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Remote Work, Employee Mix, and Performance

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Abstract: This paper studies the long-term impact of a permanent shift to fully remote work in the call center division of a major multinational firm. Using detailed administrative data, we document three key findings. First, the shift to remote work enabled the firm to tap into previously underutilized segments of the labor force and substantially reshaped the composition of its workforce—increasing the share of women (including married women), older individuals, and those living in small towns and rural areas. Second, remote work led to sustained improvements in productivity, driven primarily by shorter call durations, without compromising service quality. Third, employees who received initial in-person training prior to going remote exhibited higher long-term productivity and lower attrition, highlighting the critical role of in-person onboarding in fully remote settings.

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1. Introduction

The COVID-19 pandemic triggered a large-scale reorganization of work. In the United States, the share of paid workdays conducted from home jumped from about 7% in 2019 to over 25% by 2025 (Buckman et al., 2023), with similar increases observed across many countries (Aksoy et al., 2022, Luca et al., 2025). The pandemic introduced millions of employees to remote work. In its aftermath, many firms—particularly in finance, IT, customer support, and professional services—shifted toward fully remote or hybrid models. Yet despite the scale and persistence of this shift (Aksoy et al., 2025), its long-term consequences remain poorly understood. Does remote work broaden access to talent, and if so, does it involve trade-offs in performance? Can firms sustain productivity and service quality in a fully remote environment? And can organizations foster attachment and build high-performing cultures when employees are never physically present?

This paper provides new evidence on these questions by studying a large multinational company in Turkey that moved its call center operations, comprising over 3,500 agents, to a fully remote model in March 2020 in response to a nationwide lockdown.[1] Crucially, the shift involved no major operational changes: job descriptions, tasks, shift patterns, compensation (set at the national minimum wage), and team structures all remained unchanged. Employees continued handling randomly assigned inbound calls from the same customer queues under identical performance monitoring systems. After the lockdown ended, the firm chose to remain fully remote. This sharp and sustained transition offers a rare natural experiment to examine the long-run impacts of fully remote work on (i) workforce composition, (ii) employee productivity, (iii) service quality, and (iv) managerial practices, particularly onboarding and retention.

Our analysis leverages rich administrative data from this firm, covering the entire workforce between 2019 and 2023. The dataset includes detailed daily records on productivity, monthly service quality metrics, demographic characteristics, and attrition. A key advantage of the individual-level data is the ability to follow both the full workforce (unbalanced panel) and a stable subset of employees observed continuously before, during, and after the pandemic (balanced panel). Despite their merits, existing studies (e.g., Künn et al, 2022; Yang et al., 2022; Gibbs et al., 2023; Shen 2023; Emanuel and Harrington, 2024) focus on short-term remote work episodes during the pandemic and provide little evidence on how remote work reshapes firms and workers in the long term. In contrast, our study is the first to evaluate the long-term impact of a fully remote work model, leveraging multi-year data that cover the period before the shift to remote work, the transition itself, and the subsequent years of remote operation. This distinction is critical for assessing whether fully remote work yields sustained productivity gains and enhances labor market inclusion.

Understanding these longer-term dynamics is also important because fully remote work, unlike hybrid or flexible models, remains the least understood, yet it is projected to be the fastest-growing segment of the labor market (World Economic Forum, 2024). Reflecting this shift, the global workforce as of 2025 is broadly divided into three categories (Appendix Figure A1). Fully in-person employees, who make up roughly 60% of the labor force, are concentrated in sectors like retail, manufacturing, and essential services. Hybrid workers, about 30% of the

[1] The call center setting offers a unique empirical advantage: it generates high-frequency, granular data on individual performance, such as call volumes, durations, and service quality ratings, under standardized conditions. This allows for precise and credible measurement of productivity, independent of self-reports or subjective evaluations.

workforce, typically hold graduate-level jobs and split their time between home and office. The remaining 10% are fully remote workers, spanning roles from call center agents and data entry clerks to software engineers and digital content creators—totalling over 100 million workers globally. Our study focuses on this understudied segment and provides new evidence on the effects of fully remote work on productivity, workforce composition, and managerial practices over the long run.

We document three main findings. First, the shift to fully remote work considerably reshaped the composition of the workforce. Following the transition, the firm widened its recruitment pool, hiring more women (particularly married women) as well as more individuals from rural areas and small towns, and more college-educated workers. Notably, these changes occurred without any adjustment in compensation, as the firm continued to offer the nationally set minimum wage. For example, the share of female agents increased from 50% before the lockdown to 76% by February 2023, compared to a national average of just 36%.[2] This implies that remote work helped lower structural barriers to labor market entry, particularly for women and other underrepresented groups. The significance of these findings is especially evident in the Turkish context, where female labor force participation has consistently been the lowest among OECD countries and remains a long-standing structural challenge.[3] Turkey also has one of the largest gender gaps in labor force participation among G20 countries, with disparities particularly pronounced among married women and mothers (IMF, 2024). More broadly, similar barriers to employment persist across many developed and developing countries, making these findings relevant beyond Turkey.[4]

Second, productivity increased following the transition to fully remote work and remained high in the years that followed. The number of calls handled per hour rose by approximately 8% during the lockdown period and stabilized at over 9% above the pre-pandemic baseline in the long run. Decomposition results show that these gains were driven almost entirely by within-worker improvements, rather than changes in the composition of the workforce. Customer satisfaction ratings also improved, indicating that these productivity gains did not come at the expense of service quality. A key mechanism appears to be the home environment, which enabled agents to concentrate better and work more efficiently. This finding likely extends beyond the call center context, with important implications for other focus-intensive white-collar occupations.

Third, we find that a short period of in-person onboarding significantly improves the performance and retention of remote employees. We exploit quasi-experimental variation in start dates: due to a typical 12-week gap between job application and start date, some new hires began just before the lockdown and received in-person training before transitioning to fully remote work, while others, hired shortly after, were onboarded entirely remotely. Those who received in-person onboarding exhibited higher long-term productivity and considerably lower attrition. From a management practices perspective, this implies that incorporating a brief

[2] According to the Turkish Household Labor Force Survey, the participation rate for those aged 15 and over is 35.8% for women, compared to 71.2% for men.

[3] Female labor force participation in Turkey remains low due to persistent structural barriers, including traditional gender norms, limited access to affordable childcare, and steep participation penalties associated with marriage and motherhood. These factors have remained largely unchanged before and after the COVID-19 pandemic (IMF, 2024).

[4] These patterns echo recent evidence from the United States showing that remote job postings attract more diverse applicants (Hsu and Tambe, 2025) and increase employment among individuals with disabilities (Bloom et al., 2025), highlighting the potential of remote work to improve labor market inclusion.

period of in-person training can enhance long-term outcomes in fully remote settings by easing the transition into the organization and strengthening initial employee engagement.

Our paper contributes to several strands of literature. First, it contributes to the literature examining the role of job flexibility in promoting labor market participation among underrepresented groups. Prior work shows that women with young children and families place a particularly high value on flexible and hybrid work arrangements (Mas and Pallais, 2017; Aksoy et al., 2022; Aksoy et al., 2023; Atkin et al., 2023). Using online job application data from a major startup platform in the U.S., Hsu and Tambe (2025) find that remote work offerings attract a significantly more experienced and diverse high-skilled applicant pool, including more women and individuals from underrepresented groups. Similarly, a field experiment by Ho et al. (2023) shows that offering short-term work-from-home jobs significantly boosts labor market entry among women: take-up rises from 15% for office-based roles to 48% for jobs that can be performed from home while managing childcare, although with lower productivity. We extend this literature by examining how a firm-wide shift to fully remote work reshapes the composition of the full-time workforce. Unlike prior work based on applications or short-term hiring, our setting allows us to document sustained changes in actual employment outcomes. We show that remote work leads to lasting shifts in the demographics and qualifications of those ultimately hired, even in a low-wage, service-sector context.[5]

Second, we add to the literature on the productivity effects of hybrid and fully remote work. Some studies find positive or null impacts (e.g., Bloom et al. 2015; Choudhury 2021; Angelici and Profeta 2024; Bloom et al. 2025), while others document declines due to coordination frictions or adverse selection (e.g., Gibbs et al. 2023; Emanuel and Harrington 2024). This mix of results shows that productivity depends on organizational context and implementation.[6] We provide the first evidence on longer term- productivity after a firm-wide move to fully remote work in a developing country setting. We find large, sustained gains, especially among employees with lower baseline productivity in the office. Our setting further allows us to examine whether these gains are primarily driven by the changes in recruitment or by changes in the work environment itself. A decomposition of the results shows that demographic shifts account for only a small share of the observed productivity increase. Instead, approximately 95% of the gains arise from within-worker improvements, implying that the home setting (rather than selective hiring) is the primary driver of performance improvements.

A third body of work touches on how firms onboard and manage fully remote employees, though causal evidence remains limited. Existing studies suggest that in-person interaction may support learning and retention (e.g., Battiston et al., 2021; Bloom et al., 2025), but none has

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[5] One point of divergence in the literature is whether gains in workforce diversity come at the expense of performance. Some studies suggest a trade-off (Ho et al., 2023; Emanuel and Harrington, 2024), while others, including ours, find that remote work can enhance both diversity and workforce qualifications (Hsu & Tambe, 2025). A natural question in our context is whether these gains are concentrated among the same individuals—for example, whether the rise in tertiary-educated hires is driven primarily by married women from smaller towns. While there is some overlap, our analysis shows that the increases in education and demographic diversity reflect broader recruitment changes rather than being driven by a single subgroup. These results are available upon request.

[6] Relatedly, Choudhury et al. (2024) provides causal evidence on how the number of in-office days in a hybrid work arrangement affects employee outcomes. Employees who worked in the office approximately two days per week reported higher job satisfaction, better work-life balance, and lower social isolation, while showing no significant differences in performance ratings relative to those with more or fewer in-office days.

explored onboarding practices directly.[7] We exploit quasi-experimental variation in start dates to show that a brief in-person onboarding period boosts long run productivity and reduces attrition among remote hires. These results underscore the value of initial face-to-face training in remote settings.

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 large multinational business process outsourcing company based in Turkey. Before the COVID-19 pandemic, it operated offices across seven provinces, with its headquarters in Istanbul. The company specializes in customer experience and information technology services. As part of its operations, it provides call center support to a diverse range of clients, including banks, mobile phone operators, food chains, and embassy visa sections. This division alone employs over 3,500 agents.

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

The standard work arrangement for call center agents at Tempo consists of five 8-hour shifts per week. Each shift includes two 15-minute breaks and a 30-minute lunch break. Teams follow the same schedule and report to the same team leader, and individual agents cannot choose their shifts. A central system automatically routes incoming calls to the first available agent, ensuring an efficient distribution of workload. The team structure, shift pattern, and call routing system are identical for both office-based and remote 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. This structure remained unchanged across all provinces where Tempo operates, both before and after the shift to remote work. The company also offers a career progression path, with high-performing agents eligible for promotion to team leader positions, providing an incentive to maintain strong performance.

Despite the shift to remote work, Tempo maintained consistency in its core operations. The company's technology and software infrastructure, compensation policies, and daily work schedules remained constant throughout the transition and beyond. After the lifting of lockdown measures in Turkey on September 7, 2021, Tempo, consistent with broader industry trends, chose to continue with its fully remote work model. Figure 1 includes two pictures of employees working in the office (left side) and four pictures of employees working from home (right side).

[7] Choudhury et al. (2023) conduct a randomized field experiment at a global firm evaluating how different virtual onboarding practices affect remote interns' performance. They find that regular virtual "water cooler" sessions with senior managers, especially when there is a demographic match, improve performance and career outcomes, while other virtual formats show no effect.

2.2 Employee and Performance Data

We obtained individual-level administrative records directly from Tempo's internal database. The dataset covers all employees between 2019 and 2023 and includes detailed demographic information, daily productivity metrics, monthly service quality assessments, monthly call composition data, and attrition records.

Our analysis focuses on inbound calls handled by Tempo on behalf of a major mobile telecom company. This project was selected for four key reasons. First, it began before the pandemic and continued throughout, providing continuity in operations. Second, it involved a large number of call center agents, and the nature of the service remained stable over time. Third, inbound calls are initiated by customers and randomly routed to available agents through a centralized computerized system, ensuring that agents have no control over the type of queries they receive. Fourth, the company did not introduce any new policies aimed at increasing call-handling speed, such as implementing suggested scripts or revising performance targets. This was because the nature of the tasks remained the same throughout the period. As a result, performance expectations and evaluation metrics remained consistent before and after the shift to remote work, helping to isolate the effect of the fully remote work transition.

The data span the period from January 1, 2019, to January 31, 2023, and include 1,766 distinct agents in the full sample. Importantly, a balanced panel of 240 agents is observed continuously before, during, and after the pandemic. Descriptive statistics are presented in Appendix Table A1.

3. Workforce Composition

Figure 2 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, rising from 50% before the lockdown to 76% by January 2023. In contrast, women comprise just 33% of the overall workforce in Turkey. Panel B plots the share of married agents over time, separately for the full sample and by gender. The black line shows the overall share of agents who are married in each month, calculated as the number of married individuals divided by the total number of agents (male and female combined). The red (female) and blue (male) dashed lines display the share of married agents within each gender subgroup, based on the respective gender-specific denominators. The figure documents an increase in the share of married agents, with notable gender differences: the share of married female agents rose more than that of their male counterparts, suggesting that remote work made employment more accessible for married women. Together, these patterns indicate that remote work facilitated greater female participation in the firm's workforce.

To place these changes in broader context, Appendix Figure A2 contrasts the evolution of predicted employment rates at Tempo with trends in the Turkish labor force as a whole. While female employment at Tempo rose sharply (eventually surpassing male employment) the predicted employment rate for women in the Turkish Labor Force Survey remained largely flat between 2019 and 2022. This divergence underscores the role of fully remote work in relaxing long-standing barriers to female labor force participation, including cultural norms, geographic immobility, and caregiving responsibilities, thereby contributing to a more inclusive labor market.

Panel C reveals a notable rise in the share of agents living in smaller towns and rural areas outside major metropolitan regions after the shift to fully remote work, highlighting the expanded geographic flexibility it provided. This is consistent with evidence that geographic constraints, particularly those tied to household location and relocation decisions, limit labor market access, especially for women in specialized or geographically dispersed occupations (Benson, 2014). Remote work helps relax these constraints by allowing individuals to participate in the labor market without needing to relocate.

Panel D shows a steady increase in the average age of the workforce, illustrating how the shift to remote work during the pandemic enabled Tempo to hire older workers, rather than relying primarily on younger, city-center employees in their early to mid-20s. Panel E further shows that the share of agents with tertiary education rose markedly after the onset of the pandemic. By expanding recruitment into more marginal labor pools through fully remote work, the firm was able to attract more highly educated workers without raising wages. These findings are consistent with recent evidence that remote work can enhance firms' access to underutilized human capital by reducing geographic frictions and broadening the effective talent pool (e.g., Hsu and Tambe, 2025).

Regression estimates confirm these patterns: following the transition to fully remote work, Tempo disproportionately hired women (especially married women), workers in smaller towns, older employees, and university graduates (Appendix Table A2). This shift allowed the firm to tap into underutilized talent pools and increase the share of graduate employees without raising wages.

Employment growth and hiring dynamics

The compositional changes documented above raise a natural question: were these shifts driven by a wave of hiring or attrition following the shift to remote work, or did they emerge more gradually?

Figure A3 helps answer this by plotting monthly changes in employment growth (Panel A) and hiring rates (Panel B). Panel A shows that employment growth remained stable after the remote work transition, with no evidence of mass exits. Panel B similarly shows no spike in hiring, despite some short-term fluctuations. These patterns suggest that the observed workforce changes were not the result of sudden labor force churn but instead reflect gradual and persistent shifts in recruitment and retention, without disrupting overall employment dynamics.

4. Employee Performance

4.1 The Impact of Remote Work on Average Productivity

We present three sets of evidence to examine how the shift to fully remote work relates to productivity changes. First, we show descriptive statistics based on the raw distribution; second, we present regression-adjusted monthly productivity trends around the fully remote work transition; and third, we report individual-level regression estimates that incorporate an extensive set of controls.

Distributional shifts in calls per hour with fully remote work

Appendix Figure A4 presents kernel density estimates of individual level productivity, measured as calls per hour, across three periods: pre pandemic (Pre), during the initial lockdown (Lockdown), and in the post pandemic steady state (Post). The sample includes agents who worked at least 10 days in each period, enabling consistent within agent comparisons over time.

The distribution shifts notably to the right after the transition to fully remote work. Relative to the pre pandemic period, the entire distribution becomes more right skewed. The median number of calls per hour rose from 9.84 (Pre) to 10.81 (Lockdown) and further to 10.99 (Post). These patterns indicate that the shift to remote work was associated with a persistent improvement in productivity across the workforce.

Regression-adjusted monthly productivity trends

Figure 3 presents estimates of monthly productivity outcomes using regressions with month fixed effects, where February 2020 is omitted as the reference month. All specifications control for call composition and repeat calls, and include agent fixed effects. Panel A displays our main productivity measure, calls per hour, which rose substantially in the post-pandemic period relative to the pre-pandemic baseline. Panels B shows that the entire productivity gain is driven by a 14% reduction in average call duration.

To better understand how employees are handling calls more efficiently, Panels D, E, and F further disaggregate call duration into talk time, admin time, and hold time. The decline in total call duration is largely explained by a reduction in talk time. This appears to reflect the quieter home environment, which allows agents to communicate more clearly with customers, reducing the need for repetition and enabling faster resolution of complex issues. Admin time remains largely unchanged, while hold time also declines (likely due to improved focus and fewer distractions in the home setting).

Results from agent-level regressions

We formally estimate these patterns using equation (1), which separates the work-from-home effect into distinct during-COVID and post-COVID components. The unit of observation is the agent-day indexed by agent *i* and day *t*. For performance outcome y_{it} we estimate:

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

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 the effect of WFH during COVID-related lockdowns and the period after, 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.[8]

The inclusion of team leader and supervisor fixed effects accounts for variation in agent performance that may arise from differences in managerial style, communication practices, frequency of feedback, or enforcement of performance standards. Each team leader manages approximately 20 agents, who are randomly assigned to teams at the time of hiring, and the team leader fixed effects (γ_l) absorb systematic differences across teams in day-to-day management. Supervisor fixed effects (γ_s) capture variation in higher-level oversight, including differences in how team leaders are monitored, supported, or evaluated. Agent fixed effects (α_i) control for time-invariant individual characteristics such as ability, prior experience, or baseline motivation. The model is further saturated with γ_m and γ_d, month seasonal effects and day of the week fixed effects, respectively.[9] ϵ_{it} are clustered at the level of the agent.

Our identification strategy exploits the shift to fully remote work induced by government-imposed lockdowns and their subsequent lifting. Conditional on observable controls and fixed effects, this transition is plausibly unrelated to any individual-level characteristics that might otherwise influence outcomes. We therefore estimate the effect of fully remote work by comparing changes in agent-level outcomes during the lockdown and post-lockdown periods relative to the same agents' performance while working in the office prior to the pandemic.

Our main analysis focuses on a balanced panel of employees who were hired before the onset of the lockdowns and remained employed throughout the analysis period. To assess the stability of our findings—both in terms of magnitude and direction—we replicate the analysis using the full sample of agents, including those who joined or exited the firm during the study period. Encouragingly, the results across both samples are highly consistent (Appendix Table A3 and discussed below).

As shown in Table 1, the transition to fully remote work was associated with a statistically and economically significant increase in agent productivity. The number of calls handled per hour increased by 9.1% during the lockdown period (coefficient = 0.9) and by 10.5% in the post-lockdown period (coefficient = 1.04), relative to the pre-pandemic baseline mean of 9.89 calls per hour. These gains were primarily driven by shorter average call durations, which declined by 17.8 seconds during the lockdown and 24.9 seconds post-lockdown, compared to a pre-period average of 323.75 seconds per call.

Decomposing the change in call duration, we observe substantial reductions in both talk time and hold time, suggesting that agents were able to communicate more efficiently and resolve customer queries more quickly. In contrast, admin time increased slightly following the shift to remote work, but the magnitude of this rise was small and did not offset the overall time savings.

[8] Appendix Figure A5 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.

[9] 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 $d = 1,2,...,7$.

We also observe an 8% decline in break time during the post-lockdown period, suggesting that agents spent less time away from their desks. To better understand this pattern, we conducted qualitative interviews with employees, which suggest that the reduction may reflect greater flexibility in the home environment. Agents reported taking quicker lunches and using quieter moments during the day to make tea or coffee, reducing the need for formal breaks. Taken together, these findings point to meaningful productivity improvements under fully remote work, potentially facilitated by improved focus and increased autonomy.

The stability of estimates in the full sample

Appendix Table A3 confirms that our findings are robust to using the full sample of employees, rather than restricting the analysis to the balanced panel. This broader sample includes agents with shorter tenures or incomplete employment spells, such as those who joined or left the firm around the time of the remote work transition. Obtaining very similar point estimates in this larger and more heterogeneous sample strengthens the internal validity of our results and suggests that the observed productivity gains are not driven by selective attrition related to productivity (see Appendix Table A4) or changes in sample composition (as discussed below). The estimated magnitudes are very similar to those in the balanced panel: the number of calls handled per hour increased by approximately 7.7% during the lockdown and 9.4% in the post-lockdown period, relative to a pre-period mean of 10.6.

Decomposing productivity gains: composition effects vs. within-worker effects

A central question in evaluating remote work policies is whether observed productivity gains arise from attracting different types of workers (composition or between-worker effects) or from improving working conditions for existing employees (within-worker effects). This distinction has important implications for both public policy and firm strategy. If gains stem primarily from recruiting more skilled or better-matched workers, then the benefits of remote work may be concentrated among firms with access to such talent. In contrast, if gains are driven by environmental improvements that enhance the productivity of incumbent workers, then remote work has the potential to deliver broader productivity improvements across a wide range of settings.

To investigate this, we decompose the total productivity effect into within-worker and composition components. Panel A of Figure 4 presents coefficient estimates from two OLS regressions where the dependent variable is calls per hour. It compares the total effects and within-worker effects of fully remote work during the lockdown and post-lockdown periods, relative to the pre-pandemic baseline. The total effects (shown in red squares) are estimated using the full sample, controlling for age, age squared, call composition variables, team leader fixed effects, supervisor fixed effects, month fixed effects, and day-of-week fixed effects. The within-worker effects (shown in blue circles) are estimated using a balanced panel and additionally include agent fixed effects. Orange diamonds show the composition effect, calculated as the difference between the total and within-worker estimates. Whiskers represent 95% confidence intervals.

The figure shows that productivity rose meaningfully in both periods, driven almost entirely by within-worker improvements. During the lockdown, the within-worker effect was 0.90, compared to a total effect of 0.69, implying a composition effect of –0.21. In the post-lockdown period, the within-worker effect increased to 1.04, while the total effect was 0.75, resulting in a composition effect of –0.28. In both periods, composition effects are negative and statistically insignificant, suggesting that hiring a more diverse workforce did not come at the expense of productivity.

Panel B presents the same decomposition in a stacked bar format for ease of interpretation. The dominance of the blue (within-worker) segments in both periods visually reinforces the finding that productivity gains were not driven by changes in workforce composition or firms hiring better-matched workers. Instead, the gains are likely to reflect improvements in individual performance resulting from the shift to remote work, particularly by allowing employees to work in more focused home environments.

Heterogeneity by demographic characteristics and baseline productivity

Appendix Table A5 examines heterogeneity in the productivity response across key demographic groups, including gender, marital status, and educational attainment. We do not find strong evidence of differential effects in the number of calls per hour or call duration across these groups. This suggests that the observed productivity gains from fully remote work were not confined to a particular subgroup but instead were present across a range of worker profiles. While the underlying mechanisms may vary, these results point to a relatively broad-based response to the remote work environment and lend additional support to the overall pattern of improved efficiency following the shift to fully remote work.

One notable source of heterogeneity emerges when we examine baseline productivity levels. As shown in Appendix Table A6, agents who were lower performers during the work-from-office period experienced larger productivity gains after transitioning to fully remote work. Specifically, low-productivity agents increased their call volume by 1.34 calls per hour and reduced their average call duration by 54 seconds. These patterns imply that the remote environment played a levelling role by narrowing performance gaps and enhancing overall efficiency.

To rule out mechanical mean reversion as an alternative explanation for these patterns, Appendix Table A7 conducts a placebo analysis using only pre-pandemic data. It compares productivity outcomes between the first and second halves of 2019, a period during which no major organizational changes occurred. If the post-remote gains among low-productivity agents in Table A6 were simply a statistical artifact, similar improvements should appear in this placebo window. Yet, the interaction terms for low-productivity agents are very small in magnitude and statistically insignificant across all specifications. For example, in the balanced panel (Columns 3 and 4), the coefficients for low-productivity agents remain near zero (0.27 for calls per hour; –3.17 seconds for call duration), in stark contrast to the large gains observed under remote work. This reinforces our interpretation that the documented improvements reflect productivity effects of the remote work environment, rather than regression to the mean.

Do the productivity gains come at the expense of service quality?

One potential concern is that the observed productivity gains may have come at the expense of service quality. To examine this, we analyze two measures of quality: (i) a monthly audit score based on team leader evaluations of ten randomly selected calls, and (ii) the average rating provided by customers after completing their calls. As shown in Appendix Table A8, both measures remained stable or improved in the post-pandemic period. This suggests that the increase in productivity was not achieved by cutting corners or compromising service standards.

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

An important concern in discussions of fully remote versus in-person work is the extent to which initial face-to-face onboarding affects employees' long-term growth and retention. While executives often emphasize the value of in-person mentoring and socialization for organizational cohesion, there is remarkably little causal evidence to support or refute these claims.

We provide the first quasi-experimental evidence on this question, leveraging the COVID-19 lockdown in Turkey as a natural experiment. At Tempo, new hires typically wait 8–12 weeks between application and start date. The timing of the lockdown abruptly shifted this process, creating two comparable cohorts of workers who applied for the same in-person call center jobs but began under different onboarding modalities.

The control group, "office starters", consists of agents who began work between 16 and 4 weeks before the lockdown and received at least four weeks of in-person onboarding. The treatment group, "remote starters", includes those who applied pre-lockdown but began working during the 12 weeks following the shift to remote work, thus starting their roles entirely online.

Appendix Figure A6 confirms that these two groups are well balanced on a range of observable characteristics, including age, gender, education, marital status, and whether they received company-provided hardware or internet assistance. This balance supports the validity of the design by minimizing concerns about selection or compositional bias.

Panel A of Figure 5 shows that remote starters were initially more productive, handling more calls per hour. This early advantage reflects Tempo's shift in onboarding protocols: remote workers were put on the phones faster, with less classroom-style training. However, this gap closes over time, and by around day 175, office starters catch up and then outperform their remote counterparts. Regression results in Appendix Table A9 confirm that this divergence becomes statistically significant after 160 days on the job.

Panel B of Figure 5 reveals an even starker difference: remote starters had substantially higher attrition rates. Qualitative evidence from employee interviews suggests that initial in-person exposure helped new hires form stronger social bonds, navigate early challenges more effectively, and build a sense of belonging within the organization.

In sum, while remote onboarding may offer initial productivity gains through earlier task engagement, it appears to come at the cost of long-term productivity growth and employee retention. These findings underscore the importance of face-to-face interaction during the early phase of employment—even in jobs that can be done fully remotely. Motivated by these insights, Tempo has since revised its onboarding strategy to include at least one in-office day per month for new remote hires, aiming to replicate some of the benefits of in-person training.

5. Conclusion

Our analysis of Tempo's transition to fully remote work reveals three key insights with broad implications for workforce management and labor market inclusion.

First, remote work reshaped the composition of the workforce. By removing geographic and mobility constraints, the firm tapped into a wider talent pool: hiring more educated and older workers, and significantly increasing the representation of women and employees from non-metropolitan areas. Both groups are traditionally underrepresented in the Turkish labor market, suggesting that remote work can serve as a powerful tool for improving inclusion and access.

Second, the shift had meaningful and persistent effects on productivity. Agents handled more calls per hour, driven by shorter call durations. These performance gains were sustained over time and were not achieved at the expense of service quality. On the contrary, customer ratings and internal audit scores remained stable or improved. The productivity improvements were broad-based across demographic groups, indicating that fully remote work can raise average performance in the firm.

Third, we provide the first quasi-experimental evidence on the importance of initial onboarding modality. Remote starters (those who began their roles entirely online) ramped up more quickly and initially outperformed their peers. However, this early advantage was short-lived. By around six months on the job, in-person starters had overtaken their remote counterparts in productivity, and they were also significantly more likely to remain at the firm. These findings point to the lasting benefits of early face-to-face interaction, even in jobs that are fully remote in the long run.

Taken together, our results highlight the potential of remote work to broaden participation and boost productivity but also the need for deliberate strategies around onboarding and retention to sustain these gains over time. A simple but effective approach is to incorporate structured in-person onboarding, such as requiring new hires to attend the office for a short initial period, before transitioning to fully remote roles. This onboarding model could combine the early productivity benefits of remote work with the long-term engagement and retention advantages of face-to-face interaction.

References

Aksoy, C. G., Barrero, J. M., Bloom, N., Davis, S. J., Dolls, M., & Zarate, P. (2022). Working from home around the world. Brookings Papers on Economic Activity, 2, 281–360.

Aksoy, C. G., Barrero, J. M., Bloom, N., Davis, S. J., Dolls, M., & Zarate, P. (2023). Time savings when working from home. AEA Papers and Proceedings, 113, 597–603.

Aksoy, C. G., Barrero, J. M., Bloom, N., Davis, S. J., Dolls, M., & Zarate, P. (2025). The global persistence of work from home. Proceedings of the National Academy of Sciences, 122(27), e2509892122.

Angelici, M., & Profeta, P. (2024). Smart working: Work flexibility without constraints. Management Science, 70(3), 1680–1705.

Atkin, D., Schoar, A., & Shinde, S. (2023). Working from home, worker sorting and development (NBER Working Paper No. 31515). National Bureau of Economic Research.

Battiston, D., Blanes Vidal, J., & Kirchmaier, T. (2021). Face-to-face communication in organizations. Review of Economic Studies, 88(2), 574–609.

Benson, A. (2014). Rethinking the two-body problem: The segregation of women into geographically dispersed occupations. Demography, 51(5), 1619–1639.

Bloom, N., Dahl, G., & Roth, D.-O. (2025). Work from home and disability employment. American Economic Review: Insights. (Forthcoming).

Bloom, N., Han, R., & Liang, J. (2024). Hybrid working from home improves retention without damaging productivity. Nature, 630, 920–925.

Bloom, N., Liang, J., Roberts, J., & Ying, Z. J. (2015). Does working from home work? Evidence from a Chinese experiment. Quarterly Journal of Economics, 130(1), 165–218.

Buckman, S., Barrero, J. M., Bloom, N., & Davis, S. J. (2025). Measuring work from home (NBER Working Paper). National Bureau of Economic Research.

Choudhury, P., Foroughi, C., & Zepp Larson, B. (2021). Work-from-anywhere: The productivity effects of geographic flexibility. Strategic Management Journal, 42(4), 655–683.

Choudhury, P., Lane, J. N., & Bojinov, I. (2023). Virtual water coolers: A field experiment on the role of virtual interactions on organizational newcomer performance (Harvard Business School Technology & Operations Mgt. Unit Working Paper No. 21-125).

Choudhury, P., Khanna, T., Makridis, C. A., & Schirmann, K. (2024). Is hybrid work the best of both worlds? Evidence from a field experiment. Review of Economics and Statistics, 1–24.

Emanuel, N., & Harrington, E. (2024). Working remotely? Selection, treatment, and the market for remote work. American Economic Journal: Applied Economics, 16(4), 528–559.

Gibbs, M., Mengel, F., & Siemroth, C. (2023). Work from home and productivity: Evidence from personnel and analytics data on information technology professionals. Journal of Political Economy Microeconomics, 1(1), 7–41.

Ho, L., Jalota, S., & Karandikar, A. (2023). Bringing work home: Flexible arrangements as gateway jobs for women in West Bengal (MIT Working Paper).

Hsu, D. H., & Tambe, P. B. (2025). Remote work and job applicant diversity: Evidence from technology startups. Management Science, 71(1), 595–614.

International Monetary Fund. (2024). Labor market gender gaps in Türkiye: A bird's eye view. IMF Working Paper No. 2024/171.

Künn, S., Seel, C., & Zegners, D. (2022). Cognitive performance in remote work: Evidence from professional chess. The Economic Journal, 132(643), 1218–1232.

Luca, D., Özgüzel, C., & Wei, Z. (2025). The new geography of remote jobs in Europe. Regional Studies, 59(1), 2352526.

Mas, A., & Pallais, A. (2017). Valuing alternative work arrangements. American Economic Review, 107(12), 3722–3759.

Shen, L. (2023). Does working from home work? A natural experiment from lockdowns. European Economic Review, 151, 104323.

World Economic Forum. (2024). The rise of global digital jobs (White Paper). Available here: https://www.weforum.org/whitepapers/the-rise-of-global-digital-jobs

Yang, L., Holtz, D., Jaffe, S., Suri, S., Sinha, S., Weston, J., Joyce, C., Shah, N., Sherman, K., Hecht, B., & Teevan, J. (2022). The effects of remote work on collaboration among information workers. Nature Human Behaviour, 6(1), 43–54.

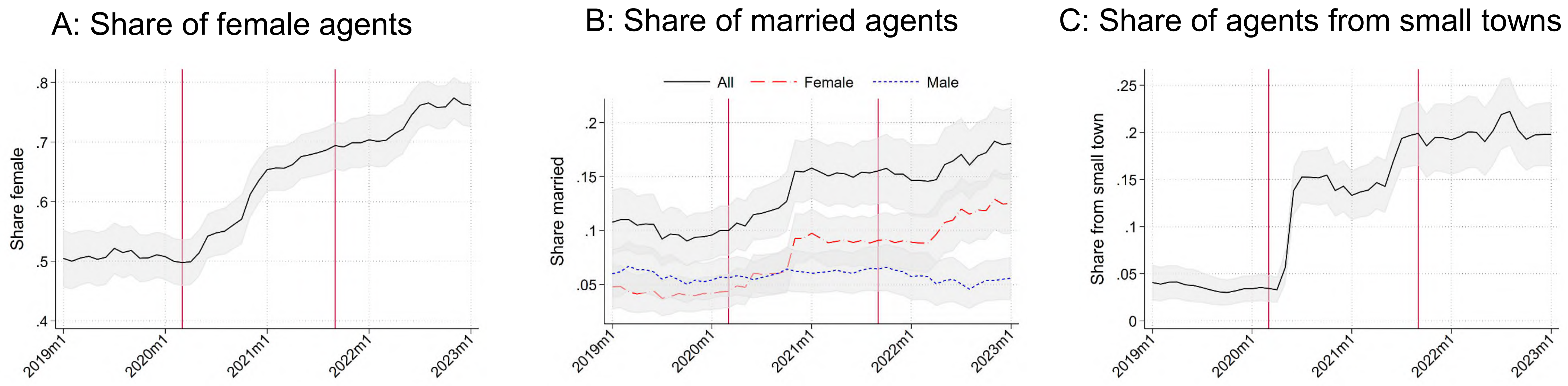
Figure 1: Agents moved from busy open-plan areas to quieter home environments

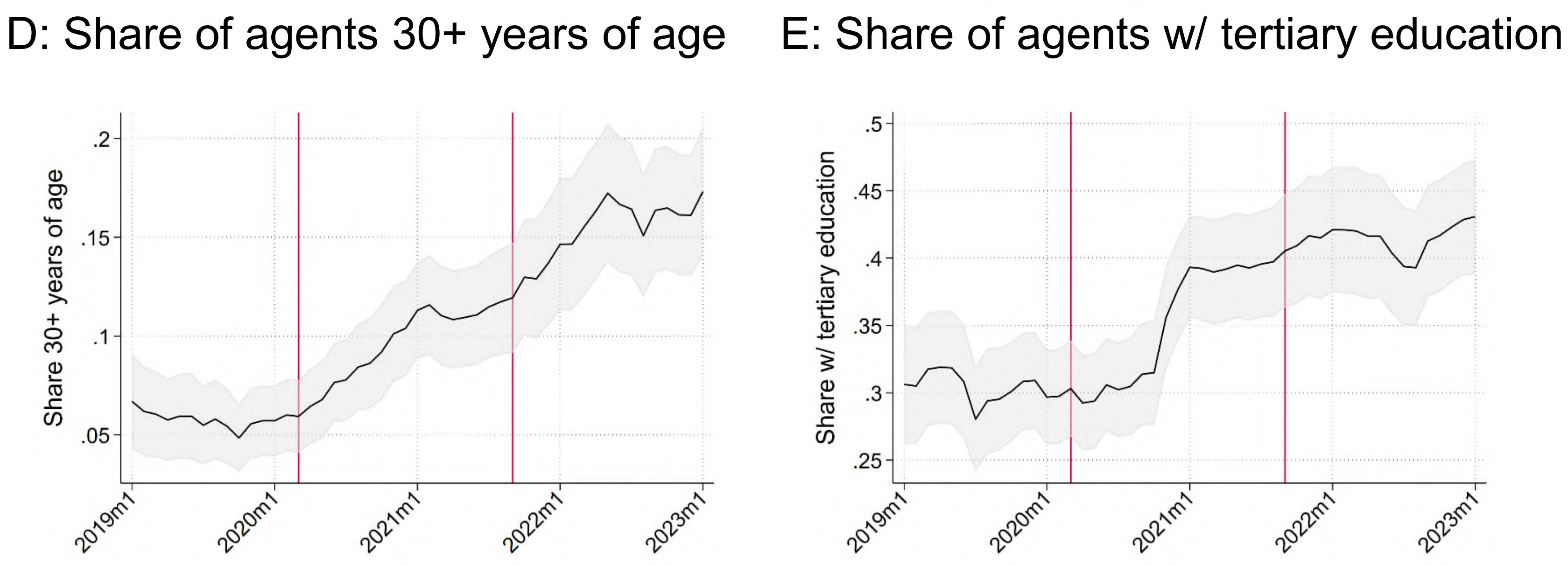
A: Working from the office

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).

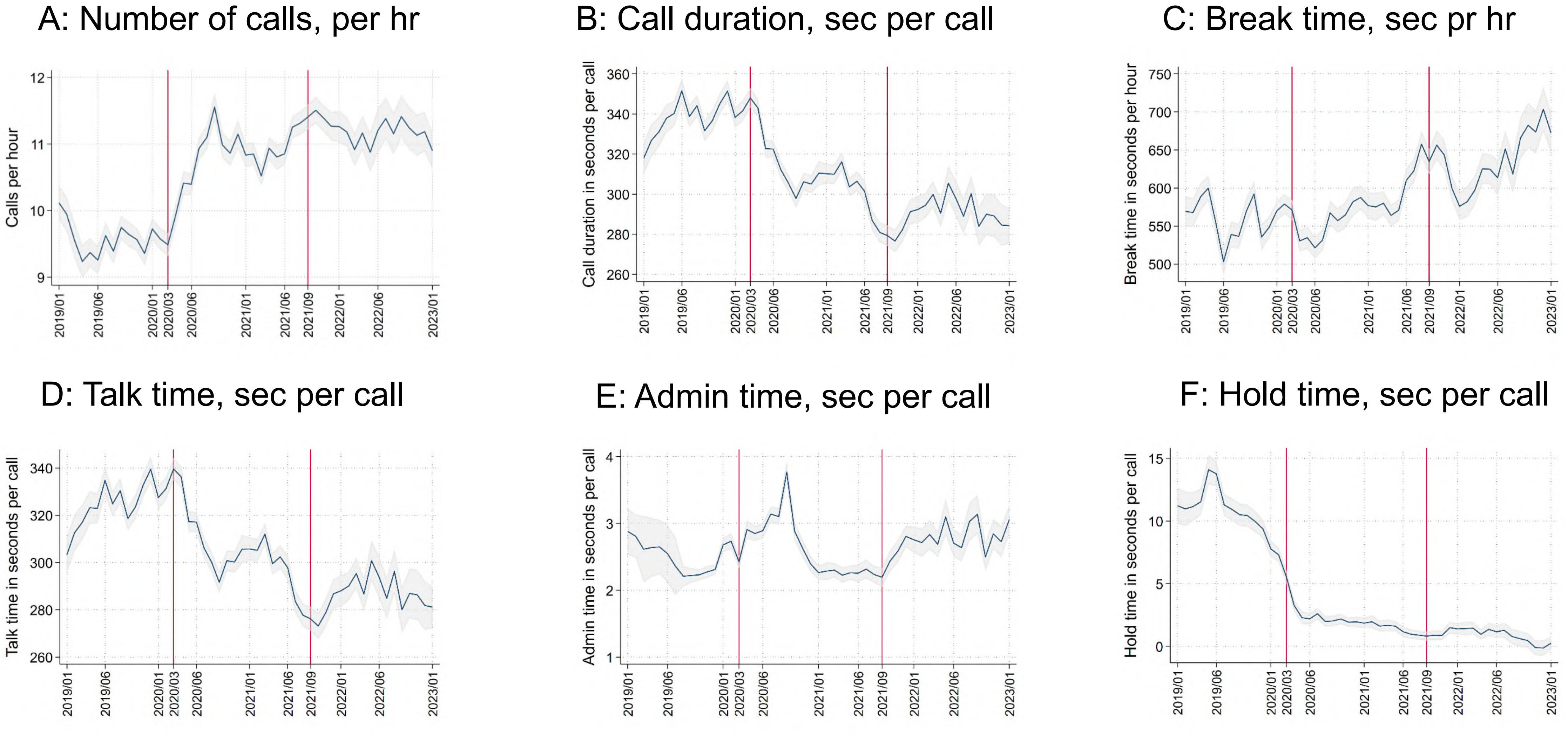
Figure 2: Remote working brought a rising share of agents who are female, married, college educated, from small towns and older





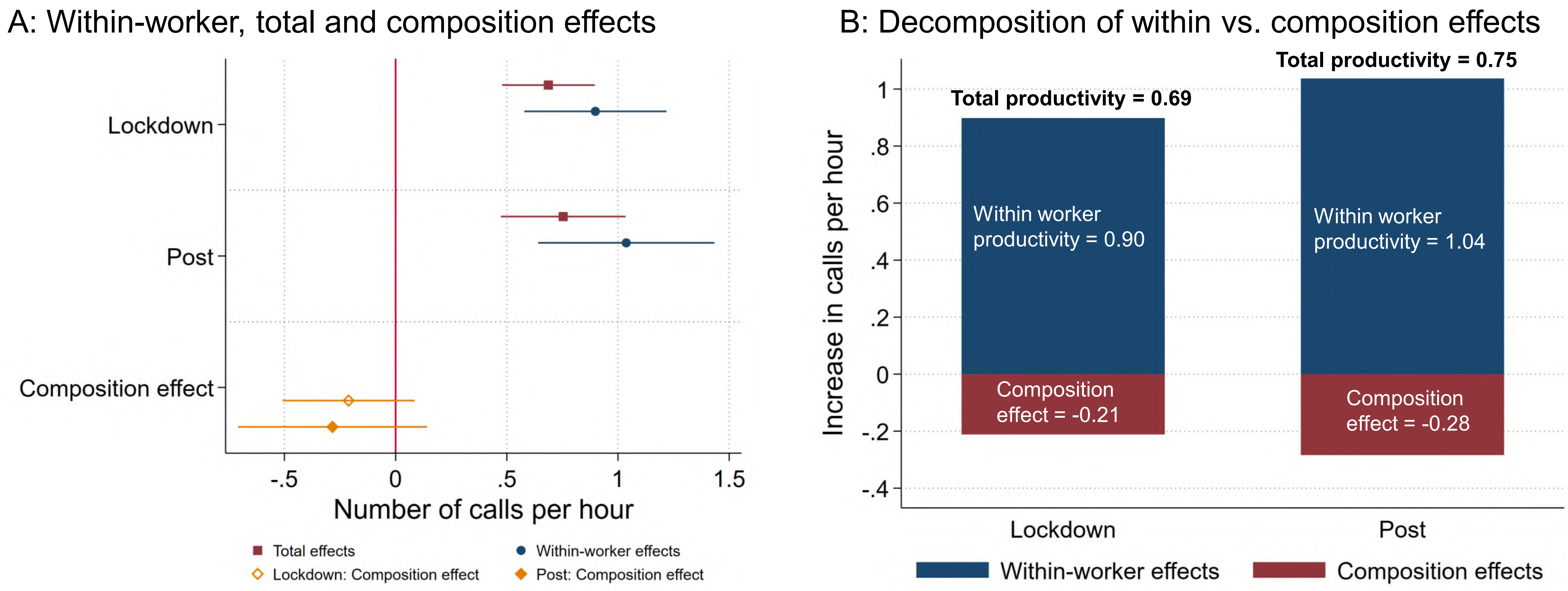
Notes: This figure shows monthly changes in the workforce due to new hires and quits. Each panel displays monthly means, with shaded areas representing 95% confidence intervals. Vertical red lines mark March 2020 and September 2021, corresponding to the start and end of the COVID-19 lockdown period in Turkey. “Small town” refers to provinces with populations under 750,000. The full sample covers 60 of Turkey’s 81 provinces, 33 of which are classified as small towns.

Figure 3: Productivity rose after the shift to remote work, with more calls per hour and shorter call durations



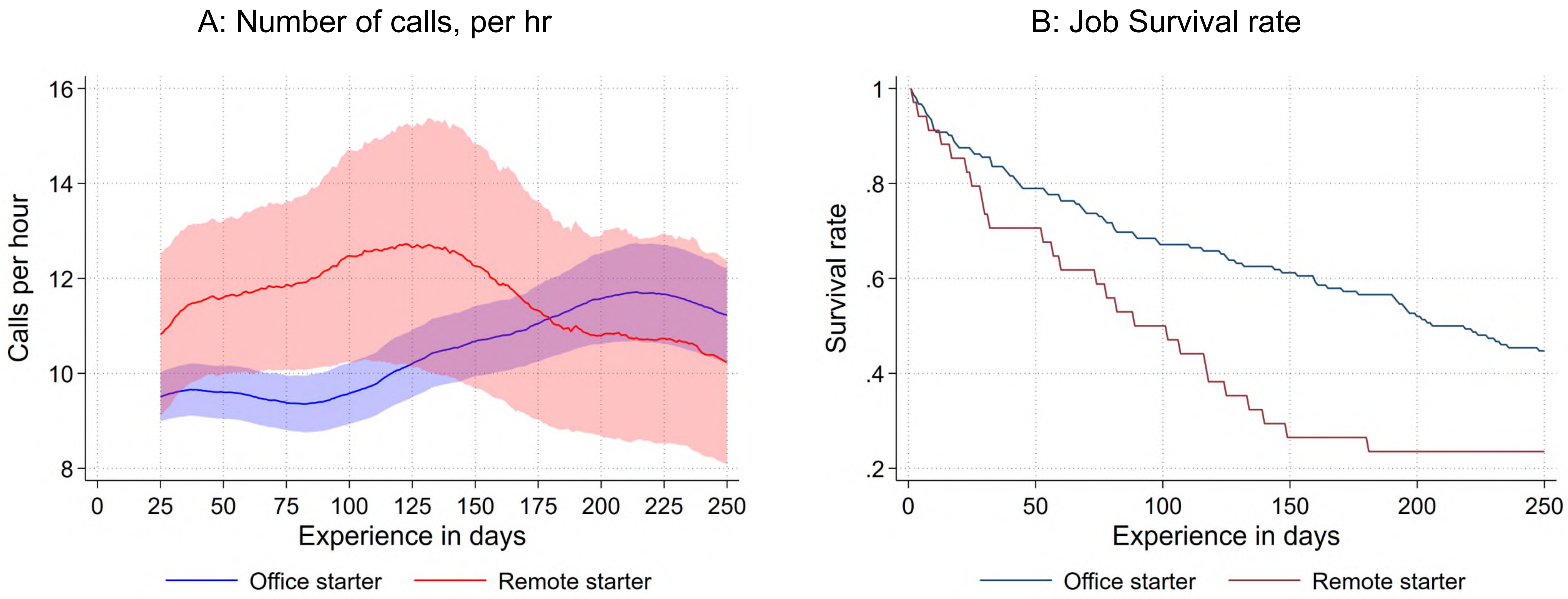
Notes: This figure shows predictions from OLS regressions of productivity outcomes (indicated in the panel titles) on month fixed effects, with February 2020 omitted as the reference month. All regressions control for call composition, repeat calls, and include agent fixed effects. Standard errors are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

Figure 4: Productivity gains reflect within-worker improvements rather than compositional changes in the workforce



Notes: Panel A presents coefficient estimates from two OLS regressions where the dependent variable is calls per hour. Lockdown is a dummy variable equal to 1 if the calendar date falls within the lockdown period in Turkey (from 11 March 2020 to 5 September 2021, inclusive), and 0 otherwise. Post is a dummy variable equal to 1 if the calendar date is after 5 September 2021, 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 March 2020. Total effects are estimated using the full sample, controlling for age, age squared, call composition variables, team leader fixed effects, supervisor fixed effects, month fixed effects, and day-of-week fixed effects. Within-worker effects are estimated using the balanced panel and additionally include agent fixed effects. Standard errors are clustered at the agent level, and 95% confidence intervals are shown as whiskers. Panel B displays a stacked decomposition, where the Composition effect is computed as the difference between the Total effect and the Within-worker effect.

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 using the standard error of the mean for each group and experience level. "Remote starters" are agents who applied before the shift to remote work but began employment within 12 weeks after the transition on 11 March 2020. "Office starters" are agents who started between 16 and 4 weeks before the lockdown and received at least four weeks of in-person training. By day 80, both groups are working fully remotely. Panel B displays the survival rates of office and remote starter employees over time.

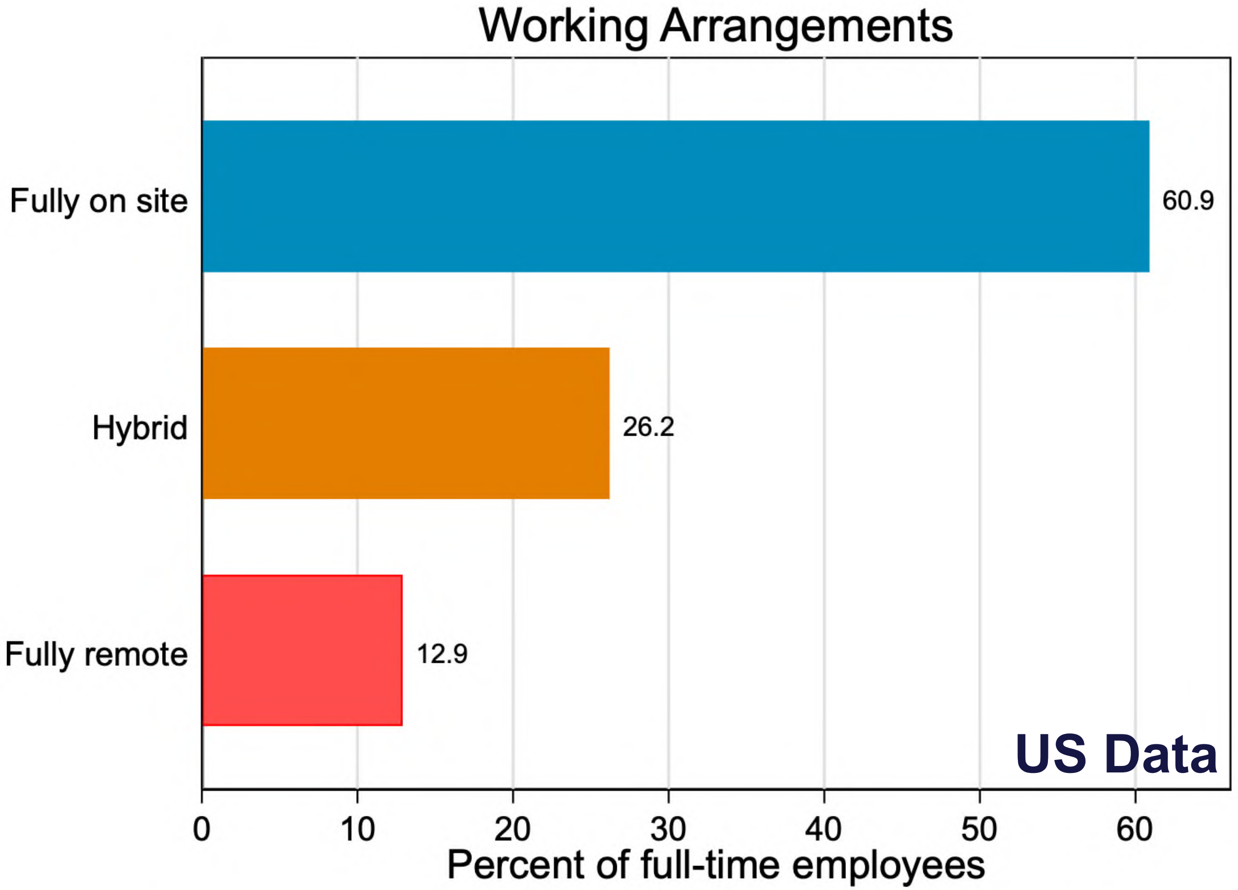
Table 1: Balanced panel – productivity rose mainly due to shorter calls and less hold time

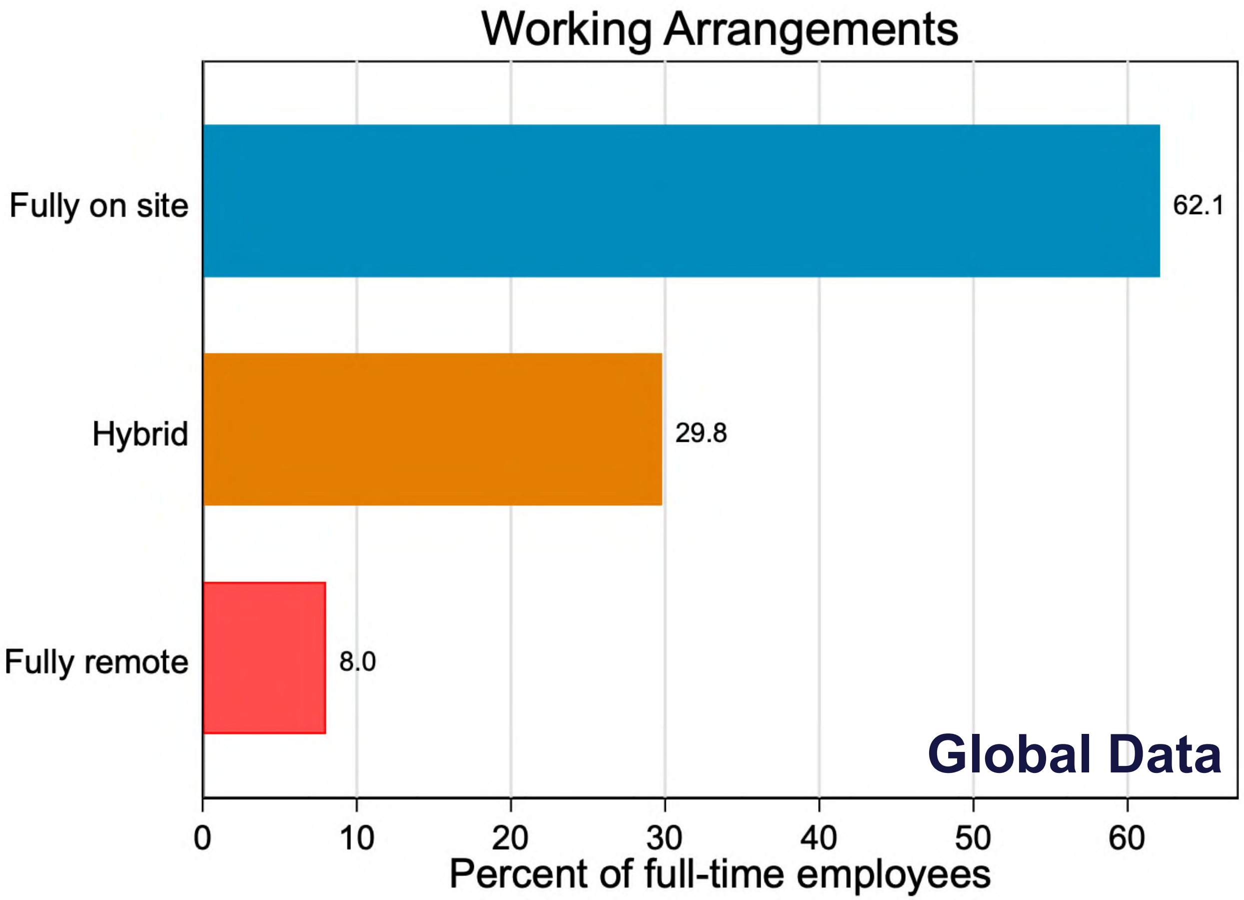
	(1)	(2)	(3)	(4)	(5)	(6)
	Number of calls per hour	Call duration in seconds per call	Break time in seconds per hour	Talk time in seconds per call	Admin time in seconds per call	Hold time in seconds per call
Lockdown	0.90***	-17.76***	-50.18***	-13.32***	0.56***	-4.99***
	(0.16)	(3.98)	(16.13)	(3.96)	(0.11)	(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: This table reports OLS regressions, with the dependent variables indicated in the column headings. All specifications include agent fixed effects, team leader fixed effects, supervisor fixed effects, month-of-year dummies, and day-of-week dummies. The variable Lockdown is a dummy equal to 1 if the calendar date falls within the national lockdown period in Turkey (11 March 2020 to 5 September 2021, inclusive), and 0 otherwise. Post is a dummy equal to 1 for dates after 5 September 2021, and 0 otherwise. The omitted category is Pre, which equals 1 for dates before 11 March 2020. Additional unreported controls include age, age squared, and call composition variables. Standard errors are clustered at the agent level. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Appendix

Figure A1: Fully Remote Workers are about 10% of All Employees

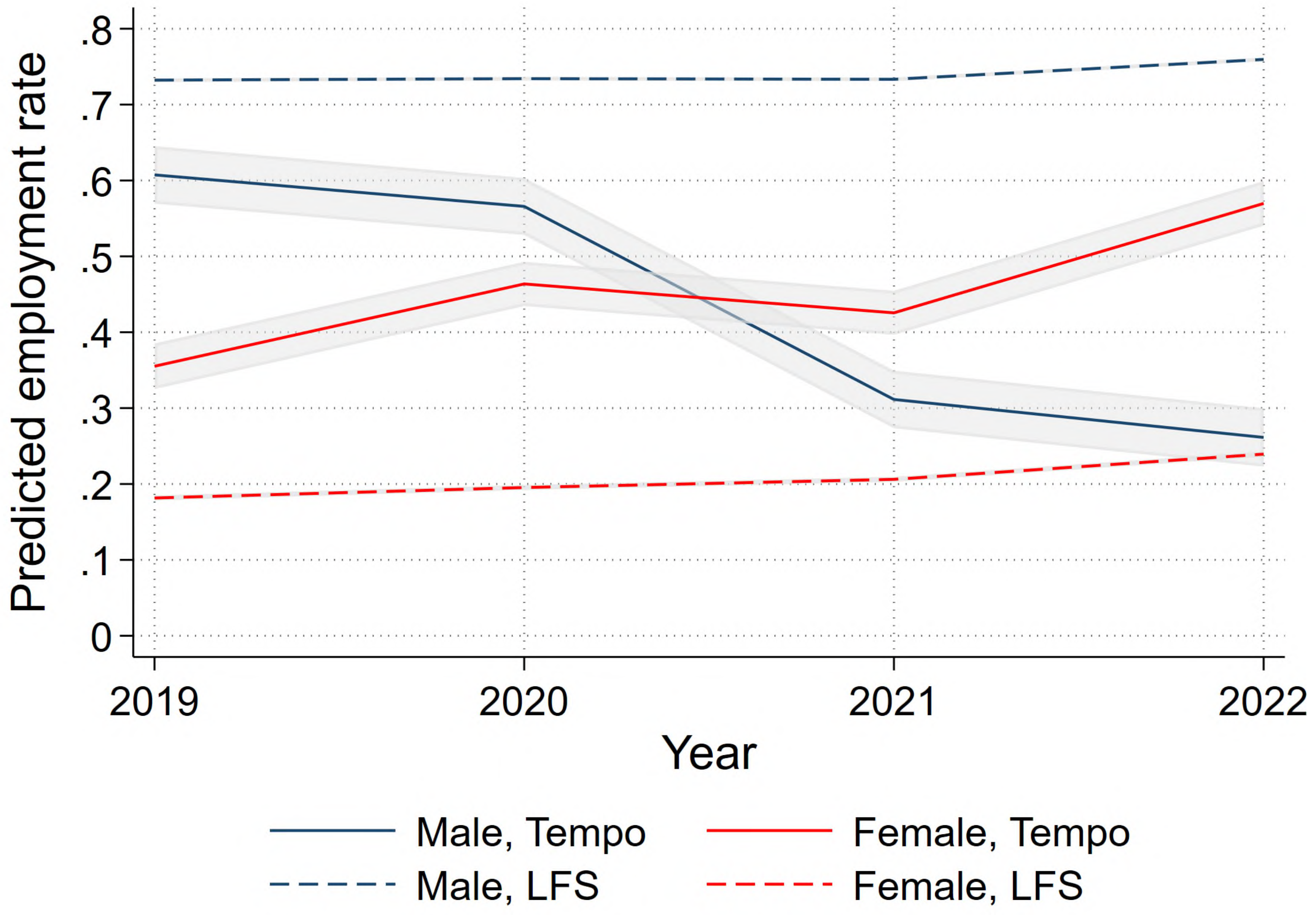




Source: Survey of Workplace Arrangements and Attitudes (SWAA), January 2024 – April 2025. Sample includes U.S. residents aged 20 to 64 who earned at least $10,000 in the prior year. Responses are weighted to match the Current Population Survey by age, gender, income, and education. N = 53,268. See Barrero et al. (2025) for details.

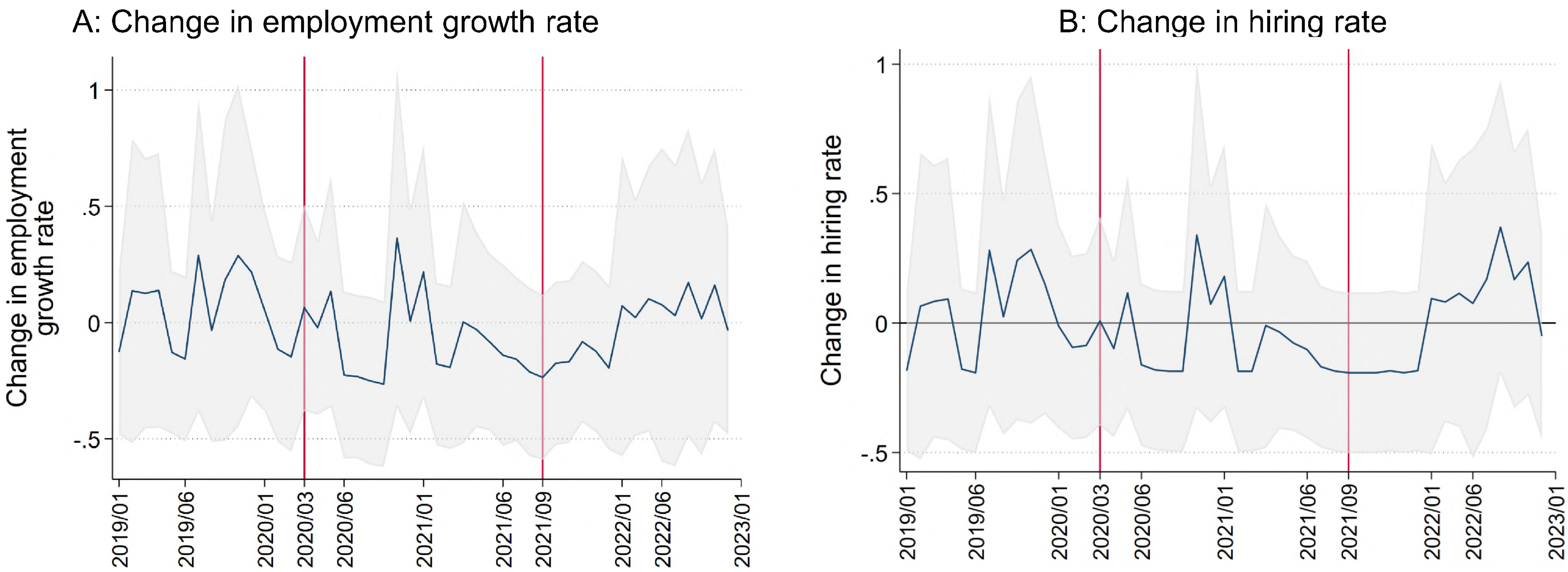
Source: Global Survey of Working Arrangements (G-SWA), November 2024 – February 2025. Sample includes residents aged 20 to 64 across 40 countries. Samples are broadly representative of national populations by age and gender. N = 26,202. See Aksoy et al. (2025) for details.

Figure A2: Larger increases in the predicted employment rate for women in Tempo than Turkey as a whole



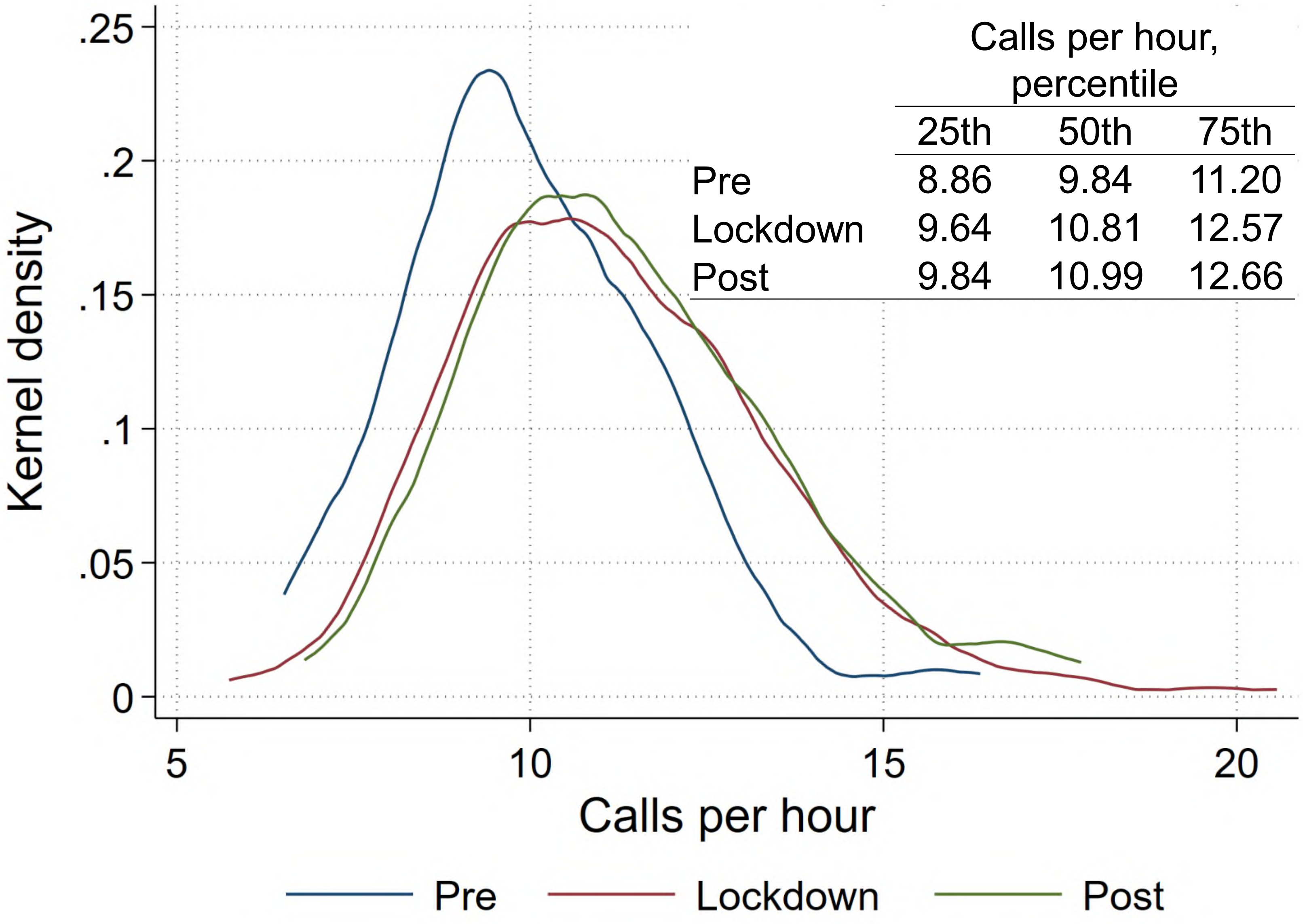
Notes: This figure presents predictions from two separate regressions. The solid lines correspond to a regression of an employment dummy (equal to 1 if the agent was employed by Tempo in a given year and 0 otherwise) on the interaction between female and year dummies, controlling for age, age squared, marital status, tertiary education, and city fixed effects. The sample includes all Tempo agents. The dashed lines correspond to a regression of an employment dummy (equal to 1 if employed and 0 if unemployed or out of the labor force) on age, age squared, marital status, tertiary education, and NUTS-2 fixed effects. The sample is drawn from the Turkish Labour Force Survey, 2019–2022. Grey shaded areas indicate 95 percent confidence intervals.

Figure A3: Employment growth and hiring rates remained stable after the shift to fully remote work



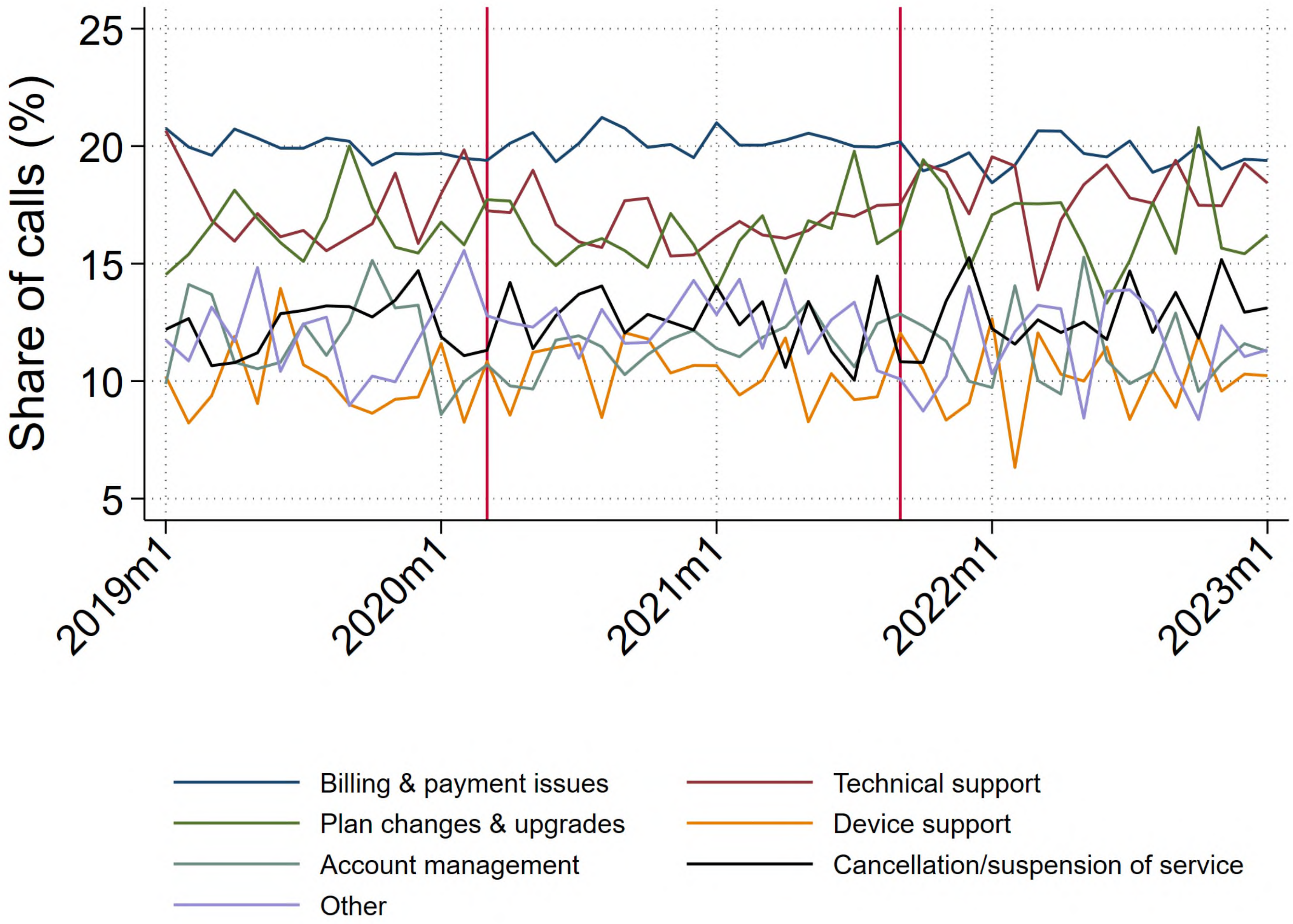
Notes: This figure plots coefficient estimates from two OLS regressions where the dependent variables are employment growth and hiring rate in Panel A and Panel B, respectively. The outcome is regressed on monthly dummies, and the base category is Feb/2020 – the month prior to the shift to remote work. Standard errors are heteroskedasticity robust and the shaded area depicts 95% confidence intervals.

Figure A4: Agents process more calls after the shift to fully remote work



Notes: This figure presents univariate kernel density estimates (Epanechnikov kernel) of calls per hour measured at the agent level across the Pre, Lockdown, and Post periods. The sample includes agents who are observed in all three periods and who worked at least 10 days in each.

Figure A5: 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 at the agent level based on 10 randomly selected calls per month. The call categories are defined as follows: (i) Billing & Payment Issues—inquiries about bills, payments, direct debits, or charge disputes; (ii) Technical Support—issues with voice calls, SMS, data connectivity, or network coverage; (iii) Plan Changes & Upgrades—calls about modifying plans, upgrading devices or services, or exploring new offers; (iv) Device Support—help with mobile device setup, troubleshooting, warranties, or app guidance; (v) Account Management—queries about personal information updates, preferences, or password resets; (vi) Cancellation or Suspension—requests to terminate or pause service; and (vii) Other—miscellaneous issues including number portability, roaming, accessibility support, lost/stolen devices, promotions, and network feedback.

Figure A6: Balance tests for the RDD sample

Notes: This figure presents a coefficient plot from a linear probability model. The dependent variable is a dummy equal to 1 if the agent joined the firm between 16 and 4 weeks before the COVID-19 lockdown, thus receiving at least four weeks of in-person training, and 0 if the agent applied before the shift to remote work but started during the 12 weeks following the transition on 11 March 2020. The regression includes unreported province fixed effects. Standard errors are heteroskedasticity-robust, and whiskers represent 95% confidence intervals.

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 for agent characteristics, productivity outcomes, and quality outcomes. Agent characteristics are based on the full sample of agents. Productivity outcomes and quality outcomes are drawn from the balanced panel and are reported at the agent-workday and agent-month levels, respectively. The Pre period includes all days up to and including 11 March 2020; Lockdown refers to the period from 11 March 2020 to 6 September 2021; and Post covers 7 September 2021 onward.

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

	(1)	(2)
	Hired pre (averages)	Remote hire
Female	0.47	0.27***
		(0.03)
Married	0.07	0.18***
		(0.03)
Completed tertiary education	0.30	0.07***
		(0.02)
Smaller town	0.03	0.33***
		(0.02)
30+ years of age	0.04	0.10***
		(0.04)
R-squared		0.199
Number of observations		1449
Sample mean		0.44

Notes: This table presents baseline averages and OLS regression results. Column (1) reports averages for agents hired before the lockdown, reporting the proportion of agents who were female, married, had completed tertiary education, were from outside metropolitan provinces, and were at least 30 years old. Column (2) reports estimates from a linear probability model. The dependent variable is Remote hire, a dummy equal to 1 if the agent was hired on or after 11 March 2020 (i.e. following the shift to remote work), and 0 if hired before that date. The unit of observation is the individual agent. Standard errors are robust. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, 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: This table reports OLS regressions, with dependent variables indicated in the column headings. All specifications include agent fixed effects, team leader fixed effects, supervisor fixed effects, month-of-year dummies, and day-of-week dummies. Lockdown is a dummy equal to 1 if the calendar date falls within the lockdown period in Turkey (11 March 2020 to 5 September 2021, inclusive), and 0 otherwise. Post is a dummy equal to 1 for dates after 5 September 2021, and 0 otherwise. The omitted category is Pre, which equals 1 for dates before 11 March 2020. Additional unreported controls include age, age squared, and call composition variables. The sample includes all agents. Standard errors are clustered at the agent level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table A4: Attrition is not associated with productivity or service quality

	(1)	(2)	(3)	(4)	(5)
	Exit dummy				
Calls per hour	-0.00				-0.03
	(0.01)				(0.03)
Call duration in seconds per call		-0.00			-0.00
		(0.00)			(0.00)
Random audit rating			-0.08		-0.07
			(0.07)		(0.07)
Customer rating				-0.00	-0.00
				(0.00)	(0.00)
R-squared	0.10	0.10	0.11	0.11	0.11
Number of observations	517	517	517	517	517

Notes: This table reports OLS regressions. The dependent variable an exit dummy equal to 1 if an agent resigned after the shift to remote work and before the end of the panel – between 12 March 2020 and 31 December 2022 and 0 otherwise. Unreported controls include the age, marital status, female, completed tertiary education, log of cumulative calls, team leader and supervisor FE. Standard errors are heteroskedasticity robust. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table A5: 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: This table presents OLS regressions with individual (agent) fixed effects; dependent variables are indicated in the column headings. All specifications include agent fixed effects, team leader fixed effects, supervisor fixed effects, month-of-year dummies, and day-of-week dummies. Lockdown is a dummy equal to 1 if the calendar date falls within the lockdown period in Turkey (11 March 2020 to 5 September 2021, inclusive), and 0 otherwise. Post is a dummy equal to 1 for dates after 5 September 2021, and 0 otherwise. The omitted category is Pre, defined as dates prior to 11 March 2020. Additional unreported controls include agent age, age squared, and call composition variables. The sample is restricted to agents observed in all three periods: Pre, Lockdown, and Post. Standard errors are clustered at the agent level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively

Table A6: 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: This table presents OLS regressions with individual (agent) fixed effects; dependent variables are indicated in the column headings. All specifications include agent fixed effects, team leader fixed effects, supervisor fixed effects, month-of-year dummies, and day-of-week dummies. Unreported covariates include agent age, age squared, the log of cumulative calls on day $t-1$, and call composition variables. Unreported coefficients include Lockdown, Lockdown × WFO: Medium Productivity, and Lockdown × WFO: Low Productivity. Lockdown is a dummy equal to 1 if the calendar date falls between 11 March 2020 and 5 September 2021 (inclusive), and 0 otherwise. Post is a dummy equal to 1 for dates after 5 September 2021, and 0 otherwise. The omitted category is Pre, defined as dates before 11 March 2020.Baseline productivity during the work-from-office (WFO) period is calculated using data from all odd calendar dates prior to the shift to remote work. WFO: Medium Productivity is a dummy equal to 1 if the agent's average call duration in this period falls into the second tercile of the baseline distribution. WFO: Low Productivity is defined analogously for the third tercile. The sample includes agents observed in all three periods—Pre, Lockdown, and Post—and excludes odd calendar dates used to construct the baseline productivity measure. Standard errors are clustered at the agent level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table A7: Placebo tests – the shift to fully remote work has a levelling effect on agent performance

	(1)	(2)	(3)	(4)
	Full sample		Balanced panel	
	Calls per hour	Call duration in seconds per call	Calls per hour	Call duration in seconds per call
H2 2019	0.22	-1.33	-0.19	5.62
	(0.16)	(3.72)	(0.17)	(5.44)
H2 2019 x H2 2019: medium productivity	0.04	-4.33	0.42	-13.33
	(0.21)	(5.12)	(0.25)	(8.46)
H2 2019 x H2 2019: low productivity	-0.15	2.39	0.27	-3.17
	(0.19)	(5.81)	(0.24)	(10.29)
R-squared	0.392	0.484	0.293	0.383
Number of observations	96,322	96,322	25,420	25,420
Number of clusters	792	792	185	185
Sample mean	12.94	301.22	11.65	326.22

Notes: This table presents OLS regressions with individual (agent) fixed effects; dependent variables are indicated in the column headings. All specifications include agent fixed effects, team leader fixed effects, supervisor fixed effects, month-of-year dummies, and day-of-week dummies. H2 2019 is a dummy variable equal to 1 if the calendar date falls in the second half of 2019, and 0 otherwise. Baseline productivity is calculated for each agent using data from the first half of 2019. H1 2019: Median Productivity is a dummy equal to 1 if the agent's average call duration during this period falls into the second tercile of the baseline distribution. H1 2019: Low Productivity is defined analogously for the third tercile. Columns (1) and (2) include all agents working in 2019, while Columns (3) and (4) restrict the sample to agents who were employed in 2019 and remained at the firm through the Post period. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table A8: 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: This table presents OLS regressions with individual (agent) fixed effects. Dependent variables are indicated in the column headings and are measured at the agent-month level. All specifications include agent fixed effects, team leader fixed effects, supervisor fixed effects, and month-of-year dummies. Unreported controls include agent age, age squared, and call composition variables. Random Audit Rating is a binary variable equal to 1 if a manager, after reviewing ten randomly selected calls from a given month, rates the agent as performing well, and 0 otherwise. Customer Rating is the average customer-provided score for the agent, ranging from 1 to 100. Lockdown is a dummy equal to 1 if the calendar month falls within the lockdown period in Turkey (March 2020 to September 2021, inclusive), and 0 otherwise. Post is a dummy equal to 1 for months after September 2021, and 0 otherwise. The omitted category is Pre, defined as months prior to March 2020.The unit of observation is the agent-month. Standard errors are clustered at the agent level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table A9: 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: This table reports OLS regressions with individual (agent) fixed effects. The dependent variable is calls per hour. Remote Starter refers to agents who applied to the firm before the shift to remote work but started within 12 weeks after the transition on 11 March 2020. Office Starter refers to agents who began working at the firm between 10 October 2019 and 10 February 2020. Unreported controls include the log of cumulative calls and call composition variables. Standard errors are clustered at the agent level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.