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 customer-service arm 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 national 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 before going remote had lower attrition, while the initial productivity advantage of fully remote starters faded over time.

JEL: J2, J3, R1

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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., 2025), 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 on 7 September 2021, the firm chose to remain fully remote. This immediate and then permanent 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.

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 January 2023 (in contrast, the female employment rate is 33% in Turkey).[2] This pattern suggests that remote work lowered 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. Relative to the pre-sample mean of 9.89 calls per hour, productivity increased by 9.1% during lockdown and 10.5% in the post-lockdown period. 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 matters for the 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. Remote starters were initially more productive, partly because they were placed on calls faster and received less classroom-style training. However, this initial advantage faded over time. By around 175 working days, office starters and remote starters had similar productivity levels. The main difference appears in retention, as employees who started in person were less likely to leave the firm. From a management-

[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., 2026), highlighting the potential of remote work to improve labor market inclusion.

practices perspective, this suggests that even in remote-first settings, a brief period of in-person onboarding can strengthen employee attachment and reduce attrition, even if its long-run productivity effects are more limited.

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 studies based on applications or short-term take-up, our setting allows us to trace sustained changes in actual employment outcomes. We show that remote work leads to lasting shifts in who is ultimately hired, even in a low-wage service-sector setting.[5]

Second, we contribute to the literature on the productivity effects of hybrid and fully remote work. Existing evidence is mixed. Some studies find positive or null effects (e.g., Bloom et al. 2015; Choudhury et al. 2021; Angelici and Profeta 2024; Bloom et al. 2024; Aksoy et al. 2026), while others document declines due to coordination frictions or adverse selection (e.g., Atkin et al. 2023; Gibbs et al. 2023; Emanuel and Harrington 2024). This mix of results suggests that productivity effects of remote work depend on organizational context and implementation.[6] Our setting helps clarify when fully remote work can work well: tasks are highly standardized, output is individually measured, and production requires limited real-time coordination across coworkers. We add to this literature by providing the first evidence on longer-term productivity after a firm-wide move to fully remote work in a developing-country setting. We find large and sustained productivity gains, especially among workers with lower baseline productivity in the office. Our setting also allows us to examine whether these gains mainly reflect changes in whom the firm hired or changes in how the same workers performed in different work environments. 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, suggesting that the productivity increase mainly reflects within-worker changes rather than selective hiring.

[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 and 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.

Finally, a related body of work examines how firms onboard and manage employees in remote and hybrid settings, with growing evidence that in-person interaction can matter for communication, learning, and retention, especially among less experienced workers. Existing studies suggest that face-to-face contact can support knowledge sharing, coordination, and attachment to the firm (e.g., Battiston et al., 2021; Sandvik et al., 2020; Bloom et al., 2024; Aksoy et al., 2026). Recent work also shows that younger and less-experienced workers who are still building their human capital may benefit more from proximity to colleagues (Emanuel et al., 2025; Wang et al., 2025). In our setting, the onboarding results speak to the practical design of remote-first work. Using quasi-experimental variation in start dates, we show that remote starters' initial productivity advantage fades over time, while workers who received in-person onboarding are less likely to exit the firm. These findings imply that fully remote work can expand hiring and sustain productivity, but that early face-to-face interaction may remain valuable for longer-run adjustment and retention.

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

2. The Company

2.1 The shift to remote work

Our study examines Tempo, a large multinational business process outsourcing company based in Turkey. Before the COVID-19 pandemic, the firm operated offices across seven provinces, with headquarters in Istanbul. It 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, the firm 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, the firm provided laptops and internet support to its employees.

The standard work arrangement for call center agents at the firm 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 the firm 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 the firm 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, the firm kept its operating model unchanged. This stability reflects the nature of the setting: the firm provides customer-service operations for large multinational and established publicly listed clients, which require standardized procedures, close monitoring, and consistent quality assurance. These practices were therefore already

embedded in the firm's operating model before the pandemic, rather than introduced as part of the remote-work transition.

For example, technology and software infrastructure, compensation policies, formal work schedules and shift lengths, team structures, and call-routing systems remained the same throughout the transition and afterwards. Agents continued to handle randomly assigned inbound calls under the same performance monitoring system, and the firm did not introduce new scripts, revise performance targets, or adopt other policies aimed at increasing call-handling speed. Finally, the transition did not involve a formal reorganization of supervisory responsibilities or scheduling practices.

After lockdown measures were lifted in Turkey on 7 September 2021, satisfied with the overall performance, the firm chose to remain fully remote rather than return to office work, and it still operates remotely today. This is therefore a setting of sustained fully remote work, not a temporary lockdown episode. Figure 1 includes two pictures of employees working in the office (left side) and four pictures of employees working from home (right side).

2.2 Employee and Performance Data

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

Our productivity analysis focuses on inbound calls handled for a major mobile telecommunications client. This client project was active before the pandemic, continued throughout the study period, and involved a large number of agents, including both new hires and existing employees. The data span January 1, 2019, to January 31, 2023, and include 1,766 distinct agents in the full sample. We also observe a balanced panel of 204 agents continuously before, during, and after the pandemic. Descriptive statistics are presented in Table 1.

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 the firm with trends in the Turkish labor force as a whole. While female employment at the firm 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.[7] 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 share of agents aged 30 and above, illustrating how the shift to remote work during the pandemic enabled the firm 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, the firm disproportionately hired women (especially married women), as well as workers in smaller towns, older employees, and university graduates (Appendix Table A1). This shift allowed the firm to tap into underutilized talent pools and increase the share of graduate employees without raising wages.[8] These patterns suggest that remote work changed who could realistically take these jobs by reducing the need to live near the workplace or commute daily.

Employment growth and hiring dynamics

The compositional changes documented above raise a natural question: did they reflect a sudden burst of hiring or attrition after the move to remote work, or a more gradual adjustment in the workforce?

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[7] Similar patterns are observed when we examine the share of agents from small towns among those who are retained until 2023. We find that the share of agents from small towns among stayers increases from around 6 percent prior to the shift to remote work and remains stable at around 22 percent after the permanent shift to remote work.

[8] The patterns we identified are not unique to this specific project but hold for the overall workforce composition of the firm. When we analyze data for the full workforce, we find very similar patterns: across the firm, remote work increased the share of agents who are female, married, college-educated, from small towns, and older. These patterns are consistent across several projects, including data entry, call center operations for financial institutions, back-office processing, and data analysis and reporting. The corresponding results are available upon request.

Appendix Figure A3 helps distinguish between these possibilities by plotting monthly employment and new hires on the project. The dashed horizontal lines show period-specific averages and point to a relatively stable pattern across phases. Total employment remains broadly stable around the transition to remote work, while the average level of new hiring does not show a sharp or sustained break after the shift. Month-to-month hiring is naturally volatile, which is expected in a customer-service setting with substantial turnover. The key point, however, is that the dashed averages do not indicate a sudden hiring surge or collapse in employment. Overall, the figure suggests that the compositional changes documented above reflect persistent changes in recruitment and retention patterns rather than sudden labor-force churn.

4. Employee Performance

4.1 Shift to Fully Remote Work and 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 monthly estimates of productivity outcomes from regressions with month fixed effects, omitting February 2020 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. Panel B shows that the entire productivity gain is driven by a reduction in average call duration.[9]

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[9] Because the transition coincided with the onset of COVID-19, part of the decline in call duration may reflect contemporaneous shifts in caller behavior or issue mix rather than the effects of remote work itself. We therefore interpret the early-2020 event-time coefficients with caution and place greater weight on the post-lockdown period, where operational conditions stabilized.

To better understand the source of these gains, Panels D, E, and F show call duration by its components: talk time, admin time, and hold time. The decline in total call duration is driven mainly by shorter talk time. This pattern is consistent with agents working in quieter home environments, which may allow them to communicate more clearly with customers, reduce repetition, and resolve issues more quickly. Admin time changes little, while hold time also falls, potentially reflecting better focus and fewer distractions.

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 5 September, and $WFHPost_t$ is a dummy indicating working from home once lockdown measures are lifted, from 6 September 2021 onwards. The two coefficients (β_1 and β_2) therefore allow us to distinguish between remote work during the lockdown phase and remote work in the subsequent period, when restrictions had ended but the firm chose to remain fully remote.

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.[10]

Team leader and supervisor fixed effects absorb persistent 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.[11] ϵ_{it} are clustered at the level of the agent.

Our identification strategy exploits the firm's abrupt shift to fully remote work at the onset of government-imposed lockdowns, followed by its decision to remain fully remote after

[10] 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.

[11] 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.

restrictions were lifted. This transition was firm-wide and was not targeted to individual agents based on their characteristics or performance trajectories. Conditional on observable controls and fixed effects, we therefore compare changes in agent-level outcomes during the lockdown and post-lockdown periods with the same agents' performance while working in the office before the pandemic. At the same time, because the shift occurred alongside the broader COVID-19 shock, we cannot fully separate the role of remote work from other contemporaneous pandemic-related changes in worker behavior or labor market conditions.

Our main analysis uses a balanced panel of employees who were hired before the lockdown and remained employed throughout the analysis period. This allows us to hold workforce composition fixed, which is important because the shift to remote work also led to changes in workforce composition by expanding the firm's access to a broader labor pool. We then repeat the analysis using the full sample, which includes employees who joined or left the firm during the study period. The estimates are very similar across the two samples, as we discuss below.

As shown in Table 2, 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 0.9 calls (9.1% relative to baseline) during the lockdown period and by 1.04 calls (10.5% relative to baseline) in the post-lockdown period. 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.[12]

Decomposing the change in call duration, as discussed above, we observe reductions in both talk time and hold time, suggesting that agents were able to communicate more efficiently and resolve customer queries more quickly. We also observe a 46.85-second-per-hour decline (8% relative to baseline) 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.

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 Table 3, both measures remained stable or improved in the post-pandemic period. Appendix Figure A6 shows the monthly pattern for random audit ratings and confirms that there was no deterioration after the shift to remote work. This implies that the increase in productivity was not achieved by cutting corners or compromising service standards.

[12] While shorter call durations may partly reflect pandemic-era changes in caller behavior, the stability of our quality metrics suggests that agents were not simply ending calls faster at the expense of service quality. It also makes it less likely that the productivity gains were driven by a shift toward simpler customer inquiries.

The stability of estimates in the full sample

Appendix Table A2 shows that the results are very similar in the full sample. 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. Appendix Figure A7 shows the corresponding monthly pattern, using a parsimonious specification and estimating it using the full sample. The pattern is very similar, with productivity rising after the shift to remote work. This reduces concerns that the main results are driven by restricting the analysis to workers observed throughout the period. It is also consistent with the attrition checks in Appendix Tables A3 and A4, which show that exit is not systematically related to pre-shift productivity.

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 matters for both public policy and firm strategy. If gains come mainly from recruiting more skilled or better-matched workers, then the benefits of remote work may be concentrated among firms with access to such talent. If they come mainly from within-worker improvements, remote work can raise productivity even when the workforce remains unchanged.

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. In Appendix Table A6, high-productivity agents are the omitted category, so the coefficient on Post captures their post-lockdown change. This coefficient is small and statistically insignificant for calls per hour, suggesting that high-productivity agents did not experience a comparable additional gain once the full set of controls is included. By contrast, agents who were lower performers during the work-from-office period experienced larger productivity gains after transitioning to fully remote work. Low-productivity agents increased their call volume by 1.37 calls per hour and reduced their average call duration by 55 seconds. Appendix Figure A8 shows the same pattern in levels: high-productivity agents remained the most productive group, but the gap with lower-productivity agents narrowed after the transition. These results point to convergence from below, suggesting that remote work narrowed performance gaps while raising overall efficiency.

Appendix Table A7 conducts a placebo analysis using only pre-pandemic data to rule out mechanical mean reversion. It compares productivity outcomes between the first and last three quarters of 2019, a period during which no major organizational changes occurred. If the gains among low-productivity agents in Appendix Table A6 were simply a statistical artifact, similar improvements should appear in this placebo window. Yet the interaction terms for low-productivity agents are small and statistically insignificant across all specifications. For example, in the balanced panel (Columns 3 and 4), the coefficients for low-productivity agents remain small (0.38 for calls per hour; –6.26 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.

Extending our analysis to the 2017–2023 period

To address concerns that the start of our sample period might coincide with unobserved factors that could bias our results, we extend the analysis back to 2017 using additional pre-pandemic data. This longer pre-period also helps assess whether the post-2020 increase reflects the continuation of a pre-existing trend. Appendix Tables A8 and A9 show that our main results remain qualitatively similar and statistically significant. Appendix Figure A9 presents the corresponding monthly series over the extended period. It does not show an upward productivity trend before March 2020, which reduces concerns that the main results capture the continuation of earlier performance improvements.

Estimating individual productivity changes before and after the permanent shift to remote work

Beyond average effects, we also examine whether remote work altered the dispersion of productivity across workers. A tighter productivity distribution during the on-site period, as shown in Appendix Figure A4, may reflect stronger conformity in performance or fewer idiosyncratic shocks in the office environment compared with remote work.

To test this, we estimate individual fixed effects from regressions of calls per hour on individual dummies, controlling age, age squared, call composition variables, team leader and supervisor fixed effects, month seasonal, and day-of-week dummies. These regressions are estimated separately for the pre- and post-remote work periods, and the resulting distributions of individual productivity effects are shown in Appendix Figure A10. Greater dispersion in these estimated effects under remote work would be consistent with the idea that the shift disrupted implicit coordination among workers to maintain uniform productivity levels (sometimes described as tacit collusion aimed at avoiding upward revisions to performance targets).

We find no meaningful change in the dispersion of individual productivity between the two periods (Appendix Figure A10). Equality-of-means tests (t-tests) and equality-of-variance tests (Brown and Forsythe, 1974) show that neither the mean nor the spread of the productivity distribution differs significantly between on-site and remote work. This suggests that remote work did not make productivity more unequal across workers.[13]

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 the firm, 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 A11 confirms that these two groups are well balanced on a range of observable characteristics, including age, gender, education, and marital status. This balance

[13] This finding is consistent with the larger gains among initially low-productivity agents documented in Appendix Table A6 where we compare average gains across baseline productivity groups. This is a separate and distinct exercise from Appendix Figure A10, which plots the full distribution of individual productivity. The evidence therefore points to partial convergence from below, rather than a broad compression of the whole productivity distribution.

supports the validity of the design by minimizing concerns about selection or compositional bias.[14]

Panel A of Figure 5 shows that remote starters were initially more productive, handling more calls per hour. This early advantage reflects the firm's shift in onboarding protocols: remote workers were put on the phones faster, with less classroom-style training. However, this gap closes over time. By around 175 working days, office starters and remote starters have similar productivity levels. Beyond this point, office starters' productivity declines somewhat and settles at a level similar to that of remote starters.[15]

Appendix Table A10 presents regression results for agents with 80+, 120+, and 160+ days of experience. By 80 days, all agents were fully remote. The estimates are consistent with the figure and show that the initial remote-starter advantage fades as experience accumulates.

Panel B of Figure 5 shows a clearer difference in retention. Remote starters had substantially higher attrition rates than office starters. Qualitative evidence from employee interviews suggests that the 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, remote onboarding appears to speed up initial task engagement, since remote starters were placed on calls faster. But this early productivity advantage does not persist. The more durable difference is retention: remote starters remain more likely to exit. These findings suggest that face-to-face interaction during the early phase of employment matters mainly for attachment and retention, even in jobs that can be done fully remotely. Motivated by these insights, the firm 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 the firm's transition to fully remote work reveals three key insights for workforce management and labor market inclusion.

First, remote work substantially reshaped the composition of the workforce. By removing geographic and mobility constraints, the firm was able to tap into a wider talent pool, hiring more educated and older workers and significantly increasing the representation of women and employees from non-metropolitan areas. These groups are traditionally underrepresented in the Turkish labor market. The results therefore show that remote work can widen access to employment not only in high-skilled professional jobs, but also in low-wage service work.

Second, the shift to remote work was associated with meaningful and persistent productivity gains. Agents handled more calls per hour, driven primarily by shorter call durations. These gains were sustained over time and were not achieved at the expense of service quality. Customer ratings and internal audit scores remained stable or improved. The productivity

[14] We also performed two-sample t-tests (not reported here) to examine differences between variables, and consistent with the regression results, none of these differences are statistically significant.

[15] Replicating Panel A of Figure 5 while restricting the sample to agents with (i) tenure of at least 65 workdays (~3 months) and (ii) at least 130 workdays (~6 months) yields virtually identical results. These results are available upon request.

improvements were also broad-based across demographic groups, suggesting that fully remote work can raise average performance while expanding access to employment.

Third, the onboarding results highlight an important management challenge in remote-first work design. Remote starters, who began their roles entirely online, ramped up more quickly and initially outperformed their peers, partly because they were placed on calls faster and received less classroom-style training. However, this early advantage faded over time. By around 175 working days on the job, the initial productivity advantage of remote starters had largely disappeared, while employees who started in person were significantly more likely to remain at the firm. These findings imply that fully remote work can expand hiring and sustain productivity, but that the way firms onboard new employees can shape longer-run adjustment and retention. Even when jobs are performed remotely in the long run, early face-to-face interaction may remain a valuable management practice.

Our findings should be interpreted in light of the setting. The job involves inbound customer-service calls, with highly standardized tasks, centrally routed calls, scripted interactions, and detailed digital measures of individual performance and service quality. The firm also provided laptops and internet support, reducing technological barriers to remote work. In addition, it entered the pandemic with established routines, monitoring systems, and quality-control procedures already in place, allowing it to move remote with limited changes to its operating model. These features likely made the transition to fully remote work more effective than it would have been in settings where tasks are less structured, output is harder to observe, or firms lack established managerial systems. The results are therefore most likely to extend to jobs with similar features, especially semi-routine service jobs in which tasks are standardized, digitally mediated, and individually measured.

A limitation of our design is that the shift to fully remote work coincided with the broader COVID-19 shock. We therefore cannot fully rule out contemporaneous pandemic-related changes in worker or customer behavior, labor market conditions, or the composition of available hires. However, several findings suggest that these factors are unlikely to explain the full pattern of results. The productivity gains persist well beyond the initial lockdown period, the balanced-panel estimates show similar gains among the same workers over time, and the analysis by components indicates that the gains mainly reflect within-worker improvements rather than compositional upgrading. We therefore interpret the early-pandemic estimates with appropriate caution and place greater weight on the post-lockdown and balanced-panel results.

Overall, the evidence suggests that fully remote work should be understood not only as a flexibility policy, but also as a management-practices question. Remote work can expand access to employment while sustaining performance when firms have standardized workflows, clear performance measurement, effective monitoring, and deliberate early social connection. The challenge is therefore not simply whether to allow remote work, but how to manage it effectively.

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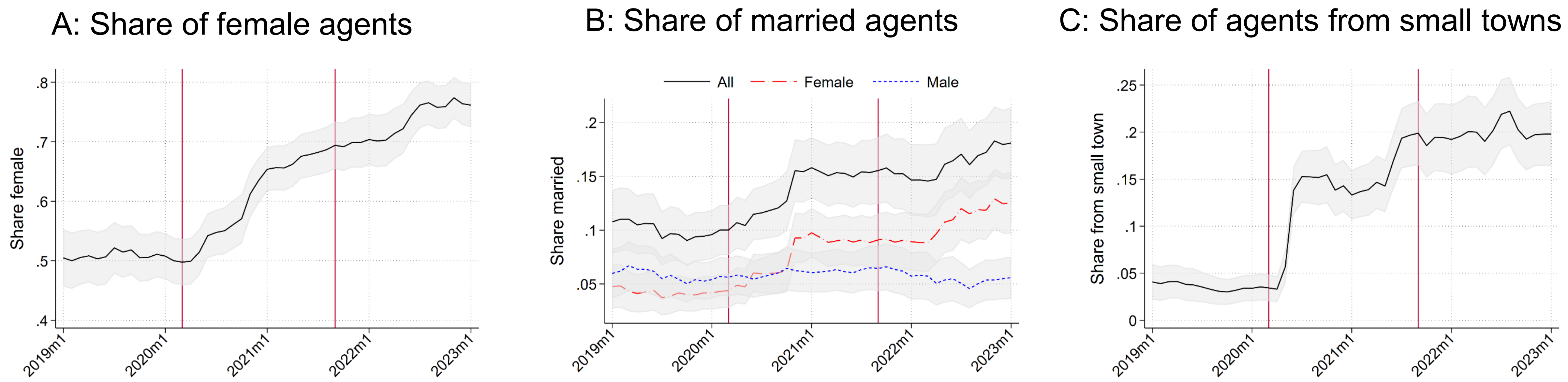
Figure 1: Agents moved from busy open-plan areas to quieter home environments

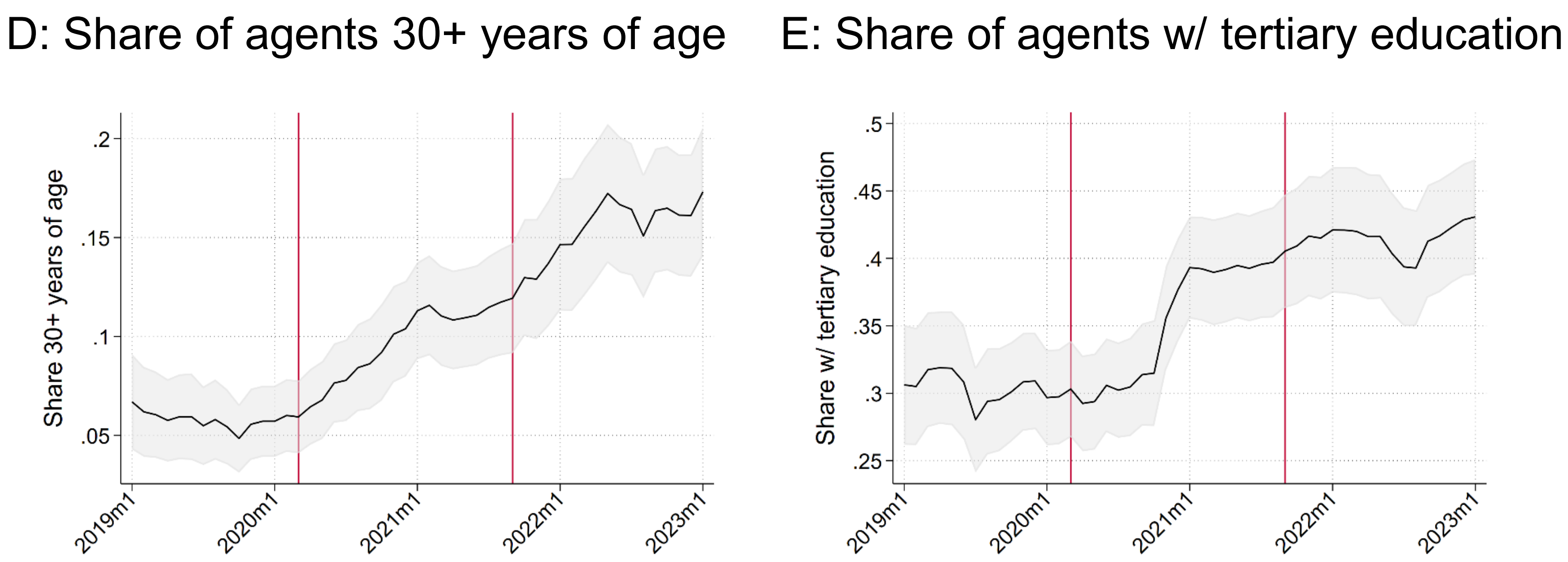
A: Working from the office

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).

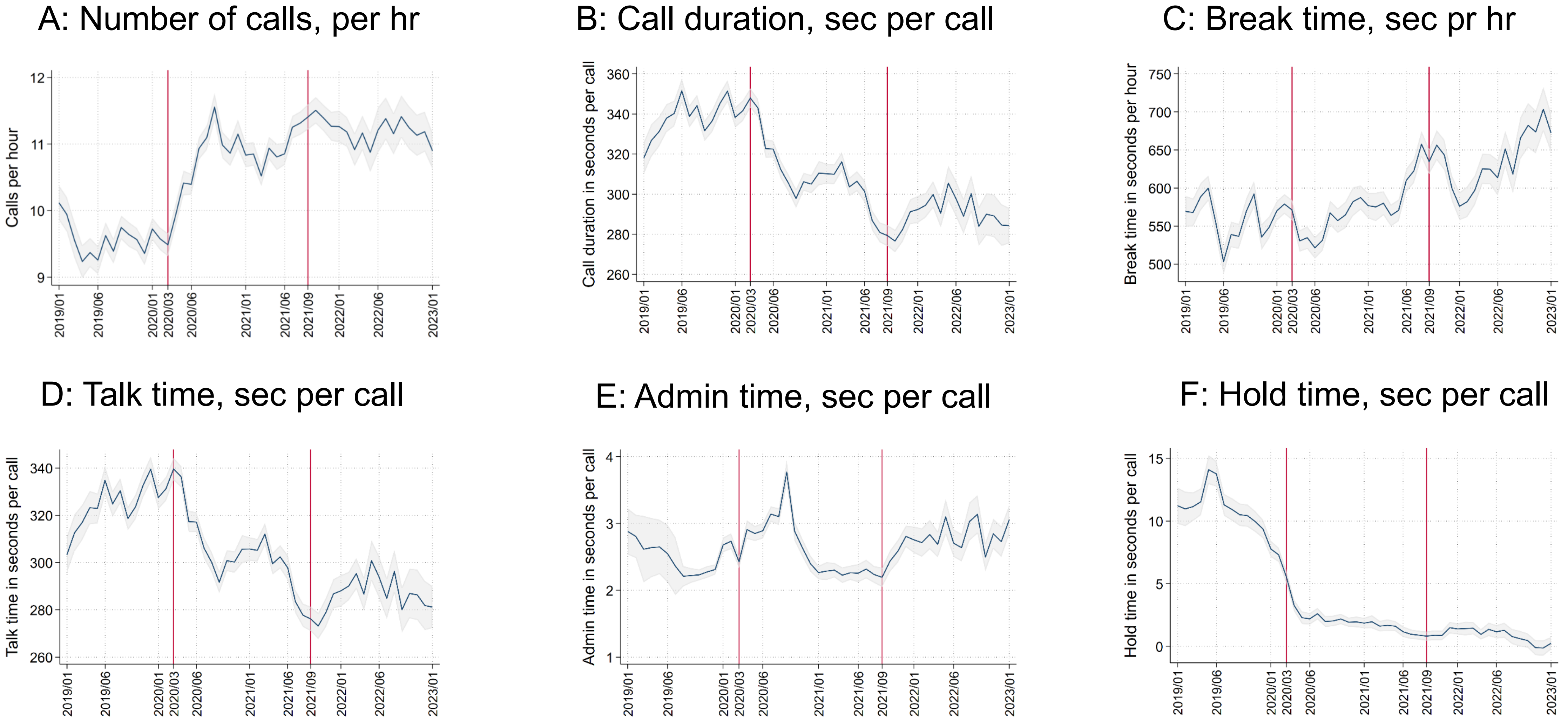
Figure 2: Remote working brought a rising share of agents who are female, married, college educated, from small towns and older





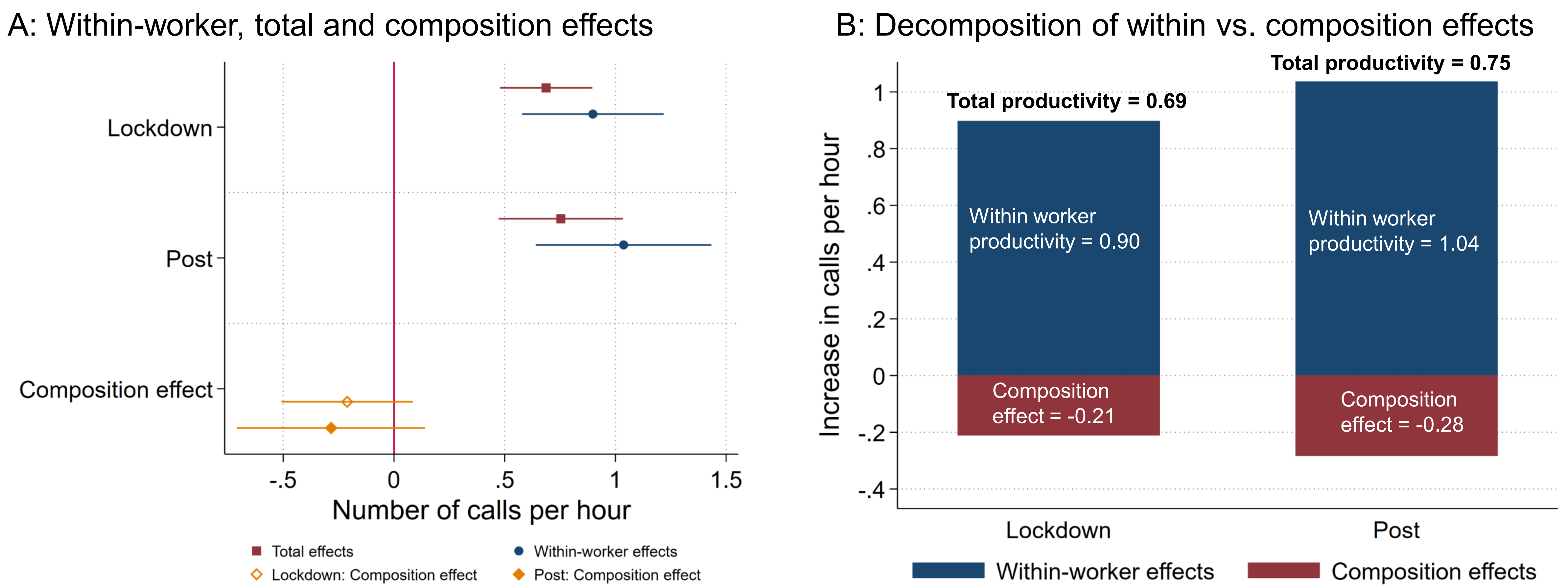
Notes: This figure shows monthly changes in the workforce due to new hires and quits. Each panel displays monthly means, with shaded areas representing 95% confidence intervals. Vertical red lines mark March 2020 and September 2021, corresponding to the start and end of the COVID-19 lockdown period in 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



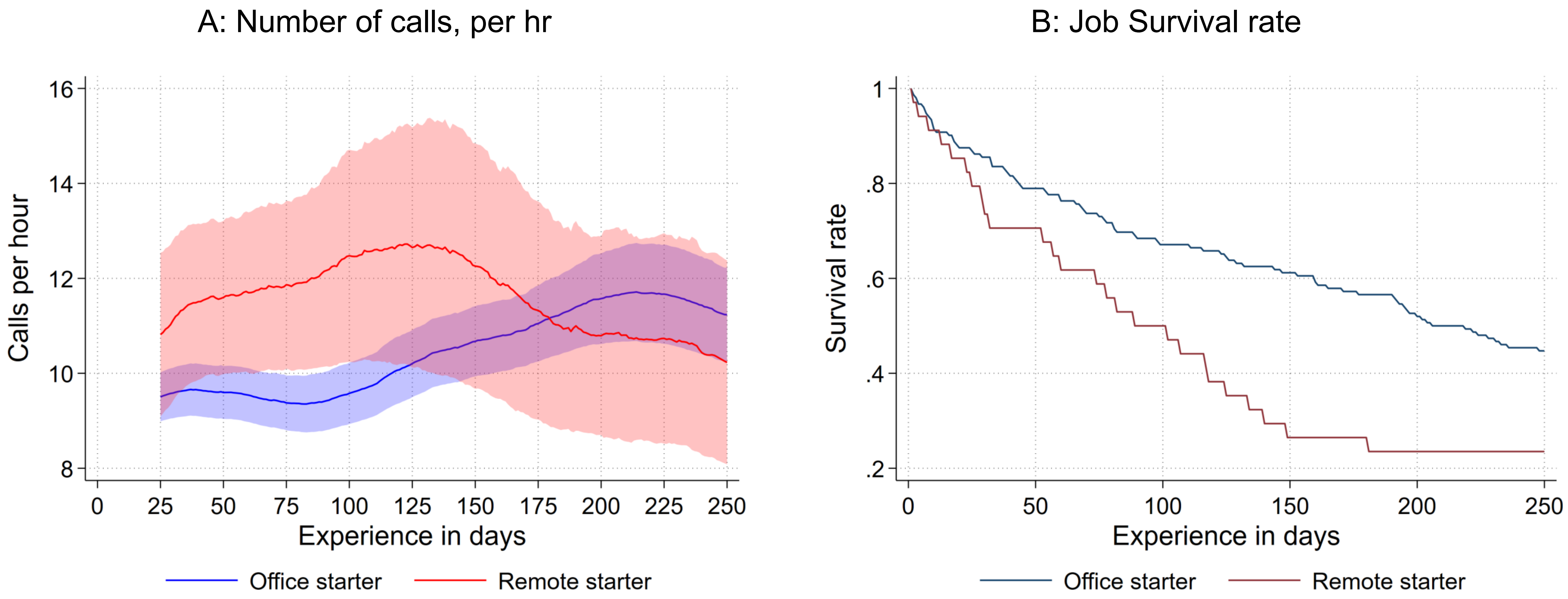
Notes: This figure shows predictions from OLS regressions of productivity outcomes (indicated in the panel titles) on month fixed effects, with February 2020 omitted as the reference month. All regressions control for call composition, repeat calls, and include agent fixed effects. Standard errors are 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: 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	0.50	961	0.61	0.49	853	0.75	0.44	0.26	0.00
Completed tertiary education	876	0.30	0.46	961	0.38	0.48	858	0.40	0.49	0.10	0.00
Age	876	23.07	3.72	961	24.35	4.20	858	24.96	4.44	1.89	0.00
Married	876	0.08	0.27	961	0.14	0.34	858	0.19	0.40	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	538.93	615.15	128.86	0.00
Calls per hour (net of break time)	35,842	11.87	3.33	74,438	13.55	4.84	35,053	14.13	5.43	2.26	0.00
Calls per hour	35,842	9.89	2.77	74,438	11.18	3.86	35,053	11.32	3.95	1.44	0.00
Break time in minutes	35,842	60.12	25.73	74,438	54.73	28.71	35,053	64.35	31.78	4.24	0.00
Break time in seconds per hour	35,842	587.58	256.25	74,438	599.68	327.00	35,053	663.38	317.14	75.80	0.00
Call duration in seconds per call	35,842	323.91	85.96	74,438	292.62	88.23	35,053	280.55	77.63	-43.36	0.00
Talk time in seconds per call	35,842	312.15	83.98	74,438	288.29	87.89	35,053	276.90	77.36	-35.25	0.00
Admin time in seconds per call	35,842	2.52	2.52	74,438	2.54	2.91	35,053	2.38	2.33	-0.13	0.00
Hold time in seconds per call	35,842	9.04	11.47	74,438	1.66	5.23	35,053	1.16	3.97	-7.88	0.00
Random audit rating	1,421	0.38	0.49	2,392	0.59	0.49	1,352	0.41	0.49	0.03	0.14
Customer rating	368	64.74	10.88	3,004	64.94	12.42	1,598	73.46	13.20	8.73	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 5 September 2021; and Post covers 6 September 2021 onward.

Table 2: 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.

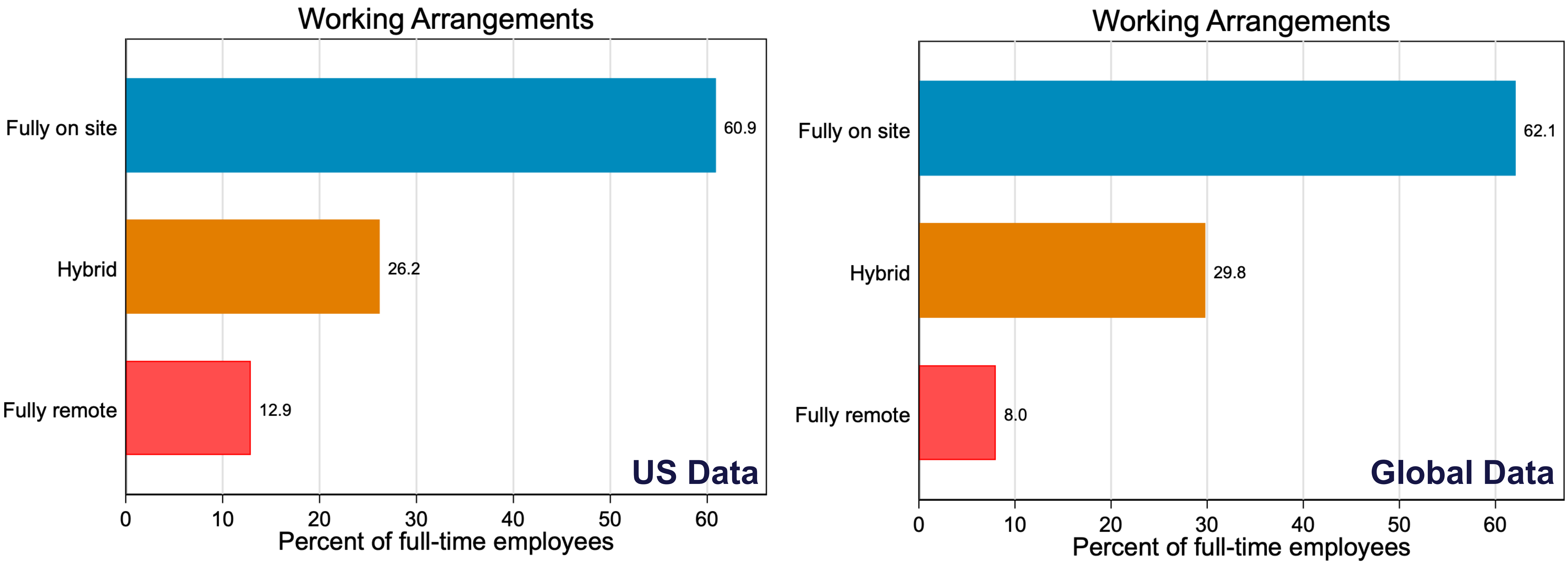
Table 3: Ratings provided by customers and mangers remained similar, if anything they rose, following the shift to remote work

	(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.

Appendix

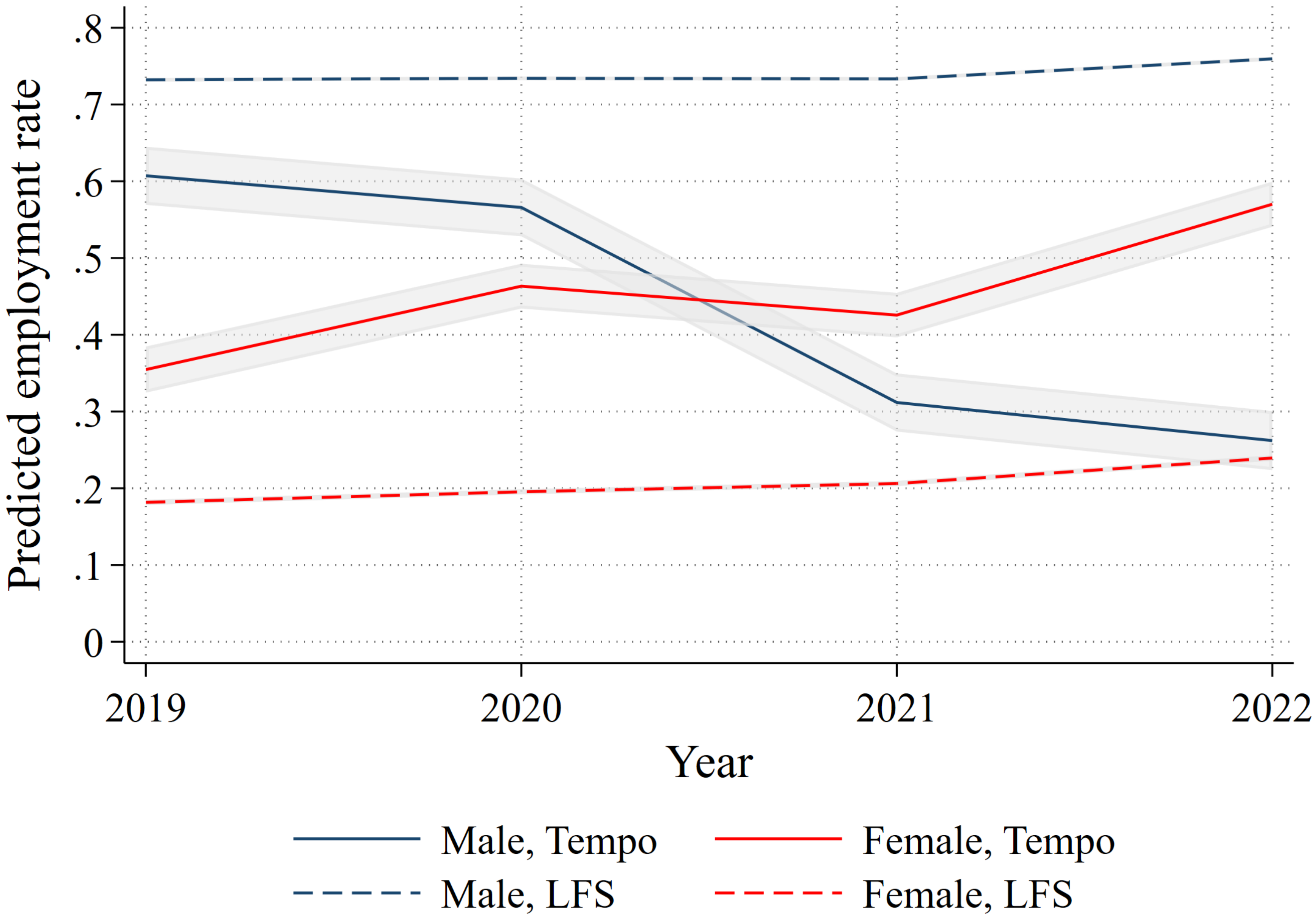
Figure A1: Fully Remote Workers are about 10% of All Employees



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 Buckman 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

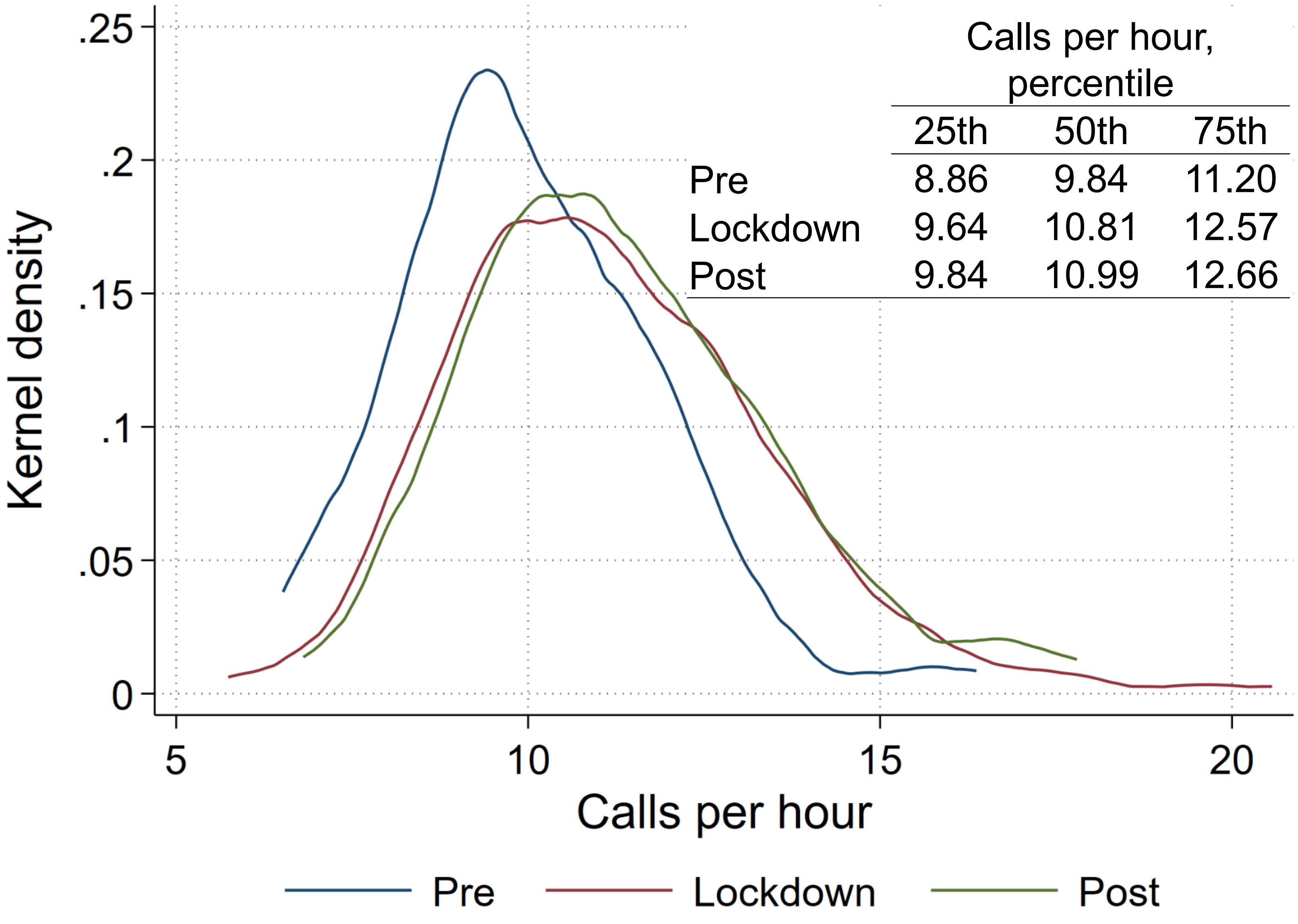


Notes: This figure presents predictions from two separate regressions. The solid lines correspond to a regression of an employment dummy (equal to 1 if the agent was employed by the firm in a given year and 0 otherwise) on the interaction between female and year dummies, controlling for age, age squared, 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, number of children and household size. The sample is drawn from the Turkish Labour Force Survey, 2019–2022. Grey shaded areas indicate 95 percent confidence intervals.

Figure A3: Workforce changes were gradual rather than driven by a hiring spike

Notes: The figure shows the monthly total number of employees working on the project (blue line, right vertical axis) and the monthly number of new hires (navy bars, left vertical axis). Dashed blue (navy) lines depict Pre, Lockdown and Post period means for total employees (new hires). The dashed horizontal lines show period-specific averages. Vertical red lines mark March 2020 and September 2021, corresponding to the start and end of the COVID-19 lockdown period in Turkey.

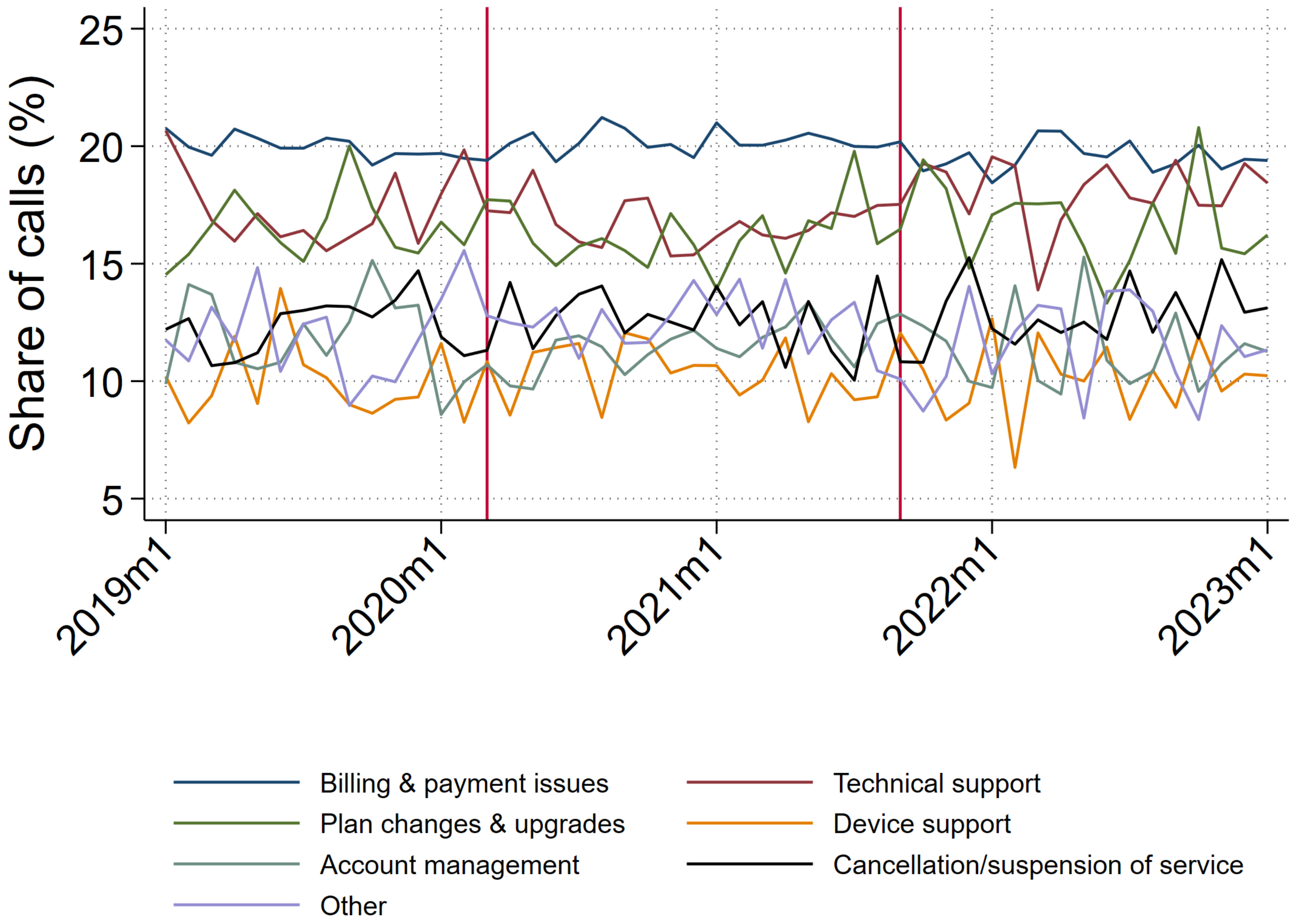
Figure A4: Agents process more calls after the shift to fully remote work



	Calls per hour, percentile		
	25th	50th	75th
Pre	8.86	9.84	11.20
Lockdown	9.64	10.81	12.57
Post	9.84	10.99	12.66

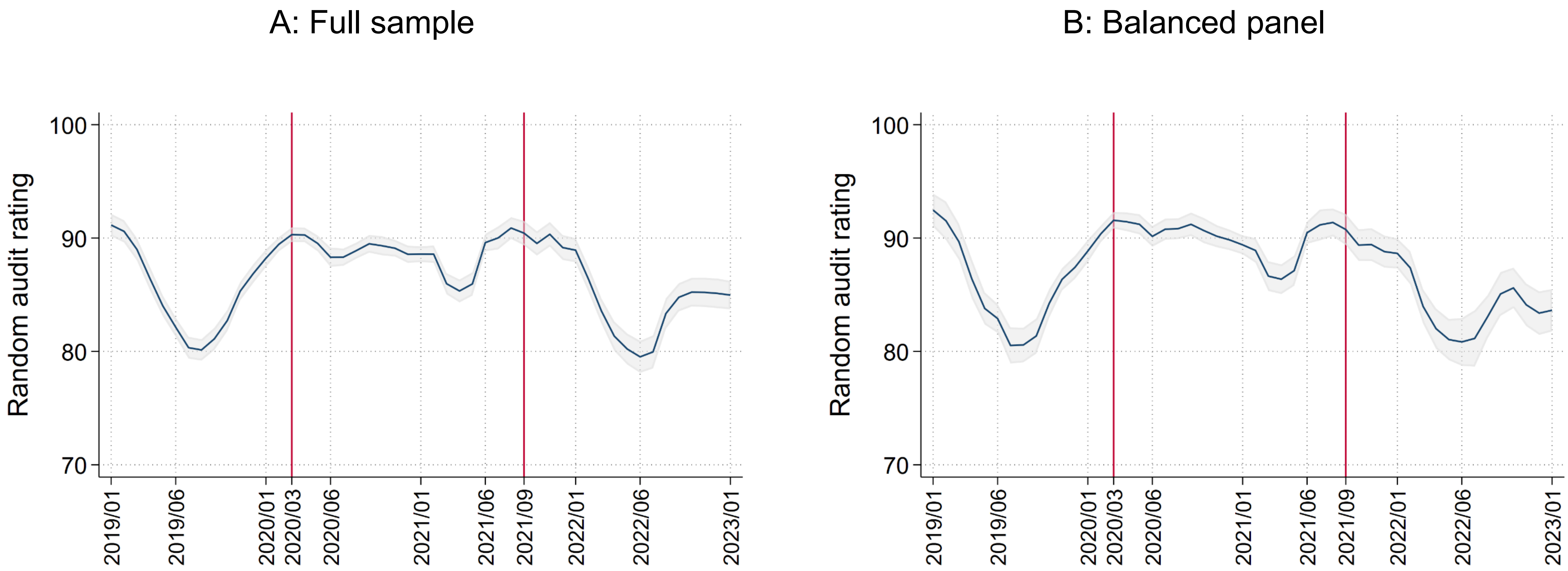
Notes: This figure presents univariate kernel density estimates (Epanechnikov kernel) of calls per hour measured at the agent level across the Pre, Lockdown, and Post periods. The sample includes agents who are observed in all three periods and who worked at least 10 days in each.

Figure A5: The composition of calls received by agents is broadly stable over time



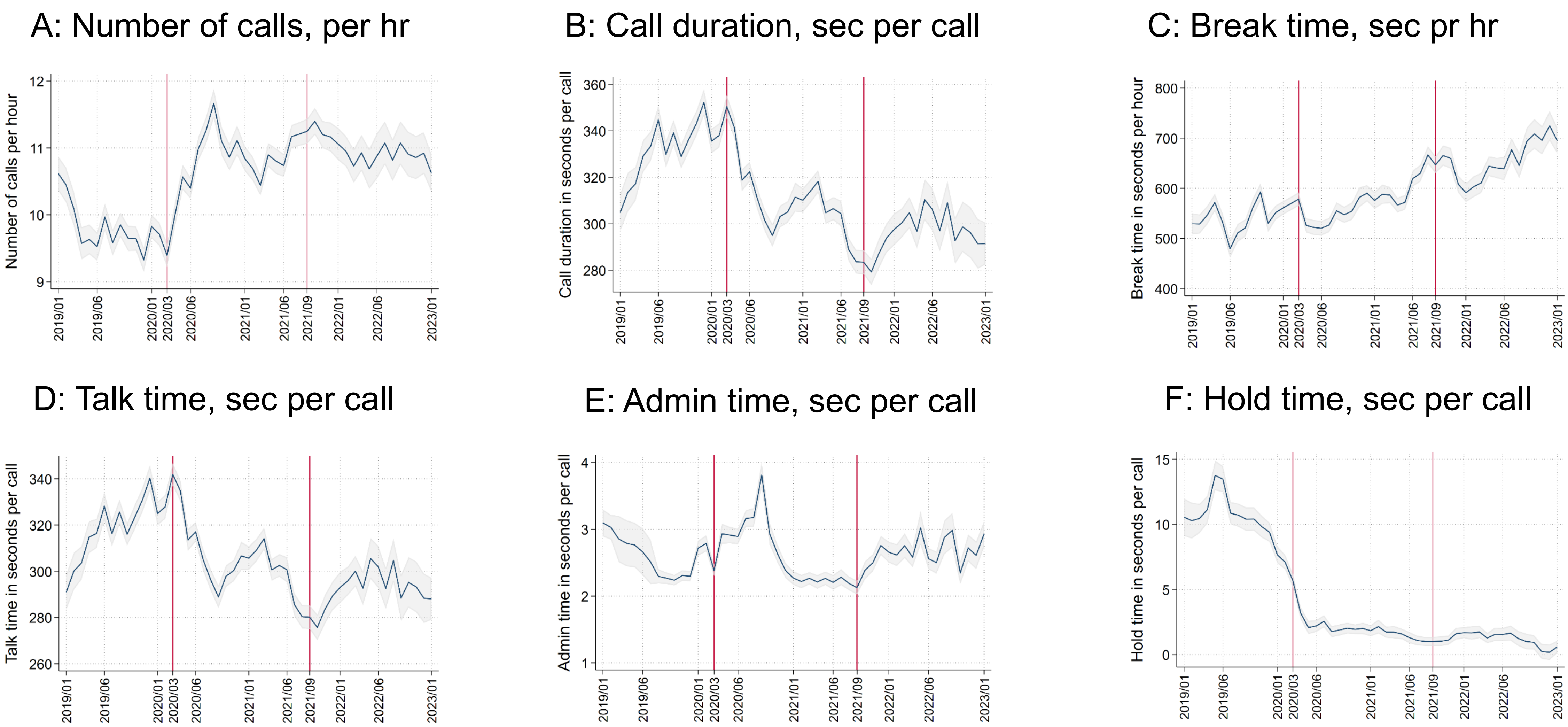
Notes: This figure shows how the composition of inbound calls changes over time. Call composition is measured at the agent level based on 10 randomly selected calls per month. The call categories are defined as follows: (i) Billing & Payment Issues—inquiries about bills, payments, direct debits, or charge 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: Ratings remained similar following the shift to remote work



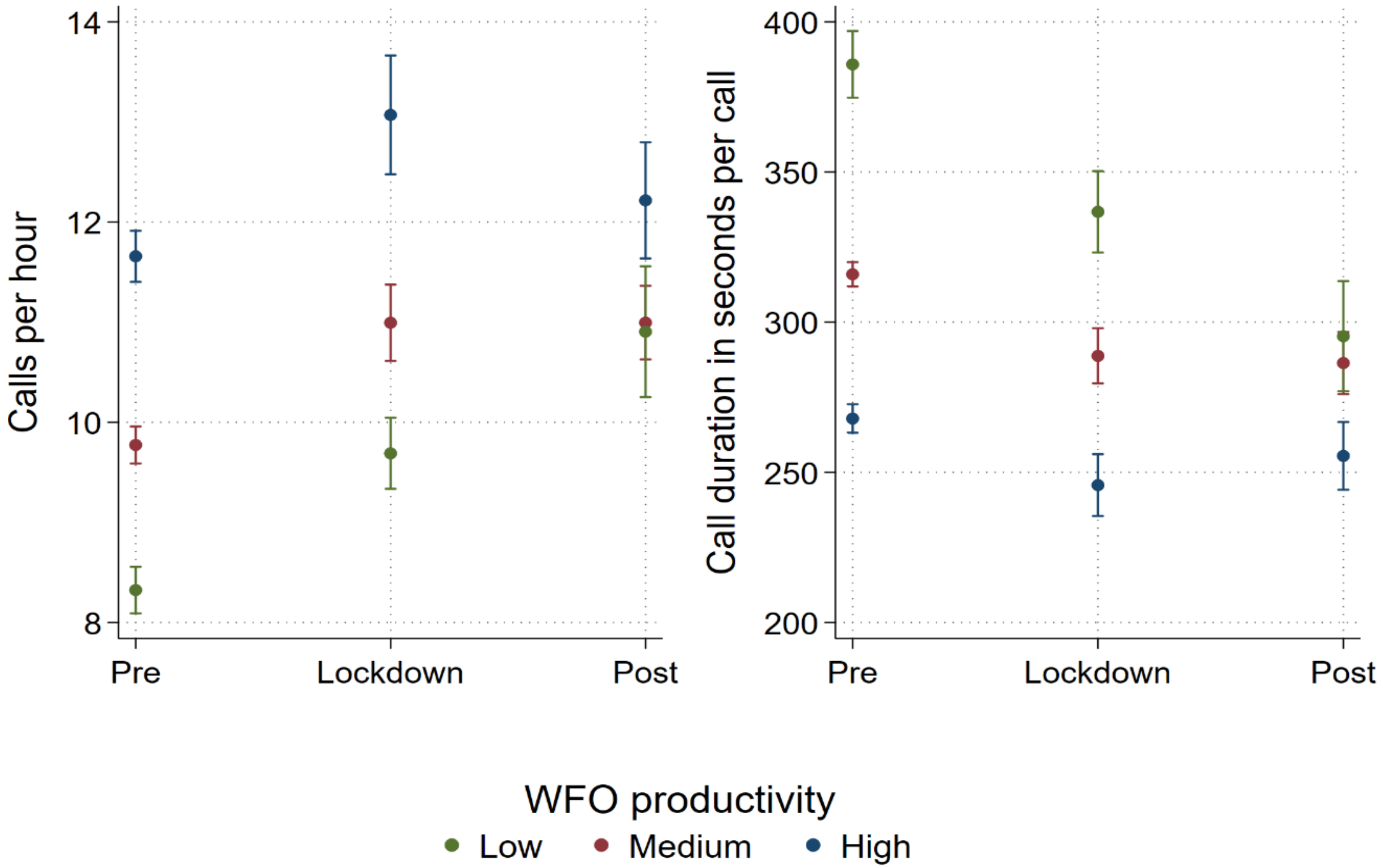
Notes: This figure shows predictions from OLS regressions of Random audit rating on month fixed effects, with February 2020 omitted as the reference month. All regressions control for call composition, repeat calls, and include agent fixed effects. Random audit rating is a 3-month trailing moving average and is the score between 1-100 that managers assign employees after reviewing ten randomly selected calls from a given month. 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 A7: Robustness – Productivity gains replicate in the full sample



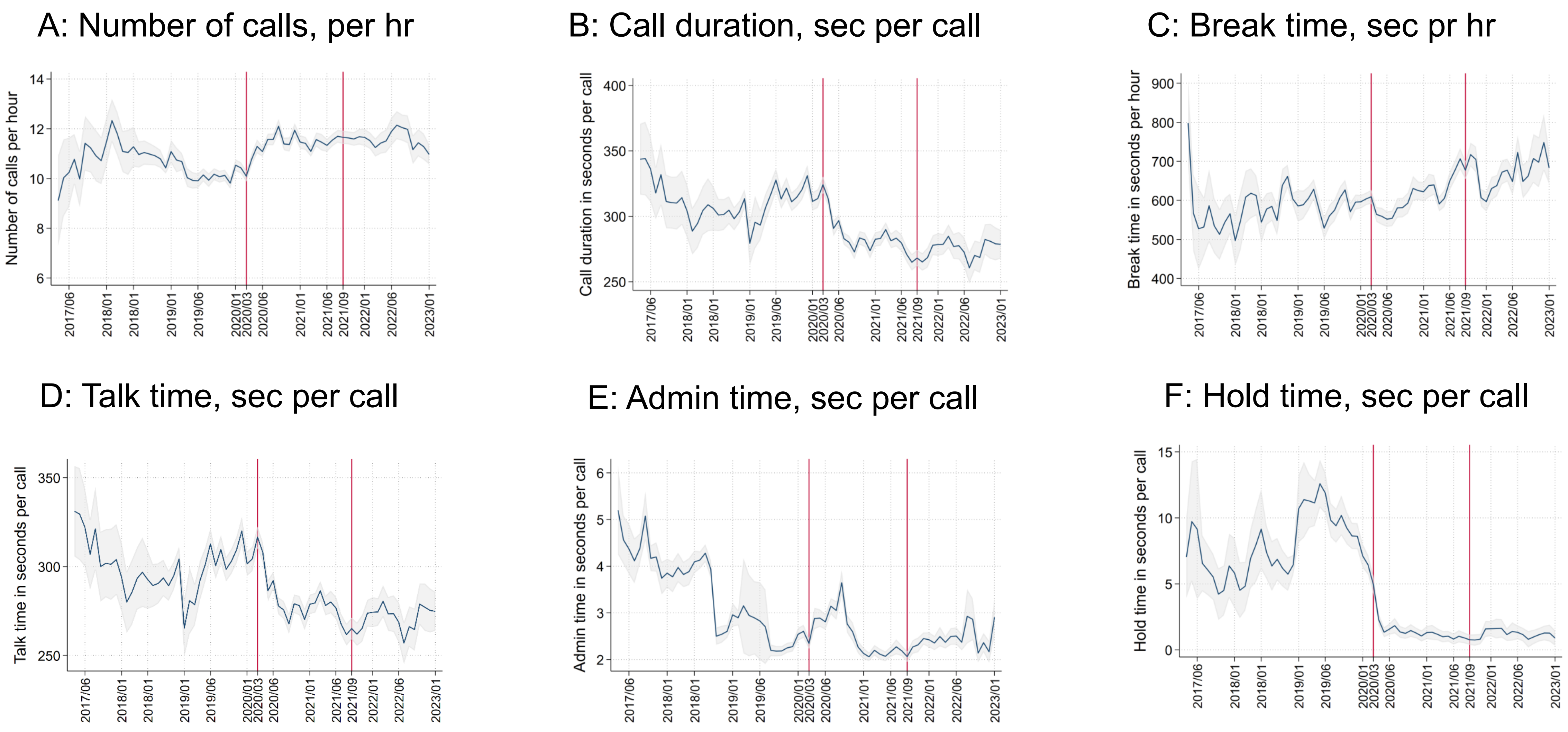
Notes: This figure shows monthly means after netting out individual fixed effects for productivity outcomes (indicated in the panel titles). Standard errors are clustered at the agent level, and 95% confidence intervals are shown as shaded bands around the point estimates. Vertical red lines mark March 2020 and September 2021, corresponding to the start and end of the COVID-19 lockdown period, respectively. The data is the full sample.

Figure A8: Productivity gains were largest among initially low-performing agents



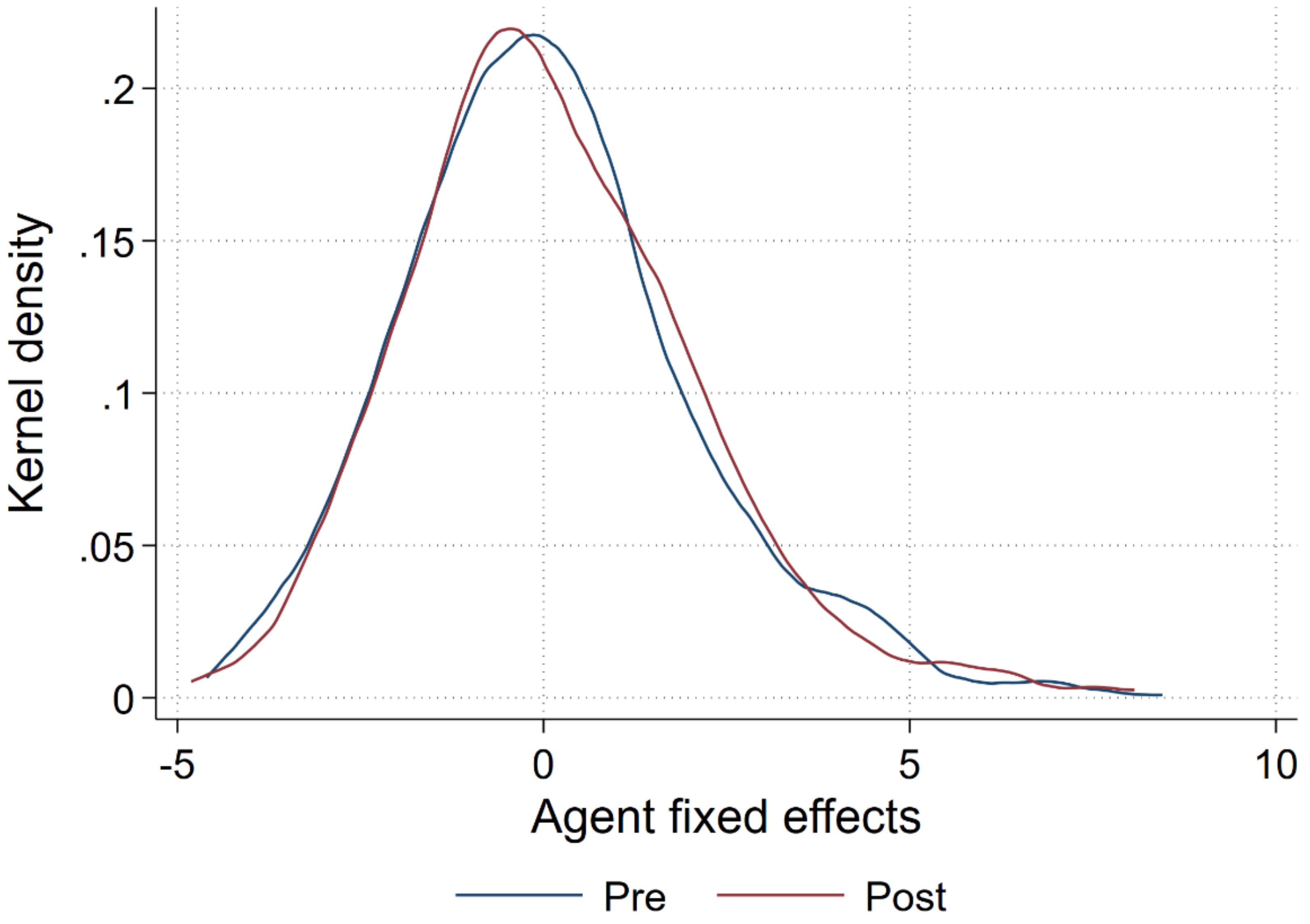
Notes: Figure showing mean calls per hour and call duration in seconds per call for high, medium and low baseline productivity. Baseline productivity during the work-from-office (WFO) period is calculated using data from all odd calendar dates prior to the shift to remote work. The sample includes agents observed in all three periods—Pre, Lockdown, and Post—and excludes odd calendar dates used to construct the baseline productivity measure. Whiskers indicate 95 per cent confidence intervals derived from standard error clustered at the employee level.

Figure A9: Robustness – Productivity gains replicate over the extended 2017–2023



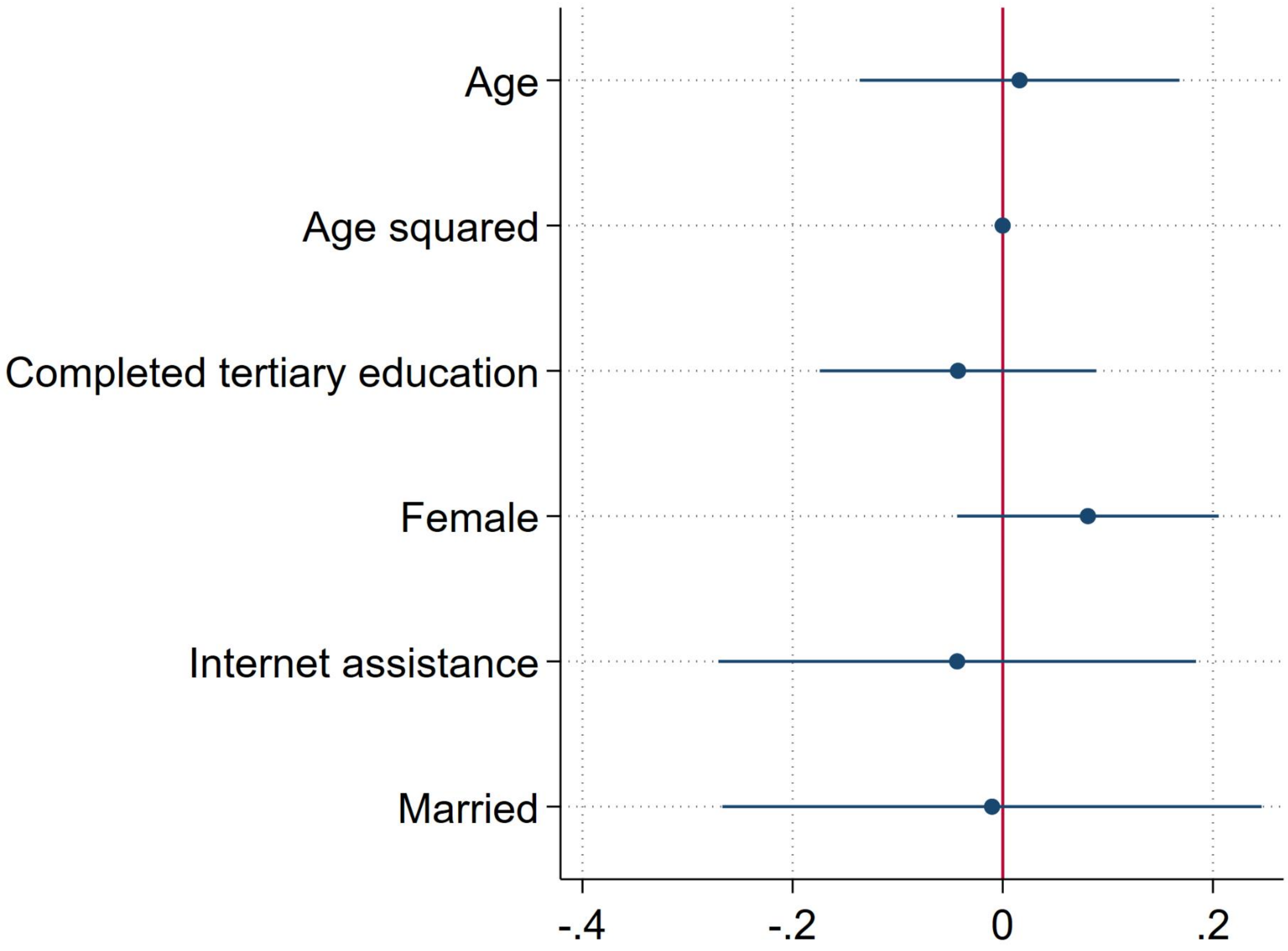
Notes: This figure shows predictions from OLS regressions of productivity outcomes (indicated in the panel titles) on month fixed effects, with February 2020 omitted as the reference month. All regressions control the pre-2019 window and agent fixed effects. Standard errors are clustered at the agent 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. The data is the balanced panel.

Figure A10: Estimating the distribution of individual-level productivity effects before and after the permanent shift to remote work



Notes: This figure shows individual productivity (fixed) effects from two separate regressions of calls per hour on individual level dummies while controlling for age, age-squared, call composition variables, team leader fixed effects, supervisor fixed effects, month seasonals and day of the week fixed effects. The regression is estimated once using agent-date observations prior to the shift to remote work on 11 March 2020 (Pre) and a second time using agent-date observations after lockdown lifted on 5 September 2021 (Post).

Figure A11: Balance tests for the start-date comparison 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 city fixed effects. Standard errors are heteroskedasticity-robust, and whiskers represent 95% confidence intervals.

Table A1: 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 A2: Full sample – productivity gains replicate in the full sample

	(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 A3: Attrition is not associated with productivity or service quality

	(1)	(2)	(3)	(4)	(5)
	Exit dummy				
Calls per hour	-0.00				-0.01
	(0.01)				(0.01)
Call duration in minutes per day		-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)
Age	-0.01	-0.01	-0.01	-0.01	-0.01
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Married	-0.04	-0.04	-0.04	-0.04	-0.04
	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)
Female	-0.10**	-0.10**	-0.10**	-0.09**	-0.09**
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
Tertiary education	-0.01	-0.01	-0.01	-0.01	-0.01
	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)
From small town	-0.26*	-0.26*	-0.26*	-0.27*	-0.27*
	(0.14)	(0.14)	(0.14)	(0.14)	(0.14)
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 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 A4: Women, married employees and those living in small towns are less likely to exit

	(1)	(2)	(3)	(4)	(5)	(6)
	Exit dummy					
Calls per hour		1.03				1.01
		(0.03)				(0.03)
Call duration in minutes per day			1.00			
			(0.00)			
Random audit rating				0.72*		0.74
				(0.14)		(0.14)
Customer rating					0.99**	0.99**
					(0.01)	(0.01)
Age	0.99	0.99	0.99	0.99	0.99	0.99
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Married	0.60**	0.61**	0.60**	0.59***	0.62**	0.61**
	(0.12)	(0.12)	(0.12)	(0.12)	(0.13)	(0.13)
Female	0.63***	0.64***	0.64***	0.63***	0.65***	0.65***
	(0.07)	(0.08)	(0.08)	(0.07)	(0.08)	(0.08)
Tertiary education	1.01	0.99	1.01	1.02	1.01	1.01
	(0.13)	(0.13)	(0.13)	(0.13)	(0.14)	(0.14)
From small town	0.32***	0.32***	0.32***	0.31***	0.29***	0.28***
	(0.12)	(0.12)	(0.12)	(0.12)	(0.11)	(0.11)
Observations	517	517	517	517	517	517

Notes: This table reports Cox Proportional Hazard Ratios estimated via maximum likelihood. 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 log of cumulative calls. 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
Pre-sample mean	9.89	9.89	9.89	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	0.15	8.43	-67.36***
	(0.33)	(7.07)	(27.33)
Post x WFO: medium productivity	0.67*	-19.31**	0.00
	(0.34)	(7.65)	(35.30)
Post x WFO: low productivity	1.37***	-55.01***	19.28
	(0.44)	(10.54)	(32.16)
R-squared	0.28	0.42	0.27
Number of observations	125,902	125,902	125,902
Number of clusters	199	199	199
Pre-sample mean	9.88	323.73	590.66

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	
	Number of calls per hour	Call duraton in seconds per call	Number of calls per hour	Call duraton in seconds per call
Q2-Q4 2019	-1.18***	33.98***	-1.02***	34.17***
	(0.20)	(4.71)	(0.26)	(9.05)
Q2-Q4 2019 x Q1 2019: medium productivity	0.20	-1.00	0.51*	-10.10
	(0.21)	(5.36)	(0.29)	(10.26)
Q2-Q4 2019 x Q1 2019: low productivity	0.26	-4.57	0.38	-6.26
	(0.20)	(5.36)	(0.27)	(10.85)
R-squared	0.417	0.499	0.313	0.398
Number of observations	86,047	86,047	23,717	23,717
Number of clusters	792	792	185	185
Sample mean	11.06	284.45	10.02	310.36

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 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. Q2-Q4 2019 is a dummy variable equal to 1 if the calendar date falls in the last three quarters of 2019, and 0 otherwise. Baseline productivity is calculated for each agent using data from the first quarter of 2019. Q1 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. Q1 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: Robustness – Productivity gains replicate over the extended 2017–2023 period (balanced panel)

	(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	0.98***	-19.53***	-42.78**	-14.62***	0.58***	-5.46***
	(0.17)	(4.04)	(17.18)	(4.03)	(0.10)	(0.45)
Post	1.52***	-36.16***	-41.60**	-32.26***	0.92***	-4.77***
	(0.23)	(6.35)	(17.25)	(6.27)	(0.13)	(0.55)
Log of cumulative number of calls (t-1)	0.23***	-9.60***	33.75***	-7.92***	-0.27**	-1.39***
	(0.08)	(2.23)	(6.68)	(2.23)	(0.12)	(0.27)
Adjusted R-squared	0.28	0.40	0.25	0.40	0.09	0.32
Number of observations	157,435	157,433	157,435	157,433	157,433	157,433
Number of clusters	205	205	205	205	205	205
Pre- sample mean	10.77	300.49	604.47	289.33	2.78	8.20

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 repeat calls. Standard errors are clustered at the agent level. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table A9: Robustness – Productivity gains replicate over the extended 2017–2023 period (full sample)

	(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	1.00***	-15.50***	-37.32***	-9.79***	0.42***	-6.26***
	(0.10)	(2.71)	(9.35)	(2.70)	(0.06)	(0.34)
Post	1.55***	-30.68***	-40.02***	-25.88***	0.98***	-5.93***
	(0.14)	(3.96)	(10.30)	(3.90)	(0.07)	(0.40)
Log of cumulative number of calls (t-1)	0.29***	-13.97***	28.88***	-12.69***	-0.08***	-1.04***
	(0.03)	(0.86)	(2.21)	(0.85)	(0.02)	(0.10)
Adjusted R-squared	0.39	0.52	0.26	0.53	0.10	0.39
Number of observations	474,406	474,398	474,406	474,398	474,398	474,398
Number of clusters	2116	2116	2116	2116	2116	2116
Pre- sample mean	11.55	278.83	632.78	267.00	2.88	8.70

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 repeat calls. 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 A10: Office starters are initially less productive but overtake remote starters over time

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	All		80+ days		120+ days		160+ days	
Office starter	0.52	0.30	0.79	0.59	1.09*	0.89**	1.26**	1.06**
	(0.47)	(0.39)	(0.52)	(0.40)	(0.55)	(0.42)	(0.59)	(0.45)
R-squared	0.09	0.16	0.10	0.17	0.09	0.17	0.11	0.18
Number of observations	50,094	49,908	38,149	38,149	33,367	33,367	29,140	29,140
Number of clusters	186	183	128	128	113	113	99	99
Controls	No	Yes	No	Yes	No	Yes	No	Yes
Team leader FE; supervisor FE; month seasonals and day of week FE.								

Notes: This table reports OLS regressions. 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.