I Z A Institute of Labor Economics

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DISCUSSION PAPER SERIES

IZA DP No. 17917

Remote Work, Employee Mix, and Performance

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ABSTRACT

Remote Work, Employee Mix, and Performance*

We study the shift to fully remote work at a large call center in Turkey, highlighting three findings. First, fully remote work increased the share of women, including married women, rural and smaller-town residents. By accessing groups with traditionally lower labor-force participation the firm was able to increase its share of graduate employees by 14% without raising wages. Second, workforce productivity rose by 10%, reflecting shorter call durations for remote employees. This was facilitated by a quieter home working environment, avoiding the background noise in the office. Third, fully remote employees with initial in-person training saw the higher long-run remote productivity and lower attrition rates. This underscores the advantages of initial in-person onboarding for fully remote employees.

JEL Classification: J2, J3, R1

Keywords: work from home, remote jobs, workforce mix, productivity

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1. Introduction

The COVID-19 pandemic triggered an unprecedented shift to remote work, with the share of paid workdays performed from home in the United States rising from around 7% in 2019 to more than 25% in 2025 (Buckman et al., 2023). But there is an ongoing debate over the productivity implications of remote work and its long-term viability (e.g., Barrero et al. 2023).

Workers are now divided into three groups. Fully-in person employees represent about 60% of employees (Figure 1) covering much of the service sector, manufacturing and essential services. Hybrid employees work from their business premises part of the week and at home part of the week, and represent around 30% of the labor force, typically graduate professionals. Finally, fully remote employees account for around 10% of the labor force, spanning a range of activities from call centers and data entry to computer engineering and writing. This paper studies these fully-remote employees, which spans over 100 million people globally.

We study a natural experiment in the call centers of Tempo BPO, a major business-process outsourcing firm located in Turkey. Tempo abruptly transitioned its entire workforce of approximately 3,500 call center agents from fully on-site to fully remote work following the national lockdown in March 2020. This comprehensive shift provides a natural experiment to identify the effects of remote work on worker mix, productivity, quality of service, and learning. Using detailed high frequency individual-level administrative data, our analysis reveals three key findings.

First, there were significant shifts in the employee mix following the transition to fully remote work. The workforce became more female, married, and non-metropolitan. This group has low employment in Turkey due to traditional norms against married women working. There was also a notable boost in the recruitment of graduates and more experienced employees, without any change in the wage costs. Fully remote work enabled the firm to access a wider labor pool, allowing it to increase the education and experience of its employees without raising wages.

Second, the shift to fully remote work led to higher productivity, with the number of calls per hour increasing by 9.1% during the COVID-19 lockdown. The firm was so impressed by this performance that it stayed fully remote after the lockdown ended. Post-lockdown productivity remained elevated, with 10.5% more calls per hour than in 2019. Importantly, customer service ratings also improved, suggesting that productivity gains did not come at the expense of service quality. The main driver of higher productivity was quieter working conditions at home, which facilitated faster and more accurate phone calls. These benefits of a quieter work setting are relevant for other jobs requiring concentration, covering many office jobs, including those working on a hybrid schedule.

Third, an initial period of in-person training for fully remote employees had positive effects on retention and longer-term productivity. We exploit the 12-week gap between job application and the start date of work for new Tempo employees to compare employees who started working remotely to similar employees who had a few weeks of initial in-person training before switching to fully remote work.

We find that those with a few weeks of initial in-person training had higher long-run productivity and retention rates. This suggests that a short period of in-person onboarding for fully remote workers can provide better mentoring and workplace attachment. That explains why many firms with fully remote employees start with a few weeks of in-person onboarding before moving them to fully-remote work.

Our paper makes three contributions to the literature on remote work. First, we show the potential for remote work to increase the employment of marginal groups. For Tempo the shift to fully remote work saw its share of women increase by 50%, particularly non-urban married women, which is a group with low employment in Turkey. This expansion of hiring in an underserved group allowed Tempo to increase its workforce education and experience without raising wages. This highlights the broader social inclusion benefits from remote work, particularly in regions with norms that make it harder for women to work outside the house.

Second, we provide new evidence showing remote workers are more productive than onsite workers in a call center setting, with no loss in service quality. This increase in performance is large, persistent and arises across all demographic groups. This highlights the potential for large performance benefits in some occupations from remote work.

Finally, our paper is the first experimental design to show the value of in-person onboarding and training. This explains why many firms with fully remote workers require an initial period of onsite work for training purposes.[1]

Our paper links to three literatures. The first studies the impact of working from home on productivity. Bloom et al. (2015) found a 13% increase in productivity at a Chinese travel agency, while Gibbs et al. (2022) saw a drop of 8% to 19% in productivity among IT workers in India. Emanuel and Harrington (2024) found an 8% drop in call volumes at a Fortune 500 company after employees switched to remote work, and Emanuel et al. (2023) find mentoring benefits from in-person work. Choudhury (2021) examines employees of the US PTO who were allowed to work from home for 4 days a week and found the number of patent actions rose by 5%. It rose by a further 8% when they were given greater locationally flexibility. Choudhury et al. (2022) study an NGO in Bangladesh whose human resources department also randomized workers into coming into work or not. Battiston et al. (2021) found positive impacts on call-centre dispatchers. Bloom et al. (2024) found null impacts of hybrid working from home on productivity for 1600 graduate employees, and a one third drop in quit rates.

The second literature studies the impact of working from home on labor supply. Recent evidence suggests that certain demographic group such as women with young children and families disproportionally value job flexibility (Mas and Pallais, 2017; Atkin et al., 2022; Aksoy et al., 2022; Aksoy et al., 2023). Analyzing online job applicant data from a major startup platform in the US, Hu and Tambe (2024) show that offering remote work attracts a significantly more experienced and diverse (i.e., more female and members of underrepresented groups) pool of applicants. Similarly, in a field experiment in West Bengal, offering flexible, short-term data entry jobs that aligned with traditional expectations of women's domestic responsibilities tripled job uptake compared to office-based roles (Ho et al., 2023). Bloom et al. (2025) show large impacts of WFH on increasing disability employment.

Finally, a broader literature studies the impact of work from home (WFH) on urban structures. Barrero et al. (2022) and Liu and Su (2023) develop evidence on how WFH affects wages. Agrawal and Brueckner (2025) theoretically analyze the wage and employment effects of state

[1] For example, Ctrip required employees to have 6 months fully in-person experience before they could work remotely (see Bloom et al. (2015)).

taxes on labor income, stressing the distinction between source-based and residence-based taxation. Ramani et al. (2024) and Gupta et al. (2024) study WFH effects on real estate values. Alipour et al. (2023), among others, provide evidence on how the shift to WFH alters the geography of consumer spending. Hansen et al (2023), Delventhal et al. (2023), Duranton and Handbury (2023) and Monte et al. (2023) analyse how remote work affects the structure of cities in quantitative spatial models. Luca et al. (2025) show that WFH uptake in Europe has been highly uneven, with the highest increases occurring in cities and capital regions.

The next section discusses the context of our study. Section 3 presents the recruitment results, Section 4 examines the productivity effects and Section 5 concludes.

2. The Company

2.1 The shift to remote work

Tempo is a major call center operating in Turkey, with a workforce of approximately 3,500 employees. Prior to the COVID-19 pandemic, the company had offices across seven provinces, with its headquarters located in Istanbul. Tempo provides call center services to a broad clientele, including banks, mobile phone operators, food chains and embassy visa sections.

In response to the national lockdown in Turkey on 11 March 2020, Tempo executed a rapid transition to remote work. Within two weeks, the company shifted its entire workforce of 3,500 call center agents to remote operations. To facilitate this transition, Tempo provided laptops and internet support to its employees.

Figure 2 contains two pictures of employees in the office (left side) and four pictures of employees working from home (right side). This highlights how the office environment is more crowded and noisier than the home working environment. Office space is expensive, so low wage call center employees have dense seating. As such, noise is a major issue in the office environment, with employees exposed to the sound from multiple nearby calls, with potentially negative impacts on productivity. There is a long literature from psychology highlighting how background noise, particularly the type of intermittent speech that is common in offices, impairs information comprehension, processing and memory (e.g. Broadbent 1979, Smith 1989, Szlama and Hancock, 2011 and Dean 2024).[2]

The standard work arrangement for call center agents at Tempo consists of five 8-hour shifts per week. Each shift includes two 15-minute short breaks and a 30-minute lunch break. Teams share the same work schedule and team leader, with individual agents unable to choose their shifts. A central system automatically directs each waiting call to the first available agent, ensuring efficient distribution of workload. The team, shift and call routing structure are identical for office and home-based employees.

Compensation at Tempo is based on the national minimum wage, which is uniform across the country. All agents receive this fixed wage, with no performance-based pay. Importantly, this structure remained unchanged across all provinces where Tempo operates, both before and after the shift to remote work. The company offers a career progression path, with high-

[2] Employees also mention other factors at the office that could impair productivity, including temperature, smell and bathroom access.

performing agents eligible for promotion to team leader positions, providing an incentive to maintain high performance standards.

Importantly, despite the shift to remote work, Tempo maintained consistency in its operations. The company's technology and software infrastructure, compensation policies, and daily work schedules remained constant throughout the transition to remote work and beyond.

After the lifting of lockdown measures in Turkey on September 7, 2021, Tempo, in line with industry trends, opted to continue its remote work model.

2.2 Employee and Performance Data

We obtained individual-level administrative records directly from Tempo's database. The dataset covers all employees between 2019-2023 and includes detailed demographic information, daily production metrics, monthly service quality assessments, monthly call composition data, and promotions (Appendix Table A1 contains summary statistics).

Our study focuses on inbound calls for a major mobile telecom company's customer services handled by Tempo. This project was selected for three reasons. First, it started prior to the pandemic and continued throughout, giving process continuity. Second, it involved a large number of call center agents, and the content of the call center services remained stable over time. Third, inbound calls involve customers contacting the agent's customer service for various tasks, with incoming calls randomly directed to available agents through a computerized system, making it easy to compare across agents.

The data covers the period from January 1, 2019, to January 31, 2023, and includes 1,766 distinct agents in the full sample.[3] We also have 240 agents over the full sample period yielding a smaller balanced panel. Descriptive statistics are available in the Appendix Tables A1.

3. Workforce Composition

Figure 3 shows the major changes in workforce composition following the onset of the COVID-19 pandemic. The vertical red lines indicate March 2020 and September 2021, marking the start and end of COVID-19 lockdowns in Turkey. The graphs illustrate the evolution of worker characteristics over time, comparing trends before and after the pandemic.

Panel A shows a steady increase in the share of female agents after March 2020. This rose from 50% before the lockdown to 76% by January 2023. In contrast, women make up 33% of the overall workforce in Turkey.[4] This suggests that remote work facilitated greater participation of women in the workforce.

Panel B highlights an increase in the share of married agents, with notable differences by gender. The share of married female agents rose more than that of their male counterparts, indicating that remote work makes employment more accessible for married women.

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[3] Due to the large-scale earthquake that occurred in Turkey on February 6 we stop the analysis on January 31.
[4] The Household Labor Force Survey labor force participation rate for those aged 15 years and over was 35.8% for females and 71.2% for males.

Panel C reveals a marked increase in the share of agents located in smaller towns and rural areas outside metropolitan areas after the shift to remote, reflecting how this enabled greater geographic flexibility.

Panel D shows rising workforce age, highlighting how the pandemic enabled Tempo to hire more older workers instead of focusing solely on younger city center employees in their early to mid-20s.

Finally, Panel E shows that the share of agents with tertiary education also rose significantly after the start of the pandemic. By expanding their hiring into more marginal labor pools via remote work the firm was able to attract more educated workers at the same wage rate.

These results are also examined in a regression format. The results show that after the shift to remote work, Tempo hired significantly more: (i) women, (ii) married agents, (iii) employees in smaller towns and rural areas, (iv) older employees and (v) graduate employees (see Appendix Table A2). So, by focusing on women, particularly married women, smaller towns and rural areas Tempo was able to significantly increase experienced graduate employment without increasing pay.

4. Employee Performance

4.1 The Impact of Remote Work on Average Productivity

Our second key result is the increase in productivity from the switch to remote work, which we plot in Figure 4. In Panel A, we plot our key productivity measure, which is calls per hour, showing this rising post pandemic vs pre-pandemic. Panels B and C of Figure 4 break down this improvement in productivity into its two subcomponents – call duration and break-time– showing the entire productivity gain stems from shorter call durations, which fell by 14%. Interestingly, in Panel C we can see break time actually rose by 13%, showing that remote work is not forcing employees into a more intense working schedule.

For more insight into how employees are processing faster calls Panels D, E and F of Figure 4 break out the actual call length into the subcomponents of talk time, admin time and hold time. We see that talk time accounts for most of the fall in overall call time. This is because the home environment is substantially quieter than the office. As a result, agents are able to communicate more easily with customers, asking them to repeat less often. This enables them to understand complex issues more rapidly, shortening the length of the conversation. Admin time remains roughly constant while hold-time also falls as home-based workers can concentrate more effectively in their quieter home environment.

We test the robustness of these findings by estimating equation (2) which splits the work from home (WFH) effect into a during-Covid and post-Covid effect. The unit of observation is the agent-day indexed by agent *i* and day *t*. For performance outcome y_{it} we estimate:

$$(2) \qquad y_{it} = \beta_1 WFHLockdown_t + \beta_2 WFHPost_t + \beta_3 Age_{it} + \beta_4 Age_{it}^2 + \beta_5 Experience_{it-1} + \Delta CT_{im} + \alpha_i + \gamma_l + \gamma_s + \gamma_m + \gamma_d + \epsilon_{it}$$

Where $WFHLockdown_t$ is a dummy variable indicating working from home during lockdown from 11 March to 6 September, and $WFHPost_t$ is a dummy indicating working from home once lockdown measures are lifted from the 7 September 2021 onwards. Thus, β_1 and β_2 capture a WFH effect during and after Covid related lockdowns, respectively.

We control for age, age squared, and experience, where experience is defined as the cumulative number of calls answered by each agent up to day t. To capture changes in outcomes that may be due to changes in call composition we include ΔCT_{im}, a vector of eight variables that reflect the composition (type) of calls received and the number of repeat calls at the agent-month level. α_i, γ_l and γ_s are agent, team leader and supervisor fixed effects, respectively.[5] The model is further saturated with γ_m and γ_d, month seasonal effects and day of the week fixed effects, respectively.[6] ϵ_{it} are clustered at the level of the agent.

Our identification comes from the move to remote work caused by government-imposed lockdowns and their subsequent lifting. This shift is unrelated to any observable or unobservable characteristics of workers, conditional on controls and fixed effects. As such, we measure the changes in the agent-level outcomes during and in the post-lockdown periods, relative to their performance in the office prior to the lockdowns.

Our main analysis is based on a panel of employees who began their employment before the lockdowns and continued working throughout the analysis period. To test the robustness of our findings, we also include all workers in an alternative specification. As shown in Table 1 the results indicate that shift to remote work led to a significant increase in productivity of 9.1% during the COVID-19 period and 10.5% in the post-COVID period. These results are similar for the full sample of employees (Appendix Table A3) and across demographic groups (Appendix Table A4). The one difference we do see is that remote work increased the productivity more for employees with lower productivity previously in the office (Appendix Table A5), reflecting the fact that employees who were most bothered by office noise saw the largest gains in moving to a home working environment.

4.2 The Impact of Starting In-Office vs. Starting Remotely

A key question in evaluating remote vs in person roles is the importance of face-to-face mentoring and learning. Many CEOs and managers have claimed in person working facilitates better mentoring and employee development.

The Turkish lockdown generated a natural experiment to investigate this by shifting a set of new Tempo employees from starting in-office to starting remotely. Employees usually take around 12 weeks from their initial application to when they start employment. To compare in-office starters to remote starters we construct two groups.

The control group is in-office starters, who started working in person any time from 16 weeks before the lockdown until 4 weeks before the lockdown. This window ensures that all employees in the group started close to the lockdown but had at least four weeks of in-person

[5] Appendix Figure A1 shows that the composition of calls received by agents remains broadly stable over time. Call composition is measured for each agent using a sample of 10 randomly selected calls per month. The different categories of calls—including billing and payment issues, plan changes and upgrades, account management, technical support, device support, and service cancellations—fluctuate slightly but exhibit no clear trend indicating major shifts in the nature of customer inquiries. This stability suggests that changes in agent productivity and performance are unlikely to be driven by systematic shifts in the types of calls handled over time.

[6] Month fixed effects are dummies for each calendar month where m = 1, 2, ...,12 and day of the week fixed effects are dummies for each day of the week where d = 1,2,...,7.

work before transitioning to remote work. Because no one in this group started earlier than 16 weeks before the lockdown, all are working remotely by their 80th day on the job.

The treatment group includes employees who applied to work in person during the 12 weeks leading up to the lockdown. However, due to the lockdown, they began working fully remotely. As we show in Appendix Figure A2, both groups share similar characteristics, since all applied pre-lockdown to the same in-person call center job.

Figure 5 (left panel) plots the number of calls per hour of these two groups in days from starting work. Initially remote starters are more productive. Without in-person training, they begin taking calls earlier and gain experience faster. However, by about day 175 in-person starters catch up, and afterwards become significantly more productive (see Appendix Table A6).

Panel B of Figure 5 shows that remote starters also have higher attrition rates. Interviews with employees suggest that starting in person fosters a stronger sense of connection with co-workers, making it easier to seek help and build bonds within the firm. Employees also report that in-person onboarding provided more effective initial training.

In summary, while remote starters begin with higher initial productivity due to immediate practical engagement, the longer-run productivity advantage favors office starters. These results underline the importance of initial face-to-face training for remote workers. Indeed, Tempo recognized these insights, and is now experimenting with bringing fully remote workers into the office for one day a month to sustain engagement and productivity.

One potential concern regarding the productivity increase from remote work is whether it came at the expense of service quality. We have two key measures of service quality. The first is a monthly audit rating from a manager evaluating ten randomly recorded calls. The second is a customer performance rating. In both cases these quality metrics saw post-pandemic improvements, with the increase in customer ratings being statistically significant (see Appendix Table A7). One reason appears to be that working from home is quieter for agents, enabling them to more rapidly and accurately handle customer calls.

5. Conclusion

Our analysis of Tempo's permanent shift to remote work shows that it significantly altered the employee mix, increasing the representation of more educated and older workers, while expanding the share of women and non-metropolitan employees. The last two groups are underrepresented in Turkish employment. By eliminating geographic and mobility constraints, remote work enabled the firm to access a broader labor market.

We also show that the permanent shift to remote work had significant and lasting impacts on worker productivity and performance. The number of calls handled per hour rose due to shorter call durations in quieter work environments at home. These gains were sustained over time and did not come at the expense of service quality, as evidenced by stable or improved customer satisfaction and audit-based quality ratings. Notably, these improvements were broad-based across demographic groups.

Finally, our comparison of remote and in-person starters highlights key tradeoffs for personnel management. Specifically, remote starters benefit from faster onboarding and initially outperform their peers who start onsite and then switch to remote work. However, this early advantage fades over time, and the productivity of onsite starters eventually overtakes that of remote starters. Moreover, remote starters are much more likely to leave the firm within the first few months. These findings underscore the long-term value of in-person onboarding, even for employees who later work in a fully remote capacity.

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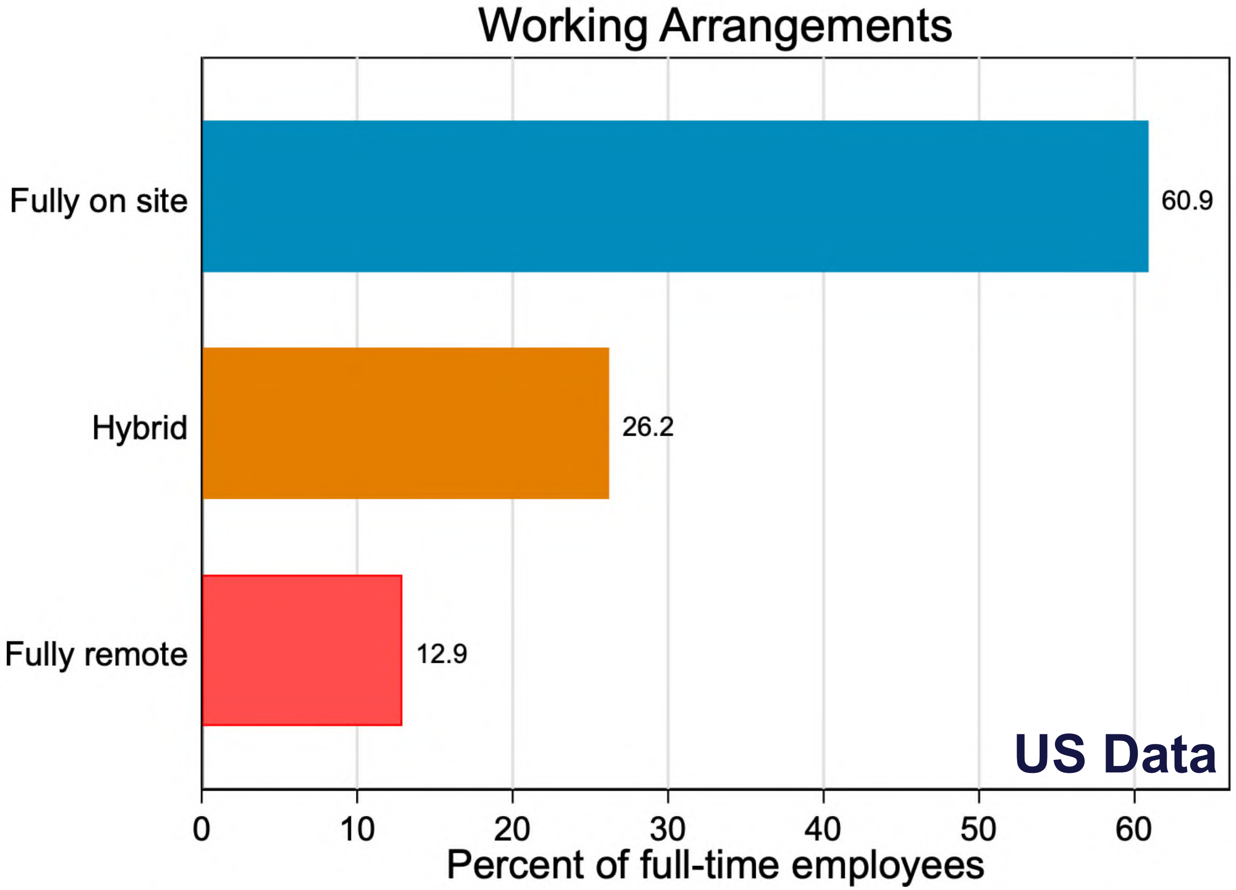
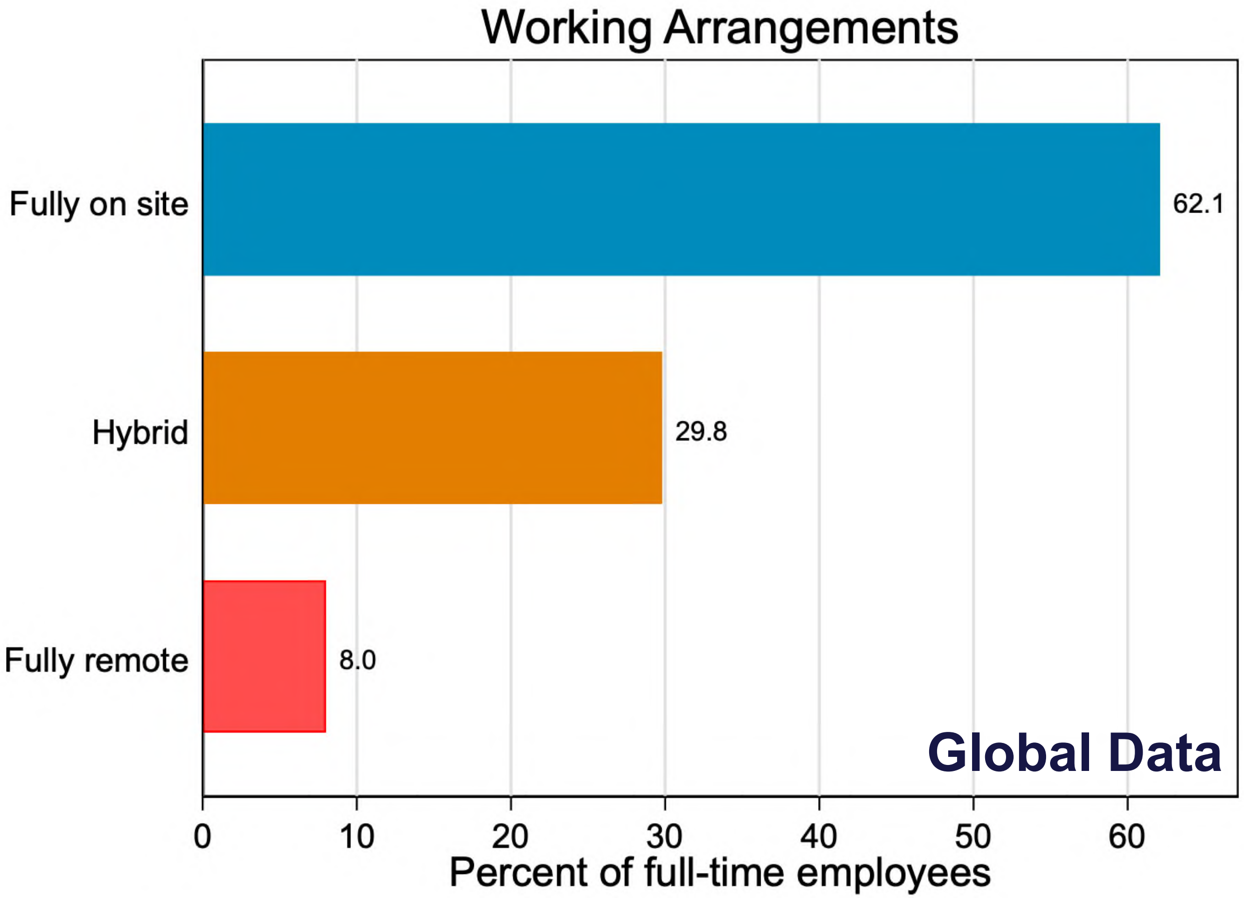
Figure 1: Fully Remote Workers are about 10% of All Employees





Source: Survey of Workplace Arrangements and Attitudes survey, January 2024 –April 2025. Residents aged 20 to 64 earning $10,000 or more in the prior year, weighted to the Current Population Survey by age, gender, income and education. N=53,268. Details in Barrero et al. (2025)

Source: Global Survey of Working Arrangements survey, November 2024-February 2025. Residents aged 20 to 64 earning across 40 countries. Samples broadly representative of population data on age and gender by country. N=26,202 Details in Aksoy et al. (2025)

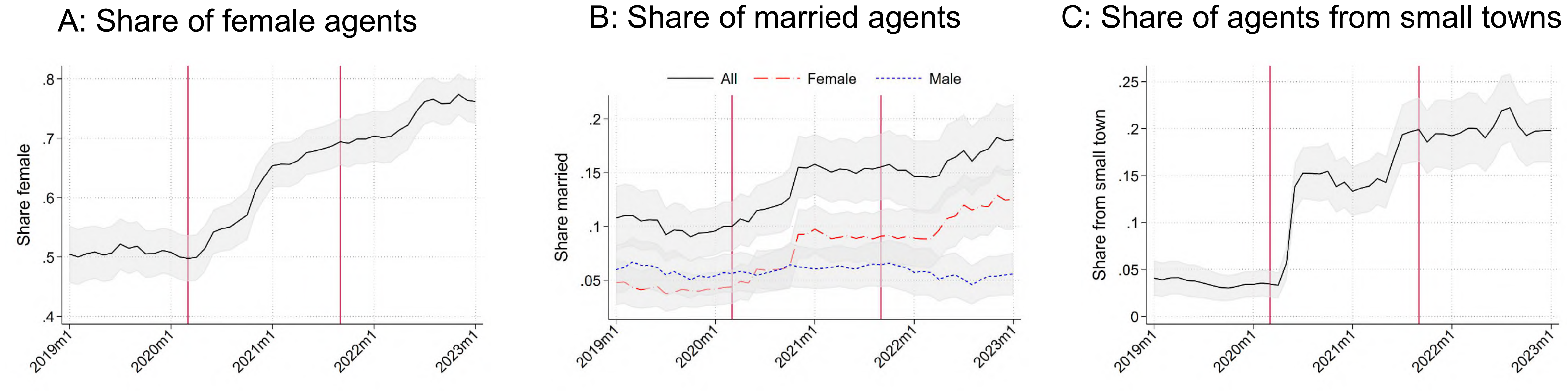
Figure 2: Agents moved from busy open-plan areas to quieter home environments

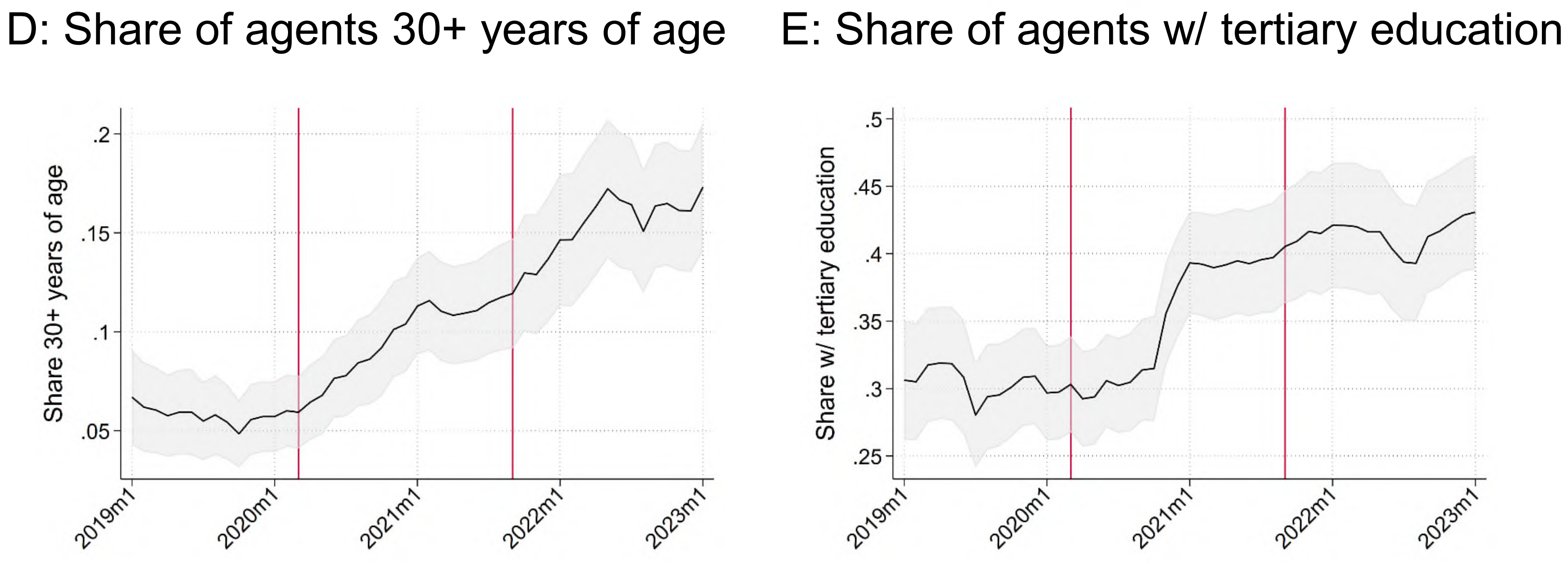
A: Working from the office

B: Working from home

Notes: Figure showing photos of the open-plan office environment prior to the shift to remote work (A) and agents working environment after the shift to remote work (B).

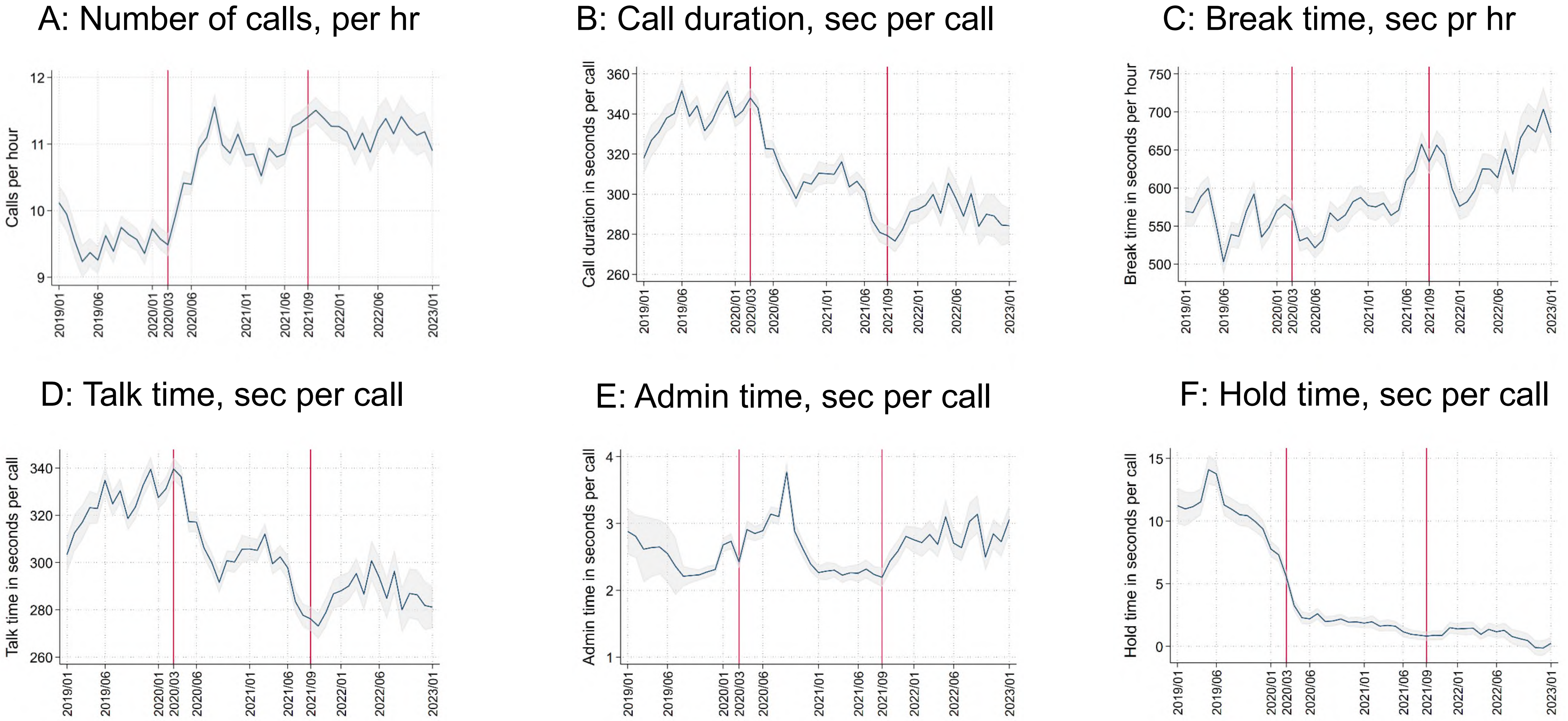
Figure 3: Remote working brought a rising share of agents who are female, married, college educated, from small towns and older





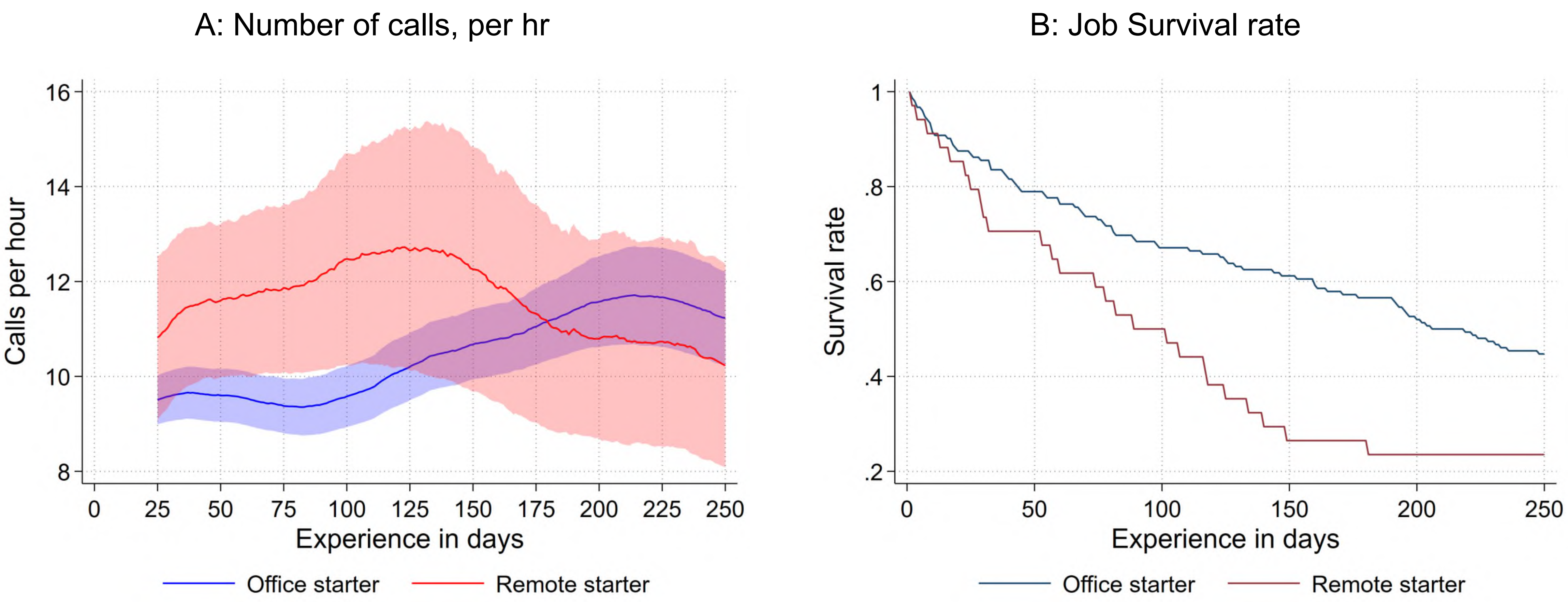
Notes: This figure shows changes in the workforce due to new hires and quits. Each panel presents monthly means, with the shaded area representing 95% confidence intervals based on robust standard errors clustered at the province level. These intervals are derived from monthly OLS regressions. Vertical red lines indicate March 2020 and September 2021, corresponding to the start and end of the COVID-19 lockdown period in Türkiye. Small town refers to provinces in Türkiye with a population of less than 750,000. The full sample includes 60 (out of 81) provinces, of which 33 are classified as Small town.

Figure 4: Productivity rose after the shift to remote work, with more calls per hour and shorter call durations



Notes: This figure shows predictions from regressions of productivity outcomes (indicated in titles) on month fixed effects, omitting February 2020 as the reference month. OLS regressions control for the composition of calls, repeat calls, and include agent fixed effects. Standard errors are clustered at the agent level, and 95% confidence intervals are calculated from these clustered standard errors and shown as shaded bands around the point estimates. Vertical red lines depict March 2020 and September 2021, the start and end of the COVID-19 lockdown period, respectively.

Figure 5: Office starters have equal productivity by 175 days and higher job survival rates



Notes: Panel A shows 50-day moving averages of calls per hour by work experience (measured in working days). Shaded areas represent 95% confidence intervals calculated from robust standard errors clustered at the agent level, based on local polynomial regression estimates for each group. Remote starter identifies agents who applied to the firm before the shift to remote work but started during the 12 weeks after the shift on 11 March 2020. Office starter refers to agents who started between 16 and 4 weeks before lockdown and received at least 4 weeks of in-person training. By day 80, both groups are working fully remotely. Panel B displays survival rate of office and remote starter employees.

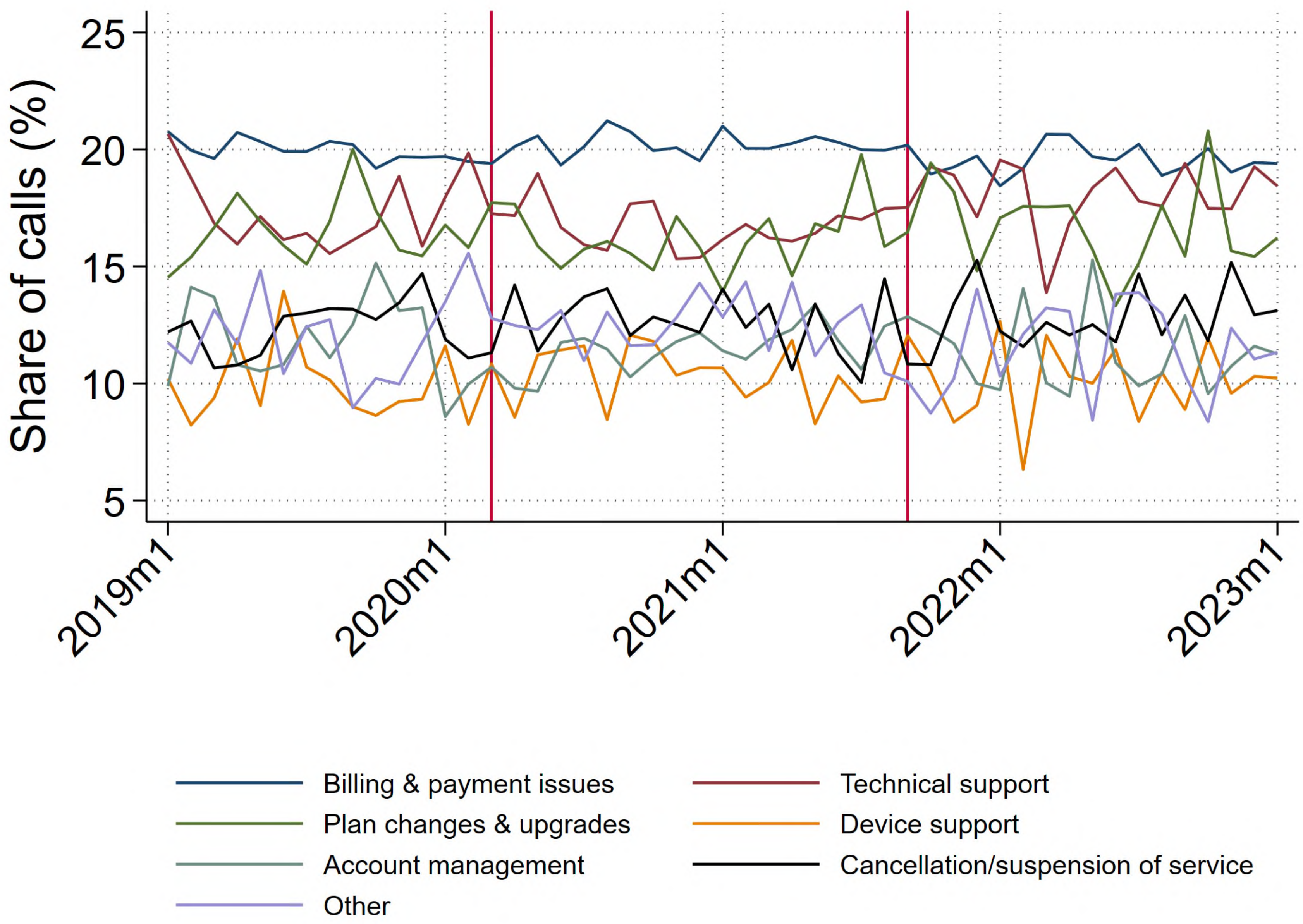
Table 1: Balanced panel – productivity rose mainly due to shorter calls and less hold time

	(1)	(2)	(3)	(4)	(5)	(6)
	Number of calls per hour	Call duration in seconds per call	Break time in seconds per hour	Talk time in seconds per call	Admin time in seconds per call	Hold time in seconds per call
Lockdown	0.90***	-17.76***	-50.18***	-13.32***	0.56***	-4.99***
	(0.16)	(3.98)	(16.13)	(3.96)	(0.11)	(0.43)
Post	1.04***	-24.94***	-46.85***	-21.58***	0.68***	-4.05***
	(0.20)	(5.70)	(15.75)	(5.62)	(0.13)	(0.50)
Log of cumulative number of calls (t-1)	0.16**	-6.22***	33.95***	-4.26**	-0.22**	-1.70***
	(0.07)	(2.14)	(5.18)	(2.13)	(0.09)	(0.24)
Adjusted R-squared	0.28	0.41	0.26	0.40	0.08	0.35
Number of observations	145,127	145,127	145,127	145,127	145,127	145,127
Number of clusters	204	204	204	204	204	204
Pre- sample mean	9.89	323.75	588.13	312.01	2.51	9.02

Notes: Table showing OLS regressions. The dependent variables are indicated in column heading. Agent FE, Team leader FE, Supervisor FE; month seasonals and day of the week FE are included in all columns. *Lockdown* is a dummy variable equal to if the calendar date falls inside the lockdown period in Türkiye, between 11/Mar/20 and 05/Sept/21 (inclusive), and 0 otherwise. *Post* is a dummy variable equal to if the calendar date is after 05/Sept/21 and 0 otherwise. The omitted category is *Pre*, a dummy variable equal to 1 if the calendar date is before lockdown was imposed on 11/Mar/20. Unreported controls are age, age squared and call composition variables. Standard errors are clustered at the agent level. ***, ** and * denote significance at the 1 percent, 5 percent, and 10 percent level, respectively.

Appendix

Figure A1: The composition of calls received by agents is broadly stable over time



Notes: This figure shows how the composition of inbound calls changes over time. Call composition is measured for each agent and is based on 10 randomly selected calls per month. The call composition variables are defined as follows. *Billing & payment issues* include inquiries about bills, payments, setting up direct debits, or disputing charges. *Technical support* are calls related to technical issues with mobile service, such as problems with voice calls, SMS, data connectivity, or network coverage. *Plan changes and upgrades* captures calls related to changing current plans, upgrading their phones, upgrading their services to include more data, or inquire about new offers and promotions. *Device support* calls include assistance with mobile devices, including troubleshooting, warranty claims, setting up new devices, or advice on features and apps. *Account management* includes queries related to account details, such as updating personal information, changing account preferences, or password resets. *Cancellation or suspension of services* are calls that customers request to cancel or suspend mobile services. Lastly, *Other* includes issues such number portability, international roaming, assistance for customers with disabilities, reporting lost or stolen devices, inquiries about promotions and loyalty programs, and network feedback.

Figure A2: Balance tests for the RDD sample

Notes: Figure show coefficient plot from linear probably model regression. The dependent variable is a dummy equal to 1 if an agent joined the firm between 16 weeks and 4 weeks before lockdown, so had at least 4 weeks of initial in person training, and 0 if the agent applied to the firm before the shift to remote work but started working at the firm during the 12 weeks after the shift to remote work which took place on 11 March 2020. Unreported coefficients are province dummies. Standard errors are heteroskedasticity robust and whiskers represent 95 percent confidence interval.

Table A1: Summary statistics

	Pre			Lockdown			Post			Two-sample t-test (Post vs Pre)	
	N	Mean	SD	N	Mean	SD	N	Mean	SD	Diff	p-value
Female	876	0.49	0.5	961	0.61	0.49	853	0.75	0.44	0.26	0.00
Completed tertiary education	876	0.3	0.46	961	0.38	0.48	858	0.4	0.49	0.1	0.00
Age	876	24.24	3.71	961	25.3	4.21	858	25.62	4.46	1.38	0.00
Married	876	0.08	0.27	961	0.14	0.34	858	0.19	0.4	0.11	0.00
Outside metropolitan province	876	0.03	0.18	961	0.17	0.38	858	0.19	0.39	0.15	0.00
Experience in days	876	410.07	423.08	961	510.37	499.15	858	519.49	608.9	109.42	0.00
Calls per hour (net of break time)	35,842	11.87	3.38	74,438	13.59	5.04	33,359	14.22	5.65	2.35	0.00
Calls per hour	35,842	9.89	2.8	74,438	11.21	4.03	33,359	11.4	4.15	1.51	0.00
Break time in minutes	35,842	60.12	25.73	74,438	54.73	28.71	33,359	63.84	31.95	3.72	0.00
Break time in seconds per hour	35,842	587.62	256.42	74,438	599.76	327.34	33,359	662.28	321.39	74.66	0.00
Call duration in seconds per call	35,842	323.91	86.02	74,438	292.46	88.55	33,359	279.75	78.46	-44.16	0.00
Talk time in seconds per call	35,842	312.15	84.04	74,438	288.15	88.2	33,359	276.1	78.17	-36.05	0.00
Admin time in seconds per call	35,842	2.52	2.54	74,438	2.53	2.86	33,359	2.36	2.36	-0.16	0.00
Hold time in seconds per call	35,842	9.04	11.5	74,438	1.66	5.24	33,359	1.18	4.06	-7.86	0.00
Random audit rating	1,421	0.38	0.49	2,392	0.59	0.49	1,288	0.42	0.49	0.04	0.06
Customer rating	368	64.74	10.88	3,004	64.94	12.42	1,534	73.37	13.34	8.63	0.00

Notes: This table reports summary statistics of agent characteristics, productivity outcomes, and quality outcomes. Agent characteristics draw on the full sample of agents. Productivity outcomes and quality outcomes draw on the balanced and report summary statistics drawing on data at the level of the agent-work day and agent-month, respectively. The *Pre* period corresponds to days up to and including 11/Mar/20, *Lockdown* is the period from 11/Mar/20 - 6/Sept/21 and *Post* is from 7/Sept/21 onward.

Table A2: More women, married agents and those residing outside metropolitan areas were hired following the shift to remote work

	(1)	(2)	(3)
	Hired pre (averages)	Hired during lockdown	Hired post
Female	0.47	0.22***	0.31***
		(0.03)	(0.03)
Married	0.07	0.11**	0.22***
		(0.04)	(0.04)
Completed tertiary education	0.30	0.04	0.01
		(0.03)	(0.03)
Small town	0.031	0.46***	0.32***
		(0.03)	(0.04)
R-squared		0.266	0.210
Number of observations		1,015	1,000
Sample mean		0.44	0.43

Notes: Table showing baseline averages and OLS regressions. Column (1) shows averaged in the form of the share of hires *Pre* lockdown who were female, married, had completed tertiary education and from outside a metropolitan province. Columns (2) and (3) and linear regressions. The dependent variable in column (2) is *Hired during lockdown*, a dummy equal to 1 if the agent was hired during lockdown between 11/Mar/20 and 6/Sep/21 – and zero if the agent was hired before 11/Mar/20. The dependent variable in column (3) is *Hired post*, a dummy equal to 1 if the agent was hired after the lockdown was lifted – 11/Mar/20 onward – and 0 if the agent was hired before 11/Mar/20. *Age* is included as an unreported control variable. The data is at the agent level. Standard errors are robust. ***, ** , and * denote significance at the 1 percent, 5 percent, and 10 percent level, respectively.

Table A3: Full sample – productivity rose mainly due to shorter calls and less customer hold time

	(1)	(2)	(3)	(4)	(5)	(6)
	Number of calls per hour	Call duration in seconds per call	Break time in seconds per hour	Talk time in seconds per call	Admin time in seconds per call	Hold time in seconds per call
Lockdown	0.82***	-10.89***	-33.82***	-5.64**	0.37***	-5.84***
	(0.10)	(2.71)	(9.19)	(2.69)	(0.07)	(0.35)
Post	1.00***	-18.62***	-31.28***	-14.67***	0.73***	-4.94***
	(0.13)	(3.72)	(10.07)	(3.68)	(0.07)	(0.39)
Log of cumulative number of calls (t-1)	0.30***	-13.56***	25.11***	-11.99***	-0.04**	-1.32***
	(0.03)	(0.88)	(1.93)	(0.87)	(0.02)	(0.11)
Adjusted R-squared	0.35	0.49	0.27	0.50	0.08	0.44
Number of observations	406,667	406,667	406,667	406,667	406,667	406,667
Number of clusters	1,766	1,766	1,766	1,766	1,766	1,766
Pre- sample mean	10.60	303.18	619.09	290.49	2.49	9.89

Notes: Table showing OLS regressions. The dependent variables are indicated in column heading. Agent FE, Team leader FE, Supervisor FE; month seasonals and day of the week FE are included in all columns. *Lockdown* is a dummy variable equal to if the calendar date falls inside the lockdown period in Turkey, between 11/Mar/20 and 05/Sept/21 (inclusive), and 0 otherwise. *Post* is a dummy variable equal to if the calendar date is after 05/Sept/21 and 0 otherwise. The omitted category is *Pre*, a dummy variable equal to 1 if the calendar date is before lockdown was imposed on 11/Mar/20. Unreported controls are age, age squared and call composition variables. The sample is the full sample. Standard errors are clustered at the agent level. ***, ** and * denote significance at the 1 percent, 5 percent, and 10 percent level, respectively.

Table A4: Changes in number of calls and call duration are similar across demographic groups

	(1)	(2)	(3)	(4)	(5)	(6)
	Number of calls per hour			Call duration in seconds per call		
Lockdown	0.94***	0.91***	0.91***	-23.50***	-17.28***	-16.22***
	(0.23)	(0.17)	(0.18)	(5.27)	(4.15)	(4.37)
Post	1.21***	0.89***	0.94***	-37.14***	-21.76***	-23.86***
	(0.33)	(0.22)	(0.23)	(8.75)	(6.04)	(6.27)
Lockdown x Female	-0.06			8.49		
	(0.25)			(5.89)		
Post x Female	-0.26			18.37*		
	(0.37)			(9.41)		
Lockdown x Married		-0.12			-1.45	
		(0.29)			(7.10)	
Post x Married		0.79*			-16.70	
		(0.44)			(11.23)	
Lockdown x Completed tertiary education			-0.04			-4.49
			(0.23)			(6.07)
Post x Completed tertiary education			0.26			-3.13
			(0.34)			(8.89)
R-squared	0.280	0.281	0.280	0.407	0.407	0.406
Number of observations	145,127	145,127	145,127	145,127	145,127	145,127
Number of clusters	204	204	204	204	204	204
Sample mean	61.07	61.07	61.07	323.75	323.75	323.75

Notes: Table showing OLS regressions with individual fixed effects, dependent variables are indicated in column headings. Agent FE, Team leader FE, Supervisor FE, month seasonals and day of the week FE are included in all columns. Lockdown is a dummy variable equal to if the calendar date falls inside the lockdown period in Turkey, between 11/Mar/20 and 05/Sept/21 (inclusive), and 0 otherwise. Post is a dummy variable equal to if the calendar date is after 05/Sept/21 and 0 otherwise. The omitted category is Pre, a dummy variable equal to 1 if the calendar date is before lockdown was imposed on 11/Mar/20. Unreported controls are agent age, age squared and call composition variables. The sample is the Sub-sample of agents who are observed in the Pre, Lockdown and Post periods. Standard errors are clustered at the agent level. ***, ** , and * denote significance at the 1 percent, 5 percent, and 10 percent level, respectively.

Table A5: Remote work improves productivity for agents who were low performers in the office

	(1)	(2)	(3)
	Calls per hour	Call duration in seconds per call	Break time in seconds per hour
Post	0.01	14.53*	-80.70***
	(0.37)	(7.46)	(28.14)
Post x WFO: medium productivity	0.65*	-18.07**	-3.14
	(0.35)	(7.53)	(35.24)
Post x WFO: low productivity	1.34***	-54.00***	20.98
	(0.44)	(10.57)	(32.19)
R-squared	0.271	0.418	0.272
Number of observations	124,260	124,260	124,260
Number of clusters	199	199	199
Sample mean	9.88	323.73	590.70

Notes: Table showing OLS regressions with individual fixed effects, dependent variables are indicated in column headings. Agent FE, Team leader FE, Supervisor FE, month seasonals and day of the week FE are included in all columns. Unreported covariates are agent age, age squared, the log of cumulative calls in t-1 and call composition variables. Unreported coefficients are *Lockdown*, *Lockdown x WFO: medium productivity* and *Lockdown x WFO: low productivity*. *Lockdown* is a dummy variable equal to if the calendar date falls within the lockdown period in Turkey, between 11/Mar/20 and 05/Sept/21 (inclusive), and 0 otherwise. Post is a dummy variable equal to if the calendar date is after 05/Sept/21 and 0 otherwise. The omitted category is *Pre*, a dummy variable equal to 1 if the calendar date is before the lockdown was imposed on 11/Mar/20. Baseline productivity during the work from office (WFO) period is calculated using the sub-sample of all odd calendar dates before the shift to remote work. *WFO: median productivity* is a dummy variable equal to 1 if the average duration of calls in this period, for a given agent, falls into the second tercile of the baseline productivity and 0 otherwise. *WFO: low productivity* is a dummy variable equal to 1 if the average duration of calls in this period, for a given agent, falls into the third tercile of baseline productivity and 0 otherwise. The sample corresponds to agents observed in the Pre, Lockdown and Post periods and excludes odd calendar dates (used to calculate baseline productivity) during the WFO period. Standard errors are clustered at the agent level. ***, ** and * denote significance at the 1 percent, 5 percent, and 10 percent

Table A6: Office starters are initially less productive although overtake remote starters by 200 days

	(1)	(2)	(3)	(4)	(5)	(6)
	All		80+ days		160+ days	
Office starter	0.52	0.30	0.79	0.59	1.26**	1.06**
	(0.47)	(0.39)	(0.52)	(0.40)	(0.59)	(0.45)
R-squared	0.09	0.16	0.10	0.17	0.11	0.18
Number of observations	50,094	49,908	38,149	38,149	29,140	29,140
Number of clusters	186	183	128	128	99	99
Controls	No	Yes	No	Yes	No	Yes

Team leader FE; supervisor FE; month seasonals and day of week FE.

Notes: Table showing OLS regressions with individual fixed effects, the dependent variable is calls per hour. *Remote starter* identifies agents who applied to the firm before the shift to remote work but started working at the firm during the 12 weeks after the shift to remote work which took place on 11/Mar/20. *Office starter* identifies agents who started working at the firm between 10/Oct/19 and 10/Feb/20. Unreported controls are log of cumulative calls, call composition variables. Standard errors are clustered at the agent level. ***, ** and * denote significance at the 1 percent, 5 percent, and 10 percent level, respectively.

Table A7: Ratings provided by customers and mangers remained similar, if anything they rose, following the shift to remote work

	(1)	(2)	(3)	(4)
	Balanced panel		Full sample	
	Random audit rating	Customer rating	Random audit rating	Customer rating
Lockdown	0.20***	-0.83	0.19***	-2.63***
	(0.04)	(0.92)	(0.02)	(0.63)
Post	0.07	6.69***	0.06*	4.45***
	(0.05)	(1.22)	(0.03)	(0.81)
Log of cumulative number of calls (t-1)	-0.03*	0.44	-0.01**	1.34***
	(0.01)	(0.63)	(0.01)	(0.19)
R-squared	0.36	0.39	0.38	0.50
Number of observations	5,155	4,965	14,201	12,974
Number of clusters	198	200	1376	1283
Pre-mean sample	0.38	64.74	0.37	62.39

Notes: Table showing OLS regressions with individual fixed effects, dependent variables are indicated in column headings and measured at the monthly level. Agent FE, Team leader FE, Supervisor FE and month seasonals are included in all columns. Unreported controls are agent age, age squared and call composition variables. *Random audit rating* is a dummy variable equal to 1 if a manager deems an agent to be performing well after evaluating ten randomly recorded calls from a given month and 0 otherwise. *Customer rating* is the average rating an agent receives from their customers ranging from 1 to 100. *Lockdown* is a dummy variable equal to if the calendar month falls inside the lockdown period in Turkey, between Mar/20 and Sept/21 (inclusive), and 0 otherwise. *Post* is a dummy variable equal to if the calendar month is after Sept/21 and 0 otherwise. The omitted category is *Pre*, a dummy variable equal to 1 if the calendar month is before lockdown was imposed in Mar/20. The sample is the agent-month level. Standard errors are clustered at the agent level. ***, ** , and * denote significance at the 1 percent, 5 percent, and 10 percent level, respectively.