow (or require) workers to work from home (Mas and Pallais, 2017; Maestas et al., 2023; Lewandowski et al., 2024). This section describes the specifics of each study.

**Mas and Pallais (2017).** This paper embeds a hypothetical-choice experiment into the application process for a national call-center, which was advertising phone-survey positions for wages of $11−$19/hour. In the application process, the researchers asked candidates to choose between two hypothetical jobs that differed in their pay and amenities. Figure A.21 shows the interface for candidates choosing between an on-site job and a job that offered the option to work from home (N= 608 participants).[58] As in our study, the workers who applied for these call-center jobs young (average age 33 versus 35 in our study) and predominantly female (75 percent versus 73 percent).

While the population is quite comparable to that in our study, a few key differences in the job choice mean that this study likely offers an upper bound on the applicable demand curve for remote work at the retailer. First, Mas

[58]The researchers told candidates that their choices would not affect hiring decisions and that the choices would be reviewed after a hiring decision was made, likely causing candidates to believe that they were making real-stakes choices. Thus, the choices were plausibly as-good-as incentivized, even though the ultimate jobs did not in fact hinge on these choices.

**Figure A.21:** Hypothetical Choice in Mas and Pallais (2017)

Tell us which of the following two positions you prefer. The type of work is the same in both jobs. Please
click on each job in order to review the work descriptions.

**It is important that you read the position descriptions carefully so you can indicate your preference below.**

Positions

Phone Survey Associate Position #309 (click for description)

This is a phone survey position.

This position is 40 hours per week.

This is a M-F 9am-5pm position. You have the option of working from home as well as on-site in downtown Albany. This position pays 18.00 dollars per hour.

Phone Survey Associate Position #472 (click for description)

This is a phone survey position.

This position is 40 hours per week.

This is a M-F 9am-5pm position. The work is exclusively on-site in downtown Albany. This position pays 19.00 dollars per hour.

**If you were selected for both positions, which one would you prefer?** Write your preferred position number in the box below. (Regardless of your choice you will be considered for all open positions. Your choice will not affect whether you receive a job offer. It will only be reviewed after hiring decisions have been made.) If you are not interested in either position, click on "No thanks, this position is not for me."

*Notes:* This figure reproduces the hypothetical-choice interface in Mas and Pallais (2017).

and Pallais (2017) estimate the demand for flexible remote work that gives workers the *option* to work from home, which may be more valuable than the fully remote work at the retailer. Indeed, most workers say they prefer hybrid schedules to either fully remote or fully on-site ones (Barrero et al., 2022) (Figure A.17).[59] Second, Mas and Pallais (2017) advertise the on-site jobs as being downtown: if downtown commutes are particularly onerous, this too will increase demand for remote work relative to that in the retailer's more commutable locations. Finally, Mas and Pallais (2017)'s jobs do not advertise opportunities for advancement, while the retailer's jobs do: if workers go on-site for greater advancement opportunities, the lack of such opportunities will also make remote work more appealing.

**Maestas et al. (2023).** This paper conducts hypothetical-choice experiments with a representative sample of Americans. The authors focus on employed workers between the ages of 25 and 74 who completed the survey.

The survey asks respondents about the characteristics of their current job and then asks them to choose between hypothetical jobs that differ in their pay and two (dis)amenities but are otherwise similar to respondents' current job. Figure A.22 shows an example of this interface. Our empirical analysis focuses on the 1,738 participants who chose between 3,477 hypothetical jobs that differed in the option to work remotely or "telecommute." We control for other differences in job (dis)amenities between the two options to isolate the demand for remote work.

Elements of these job choices may put less upward pressure on demand

[59] Firms may not be able to easily accommodate a preference for hybrid work since offering hybrid work is costlier because of the greater office footprint.

than in Mas and Pallais (2017). Particularly, the respondents likely compared the offered job with their current position. Thus, they would likely consider the benefits of potentially avoiding their current commute, which might be less onerous than one downtown. Similarly, respondents might consider the consequences of remote work for their current promotion chances, which may not be zero.

**Lewandowski et al. (2024).** This paper surveys a representative sample of Polish workers between the ages of 20 and 64 working in occupations that can be done from home.[60]

Like in Maestas et al. (2023), the survey first asks each respondent about her current job. The survey then asks her to choose between hypothetical jobs that differ in their remote-work arrangements and their pay with the other attributes of the positions anchored on those of the respondent's current job. Figure A.23 shows the interface.

This study is the only one of the three to ask respondents about fully-remote positions like the ones at the retailer. Some hypothetical choices contrasted on-site jobs and fully remote ones (with 5 days/week at home), while others contrasted on-site jobs and hybrid ones (with 2−3 days/week at home). This allows us to estimate the demand for fully remote work as well as the potentially more popular option to mix on-site and remote work. We focus on the 8,115 respondents who made choices between on-site work and fully remote work. We also probe the effects of limiting the sample to 995 workers in sales occupations, who might be more comparable to the

[60]We focus on the sample to workers who are currently employed to make the sample more comparable to Maestas et al. (2023).

## Figure A.22: Hypothetical Choice in Maestas et al. (2023)

Imagine you are offered tile two jobs shown below. Except for the characteristics highlighted below. Please assume the jobs are the same in all other ways, including on characteristics not listed in the table. You may scroll over the characteristics to see their definitions. Please review the jobs and indicate below whether you prefer Job A or Job B.

| | Job A | Job B |
|---|---|---|
| **Hours** | Part-time – 20 hours per week | Part-time – 20 hours per week |
| **Control over Hours** | Set your own schedule | Schedule set by manager |
| **Option to Telecommute** | Yes | No |
| **Physical Demands** | Moderate physical activity | Moderate physical activity |
| **Pace** | Relaxed | Relaxed |
| **Independence** | Your tasks and procedures are well-defined | Your tasks and procedures are well-defined |
| **Paid Time Off (Vacation and Sick Leave)** | None | None |
| **Working with Others** | Mainly work by yourself | Mainly work by yourself |
| **Training** | You have the skills for this job and there are opportunities to gain valuable new skills | You have the skills for this job and there are opportunities to gain valuable new skills |
| **Impact on Society** | Occasional opportunities to make a positive impact on your community or society | Occasional opportunities to make a positive impact on your community or society |
| **Pay** | $18.50 per hour ($370 per week) | $19.50 per hour ($390 per week) |

| | Strongly Prefer Job A | Prefer Job A | Prefer Job B | Strongly Prefer Job B |
|---|---|---|---|---|
| **Which job do you prefer?** | | | | |

< Back    Next >

*Notes:* This figure reproduces the hypothetical-choice interface in Maestas et al. (2023).

## Figure A.23: Hypothetical Choice in Lewandowski et al. (2024)

| | Job offer A | Job offer B |
|---|---|---|
| **Occupation** | Application developer | Application developer |
| **Work hours** | This is a full-time position. You will work from Monday to Friday from 9 a.m. to 5 p.m. | This is a full-time position. You will work from Monday to Friday from 9 a.m. to 5 p.m. |
| **Work from home** | You will be doing the job in the office. You will not have an option to work from home. | You will have an option to work from home 2 or 3 days per week. |
| **Wage** | You will be earning a monthly wage of 4,900 PLN net. | You will be earning a monthly wage of 5,684 PLN net. |

*Notes:* This figure reproduces the hypothetical-choice interface in Lewandowski et al. (2024).

customer-service workers whom we study.

### II.B Measuring Inattention

Each paper addressed concerns that respondents did not carefully consider the hypothetical choices.

**Mas and Pallais (2017).** This paper estimates inattention in three ways.

**1. Trick Questions:** Some respondents saw a "trick" hypothetical choice, where they were told that one of the two hypothetical jobs was unavailable and so they should choose the other. Thirteen percent of respondents chose the unavailable job. Assuming that inattentive respondents chose randomly — and so happened upon the available job half the time — we must double the realized error rate to arrive at an implied inattention rate of 26 percent. This is our preferred estimate.

**2. Recall of Choices:** Some respondents were asked to recall the characteristic of the job that they had chosen in their hypothetical choice. Similar to above, 13.3 percent of respondents did not accurately recall the characteristic of the job they had chosen. Since inattentive respondents could have guessed the right answer half the time, this suggests 26.6 percent of participants were inattentive.

**3. Choosing Dominated Options:** They finally evaluate how many respondents choose "dominated jobs" with lower pay and worse amenities. Across their suite of ten amenities, the implied inattention rate is 29 percent. However, for some amenities — including the option to work remotely — the implied inattention rate is twice as high. This discrepancy may reflect unconventional preferences: for example, some respondents may prefer jobs that require everyone to work on-site because they want to learn from their coworkers (e.g., Sandvik et al., 2020; Emanuel et al., 2023) or curb self-control problems (e.g., Kaur et al., 2015), and so attentively choose seemingly dominated jobs. Given this possibility, we prefer the simpler measure of inattention based on trick questions.

**Maestas et al. (2023).** This paper presents respondents with two trick questions that have the correct answer embedded in the question text. These questions have many possible responses, making it unlikely that respondents guess the right answer. They define the inattentive population as those who answered both trick questions incorrectly. Under this definition, 35 percent of respondents are inattentive.

**Lewandowski et al. (2024).** This paper asks respondents two factual, arithmetic questions. They find that vanishingly few respondents answer either question incorrectly (0.6 percent). Since these questions are not as tricky as those in the other papers, our preferred approach is to assume a similar rate of inattention as in Maestas et al. (2023). However, we also consider the results without correcting for inattention, which is isomorphic to assuming that all respondents are attentive.

### II.C Choice Model

An attentive respondent will choose a remote job if her willingness to pay for remote work exceeds the wages that she must forego, $\Delta w = w_{\text{on-site}} - w_{\text{remote}}$. The share of attentive respondents who choose remote jobs will then be $\Pr(\text{WTP}_i > \Delta w)$. However, the observed choices will also reflect inattention if a share $\alpha$ of respondents pay little attention and choose between jobs randomly:

$$\Pr(\text{Choose WFH}_i \mid \Delta w) = (1-\alpha)\Pr(\text{WTP}_i > \Delta w) + \frac{\alpha}{2}.$$

For a given estimate of inattention ($\hat{\alpha}$), we can correct the observed choice probabilities to back out how many workers would choose the remote job at wage penalty $\Delta w$ if all workers were attentive. This yields:

$$\hat{\Pr}(\text{WTP}_i > \Delta w) = \frac{1}{1-\hat{\alpha}}\left[\hat{\Pr}(\text{Choose WTP}_i \mid \Delta w) - \frac{\hat{\alpha}}{2}\right], \tag{16}$$

which yields non-parametric, attention-corrected choice probabilities.

To increase precision, we can impose more structure on the choices. We assume that utility takes the following form $U_i = \alpha + \beta_i \text{WFH}_{ij} + cw_{ij}$, where workers' weights on working from home vary $\beta_i = b + b_i$ where $b_i \sim \text{Logistic}(0, s)$ with CDF, $F(\cdot)$. We then have:

$$\begin{aligned}
\Pr(\text{WTP}_i > \Delta w) &= \Pr(\beta_i + cw_{\text{remote}} > cw_{\text{on-site}}) \\
&= \Pr(b_i > c\Delta w - b) \\
&= 1 - F(c\Delta w - b) \\
&= F(b - c\Delta w).
\end{aligned}$$

We then embed this into the model with inattention:

$$\Pr(\text{Choose WFH}_i \mid \Delta w) = (1-\alpha)F(b - c\Delta w) + \frac{\alpha}{2}$$

and estimate the parameters by maximum likelihood. At the average willingness to pay, the typical worker is indifferent between the two jobs:

$b - c\Delta w^* = 0$, which implies:

$$\overline{WTP} = \hat{b}/\hat{c}. \tag{17}$$

The parameter $\hat{c}$ also pins down the variation in willingness to pay. The smaller is $\hat{c}$, the more inelastic the demand for remote work and the more variable is willingness to pay, $\hat{\sigma}_{\text{WTP}} \propto 1/\hat{c}$. The parameters $\hat{b}$ and $\hat{c}$ further pin down every percentile $p$ of the willingness to pay distribution: $\text{WTP}_p = (\hat{b} + \ln(p/(1-p)))/\hat{c}$ at percentile $p \in [0, 1]$. This allows us to trace out the implied demand for remote work, by mapping between each share of the market choosing remote work (on the x-axis) and willingness to pay at that marginal percentile (on the y-axis).

### II.D RESULTS

Figures A.24-A.26 illustrate the demand curves for remote work implied by each hypothetical-choice experiment. We first describe how to read each plot and their commonalities. We then discuss the specific implications of each hypothetical-choice experiment.

**Interpreting these plots.** In each plot, the y-axis represents the price of remote work, paid in the form of foregone wages in either dollar or percentage terms. The x-axis represents the quantity of remote work, which is determined by the share of workers who choose the remote job at the corresponding price (or wage penalty).

The open circles show the raw share of respondents who select the remote job at various wage penalties, and the closed circles show the inattention-corrected estimates (using Equation 16). The fitted lines are estimated by maximum likelihood using the choice model (in Section II.C).

Assuming a logistic distribution of willingness to pay (WTP) for remote work, the mean and median WTP coincide and are both identified by the wage penalty where half of respondents choose the remote job and half choose the on-site job. At this point, the models with and without attention corrections coincide because both attentive and inattentive workers are equally likely to choose the remote job. The attention correction has an increasingly big impact away from the average WTP. Since our models tend to rely on demand estimates near the average WTP, the attention correction will have a more muted impact on our model's implications.

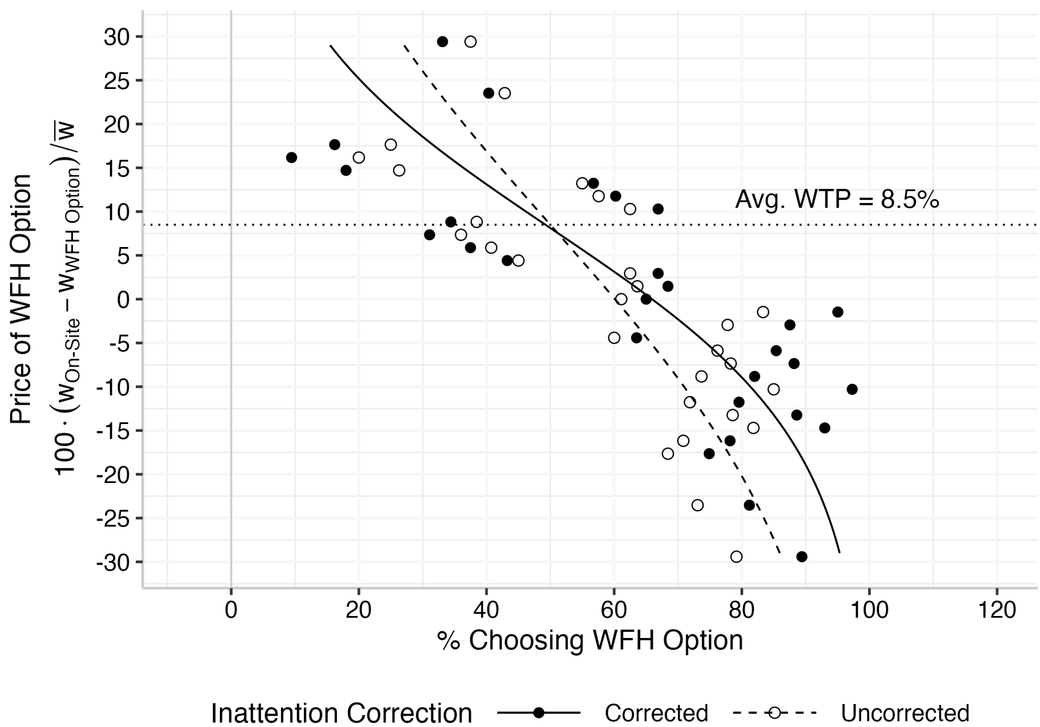
**Mas and Pallais (2017).** As illustrated in Figure A.24, the typical worker would sacrifice 8.5 percent of their pay for the option to work from home instead of commuting into a downtown office. This estimate likely offers an upper bound on the demand for the fully remote work in our context, where remote workers must work from home everyday instead of commuting into a more suburban location and may worry more about the promotion consequences of working from home.

**Maestas et al. (2023).** As illustrated in Figure A.25, the average WTP for the option of remote work is 4.5 percent of the offered wage in Maestas et al. (2023)'s data. This demand is lower than in Mas and Pallais (2017), which is consistent with workers comparing WFH to their current commute (which need not be to a downtown location) and their current promotion chances (which need not be zero).

**Lewandowski et al. (2024).** The estimated demand for hybrid work among the Polish workers surveyed by Lewandowski et al. (2024) is similar to the estimated demand for the option to work from home among the American workers surveyed in Maestas et al. (2023) (see Figure A.27(a) versus Figure A.25). Not only are the average WTP similar (at 5.1 percent versus 4.5 percent) but so too are the elasticities. These similarities provide suggestive evidence that the workers' preferences for remote-work arrangements are similar in the U.S. and Poland.

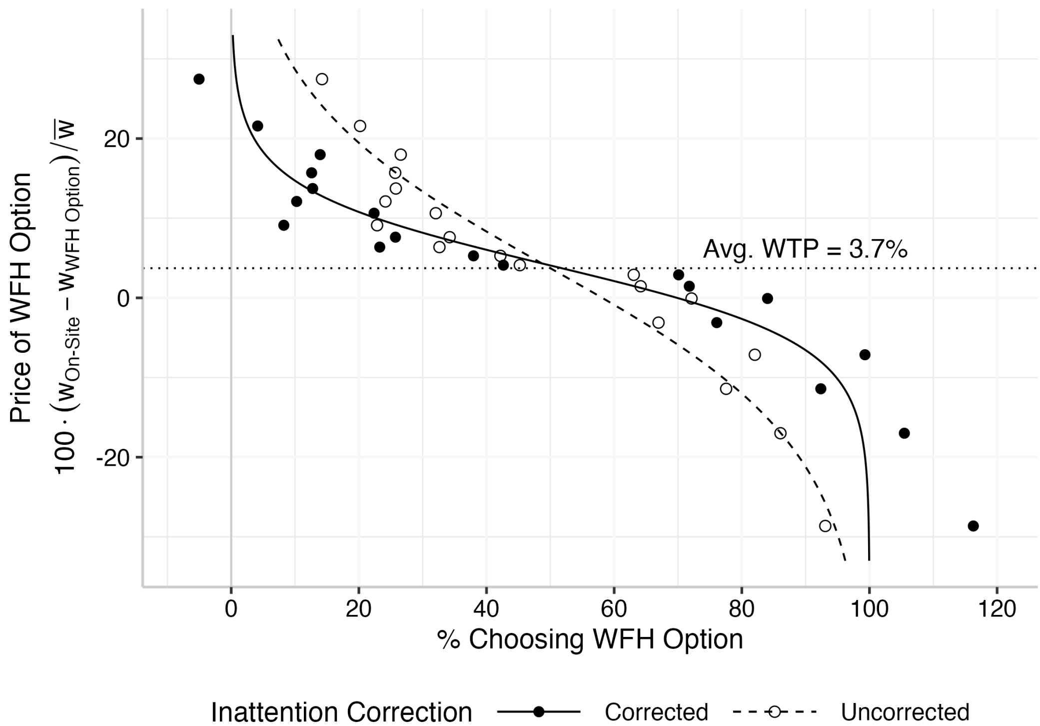
Crucially for our purposes, Lewandowski et al. (2024) also elicit workers' preferences for *fully* remote work versus fully on-site work. Figure A.26 shows the implied demand curve. On average, workers are nearly indifferent between fully remote and fully on-site work, with the average worker willing to sacrifice just 0.9 percent of their wage for a fully remote job instead of a fully on-site one. The demand for fully remote work is more inelastic than the demand for hybrid work, consistent with workers having stronger preferences about working fully remotely than only partially from home. Among a potentially more comparable population of workers in sales occupations, we find a similar demand for fully remote work (Figure A.27(b)), with the average worker still willing to sacrifice just 2 percent of wages to work fully from home rather than fully from the office.

**Figure A.24:** Demand for the Option to Work from Home in Mas and Pallais (2017)



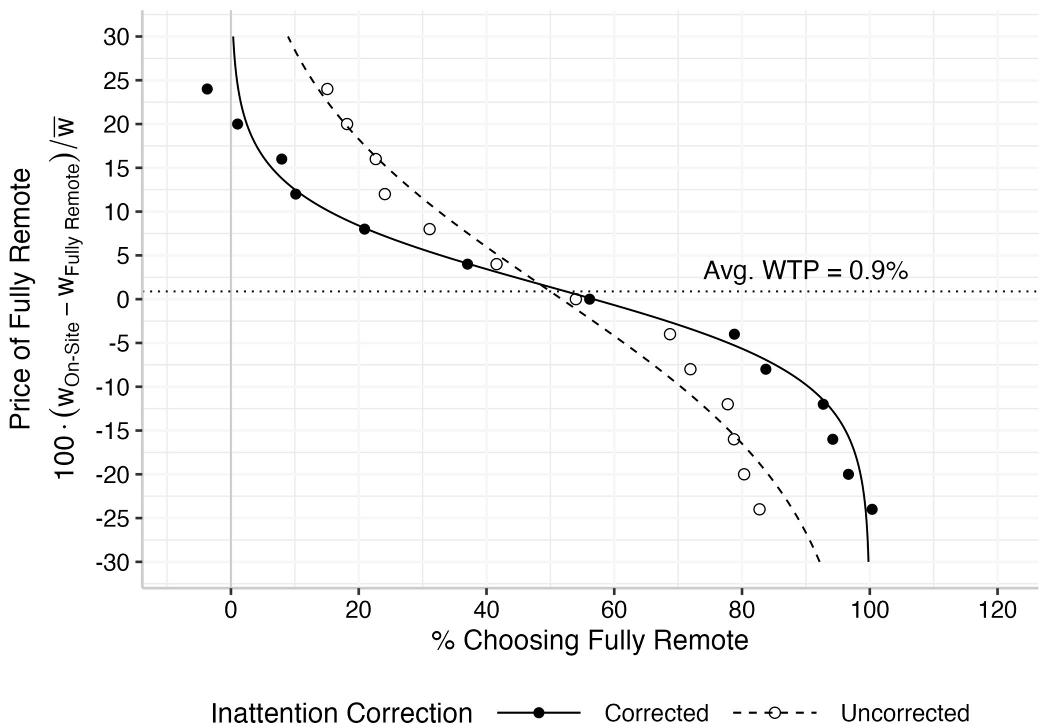

*Notes:* This figure presents the results of the hypothetical choices in Mas and Pallais (2017) that ask workers to choose between two jobs that differ in their wages and their work-from-home (WFH) arrangements (N=608). The y-axis is the wage difference between a hypothetical on-site job and a hypothetical WFH-option ones where workers had the "option of working from home as well as on-site." Each point represents a different wage difference. The x-axis plots the share of workers who choose the WFH option. The open circles show the raw averages. The closed circles show the inattention-corrected estimates based on Equation 16, using an estimated rate of inattention of 26 percent from the fraction of respondents answering trick questions incorrectly. The fitted lines assume a logistic distribution of willingness to pay. The horizontal line and annotated coefficient reflect the estimated average of this distribution using maximum likelihood (Equation 17). The percentage willingness to pay utilizes the fact that the average offered wage is $17/hour.

**Figure A.25:** Demand for the Option to Work from Home in Maestas et al. (2023)




*Notes:* This figure presents the estimated demand curve based on the hypothetical-choice data in Maestas et al. (2023), who ask workers to choose between two jobs that differ in their wages and their work-from-home (WFH) arrangements (3,477 choices made by 1,738 participants). The y-axis is the wage difference between a hypothetical on-site job and a hypothetical WFH-option ones where workers had the "option of telecommuting." Each point represents a different wage difference. The x-axis plots the share of workers who choose the WFH-option at the given wage gap. The open circles show the raw averages, residualized by the effects of the other (dis)amenities of the offered jobs. The closed circles show the inattention-corrected estimates based on Equation 16, using an estimated rate of inattention of 35 percent from the fraction of respondents answering trick questions incorrectly. The fitted lines assume a logistic distribution of willingness to pay. The horizontal line and annotated coefficient reflect the estimated average of the WTP distribution (Equation 17).

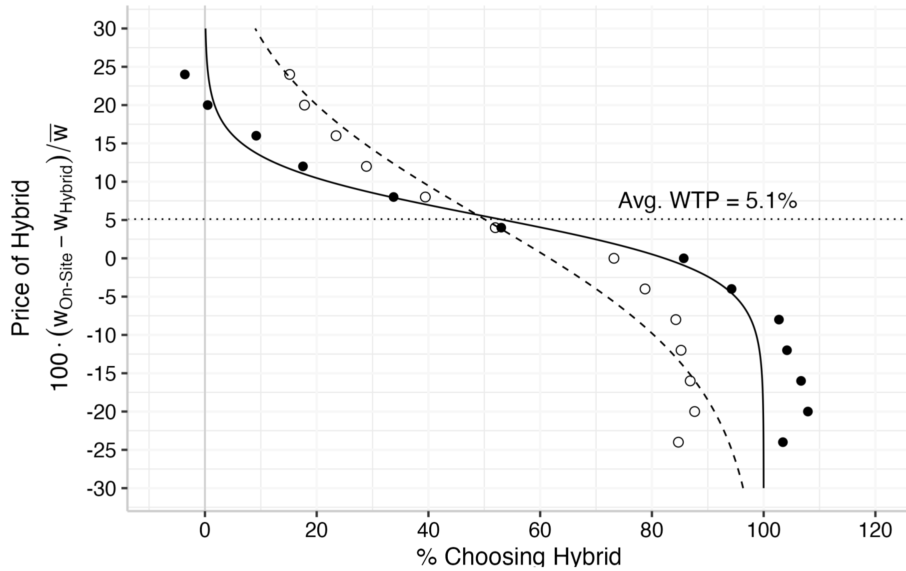
**Figure A.26:** Demand for Fully Remote Work in Lewandowski et al. (2024)



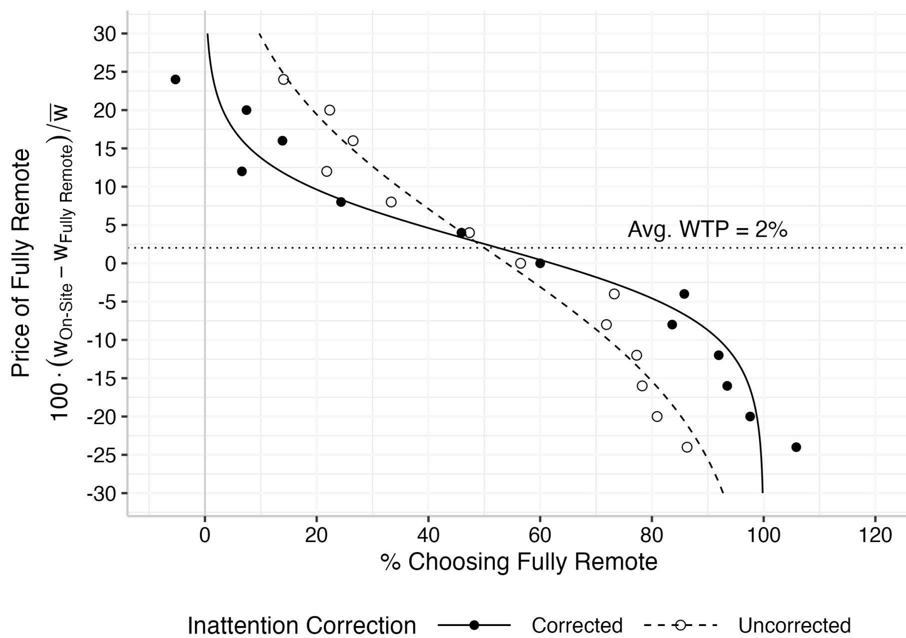

*Notes:* This figure presents the estimated demand curve based on the hypothetical-choice data in Lewandowski et al. (2024), who ask workers to choose between two jobs that differ in their wages and their work-from-home (WFH) arrangements (20,928 choices made by 8,115 respondents). The y-axis is the wage difference between a hypothetical on-site job and a hypothetical fully remote job where workers work from home everyday. Each point represents a different wage difference. The x-axis plots the share of workers who choose the remote job at the given wage gap. The open circles show the raw averages. The closed circles show the inattention-corrected estimates based on Equation 16, using an estimated rate of inattention of 35 percent from the fraction of respondents answering trick questions incorrectly in Maestas et al. (2023). The fitted lines assume a logistic distribution of willingness to pay. The horizontal line and annotated coefficient reflect the estimated average of the WTP distribution (Equation 17).

**Figure A.27:** Alternate Demand Curves in Lewandowski et al. (2024)

**Panel (a):** Demand for Hybrid Work (2−3 Days/Week From Home)




**Panel (b):** Demand for Fully Remote Work among Sales Workers




*Notes:* This figure replicates Figure A.26 with two alternative demand estimates. Panel (a) focuses on the demand for hybrid work versus fully on-site jobs in the full population (20,767 choices made by 8,076 respondents). Panel (b) focuses on the demand for fully remote jobs among sales workers (2,563 choices made by 995 respondents).