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DISCUSSION PAPER SERIES

IZA DP No. 18278

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ABSTRACT

The New Geography of Labor Markets*

We study where Americans live in relation to their employer's worksite using matched employer-employee data, and how that relationship changes with the rise of work from home (WFH). Mean distance from home to employer's worksite rose more than 70% between 2019 and 2024 in our dataset. Twelve percent of employees hired after March 2020 reside fifty or more miles from their employer by 2024, triple the pre-pandemic share. Distance to employer rose most for those in their 30s and 40s, among highly paid employees, and in Finance, Information, and Professional Services. Especially for the affluent, the pandemic-instigated rise in WFH initiated a multi-year pattern of net migration to areas with cheaper housing and states with lower tax rates. Finally, we show that distant employees exhibit more sensitivity to firm-level adjustments on hiring and separation margins. These developments have implications for residential location, state-level tax revenues, labor markets, and household welfare.

JEL Classification: J2, J3, R1

Keywords: work from home, remote jobs, distance to employer, hires and separations, taxes and relocation, housing costs and relocation, worker migration, geographic extent of labor markets

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1. Introduction

The COVID pandemic instigated a large, lasting shift to work from home (WFH). As a share of paid workdays in the United States, full WFH days rose from 7% in 2019 to 26% in 2025 (Barrero, Bloom and Davis, 2023). This shift is especially pronounced among the college educated, the highly paid, and in sectors like Finance, Information, and Professional & Business Services.

Historically, the choice of where to live was tightly tethered to the location of one's job. Likewise, an employer's catchment area for employees was largely determined by its worksite locations. WFH relaxes these constraints. In doing so, it creates new employment options for anyone who can work in jobs that are suitable for hybrid or fully remote work. It expands residential location options and relaxes joint location constraints for working couples. And it offers new opportunities for employers to recruit widely, including from areas with lower wages or deeper talent pools. In all these ways, the rise of WFH has the potential to reshape the geography of labor markets.

To study this development, we use monthly payroll data from Gusto, a leading US-based provider of payroll services. These matched employer-employee data are ideal for our purposes because they include each employee's residential address and employer worksite location as well as monthly pay observations and basic demographic and industry information. Home and employer addresses are required for payroll tax compliance. These data allow us to quantify home-employer distances, study their evolution over time, characterize their relationship to age, sex, earnings, industry, and business growth, and consider how they relate to taxes and housing costs.

We uncover four main findings. First, mean distance between home and employer worksite locations rose sharply after the pandemic struck in March 2020, increasing from 15 miles in 2019 to 26 miles in 2024. The share of employees residing more than 50 miles from their employer's nearest worksite rose from under 4% in 2019 to nearly 10% in 2024. This rise in "distant" employees is almost entirely due to employees hired after March 2020. Indeed, among employees hired after March 2020, 12% live more than 50 miles from their employer as of 2024.

Second, home-employer distances vary greatly with worker and industry characteristics. Distance rises sharply with earnings: Only 5% of employees earning less than $50,000 per year live 50 miles or more from their employers in 2024, as compared to 20% for those earning at least $200,000. High earners are more likely to be in managerial and professional occupations, which often allow one or more WFH days a week. Age also matters: Home-employer distances rose most sharply for employees in their 30s and 40s, when workers are most likely to have children in the household. Industry matters: As of 2024, about 30% of employees in the Information sector, 20% in Professional & Business Services, and 16% in Finance & Insurance live 50 miles or more from employer worksites. In contrast, only 3% of employees in Accommodation & Food Services, 5% in Construction, and 6–7% in Healthcare, Retail Trade, and Manufacturing live more than 50 miles from employer worksites.

Third, when we follow employees who stay with the same firm from one year to the next, we find a pattern of net migration to states with lower tax rates and areas with lower housing costs. These patterns greatly intensified in 2020 and 2021 and continued with less force in later years. Net migration rates away from high-tax states rise with earnings, especially after the pandemic. These findings suggest that the rise of WFH made local tax revenues more sensitive to local tax rates, especially for highly compensated workers with WFH-suitable jobs. We also find that highly paid employees have moved to areas with cheaper housing since 2020. Often, that means departing city centers for lower cost suburbs and exurbs, as suggested by Ramani et al. (2024). Cities like San Francisco, New York, and Washington, D.C. are at the challenging end of both adjustment margins, as highly paid employees leave to escape high taxes and high housing costs.

Conditional on relocating, the realized reduction in state tax rates and housing costs are often large, especially for highly compensated employees. Consider employees with annual earnings greater than $250,000. Persons in this group who moved between states in 2021 lowered their average state-level tax rate by 2.4 percentage points. Persons with annual earnings greater than $150,000 who stayed with the same employer but moved to a new zip code in 2020 experienced a 16% reduction in local housing costs, on average. Thus, WFH can yield large individual-level welfare gains even when abstracting from its effects on productivity, commuting costs, flexibility in time use and scope for personal autonomy, which helps explain why many employees resist return-to-office mandates.

Fourth, separation and hiring behavior differs between far and near employees. Among shrinking firms, separation rates are higher for employees who live more than 50 miles away *and* more responsive to the firm's contraction rate. Among growing firms, hiring rates for distant employees are greater *and* more sensitive to the firm's expansion rate. In short, distant employees function as a more flexible margin of adjustment in firm-level employment changes.

Our study contributes to a large and growing literature on WFH. Early work includes Bloom et al. (2015) and Mas and Pallais (2017). Adams-Prassl et al. (2020), Barrero et al. (2021a), DeFilippis et al. (2020) and Bick et al. (2023), among others, describe WFH outcomes during the early stages of the pandemic. Another stream of research focuses on productivity effects. See Choudhury et al. (2021) for an early contribution and Anakpo et al. (2023) for a recent review. Barrero et al. (2023) and Burdett et al. (2023) stress heterogeneity across workers and firms and adaptation over time in assessing the productivity effects of WFH. Aksoy et al. (2023) provide evidence on the savings in commute time afforded by WFH.

Barrero et al. (2022) and Liu and Su (2023) develop evidence on how WFH affects wages. Agrawal and Brueckner (2025) theoretically analyze the wage and employment effects of state taxes on labor income, stressing the distinction between source-based and residence-based taxation. Pagano et al. (2023), Davis et al. (2021), Favilukis et al. (2020) and Papanikolaou and Schmidt (2022) investigate how firm-level stock price reactions to the pandemic vary with the capacity of employees to work remotely. Arjun and Bloom (2024) and Gupta et al. (2024) study WFH effects on real estate values. Alipour et al. (2023), among others, provide evidence on how the shift to WFH alters the geography of consumer spending. Davis et al. (2024), Delventhal et al. (2023), Delventhal and Parkhomenko (2023), Duranton and Handbury (2023) and Monte et al. (2023) analyze how remote work affects the structure of cities in quantitative spatial models. Our study also contributes to an older body of work on the geography of labor markets. See Moretti (2012) for a well-known contribution that offers a broad-sweep analysis and literature review.

The next section describes our main data sources and confirms that home-employer distances rise with WFH intensity. Section 3 investigates how home-employer distances evolved over time and how they relate to employee age, sex, earnings, job tenure, and industry. Section 4 considers employee migration across states and local areas as a function of state income tax rates and local housing costs. Section 5 shows that hiring and separation rates differ between far and near employees in how they vary with employer growth rates. Section 6 offers concluding remarks.

2. Data Sources and Measurement

a. Payroll data and home-employer distances

We construct a matched employer-employee dataset using anonymized payroll records from Gusto, which provides payroll processing and HR services to its clients. The data run from January 2017 to December 2024 and include employee age, sex, earnings, pay frequency, and employer SIC or NAICS codes. We treat employees with zero pay in the raw data and those paid at a quarterly, semiannual or annual frequency as out of scope. We also exclude employers who never had five or more employees in a single month. If the NAICS code is missing, we map the SIC code to a NAICS code using a crosswalk. We drop employees with missing data on demographics, earnings, pay frequency, home address or employer NAICS code (after mapping from SIC codes). Our full dataset contains about 74 million monthly employee-level observations from 2017 to 2024 and covers 4.8 million employees at 171,000 employers.

The Gusto data also include the employee's residential address (home), the worksite address of his or her employer, and the employer's address for tax-filing purposes. Gusto uses this information to comply with the tax reporting requirements of its clients. After geolocating the addresses, we compute each employee's haversine distance from home to the employer's worksite. For employees that Gusto flags as fully remote, we compute the haversine distance from the employee's home to the employer's tax filing address. Much of our analysis focuses on employees in a balanced panel of firms that operated continuously from January 2019 through December 2024. We use the balanced panel when we want to ensure that changes in employer mix do not drive measured changes over time in certain outcomes of interest.[1]

Even before the COVID-19 pandemic, some employers had many employees residing far from their employer locations of record. One possible reason is that some multi-location employers report a single location for tax-filing purposes. That could lead us to overstate the home-employer distances for such firms. Given this, we drop firms from the balanced panel if the measured home-employer distance exceeds 50 miles for at least one quarter of its employees, on average, before March 2020. This is a conservative approach to assessing home-employer distances, and we recognize that it tends to drop employers who actually had an unusually high share of distant employees before the pandemic. Our balanced panel contains about 7.7 million employee-month observations for roughly 370,000 employees at 12,454 employers.

Compared to the Current Population Survey (CPS), employees in our balanced panel are younger, earn more, and are much more likely to work in the Professional & Business Services and Information sectors. To improve representativeness, we reweight the employee-level data in the balanced panel to match the 2018-2024 CPS sample shares in cells defined by the cross product

[1] Gusto's client base expanded during our sample period.

of annualized earnings bins, age bins, sex, and industry (2-digit NAICS). Appendix Figure A1 compares our employee-level sample in the balanced panel to the CPS.

b. Survey of Working Arrangements and Attitudes (SWAA)

The Gusto data do not record the incidence of WFH, except insofar as some employees are designated as fully remote. Accordingly, we turn to data from the Survey of Working Arrangements and Attitudes (SWAA) to directly assess the relationship of home-employer distances to the WFH propensity of employees.

The SWAA is a monthly online survey of U.S. residents, 20 to 64 years of age, that commences in May 2020. It includes information about demographics, labor force status, working arrangements, earnings, and more. It also includes the residential zip code for each respondent and, for employed respondents, the zip code of the employer's worksite. When using the SWAA data, we drop "speeders" (respondents who answer too quickly) and individuals that fail any of four attention checks in the survey instrument.[2] Collectively, these quality controls drop around 20% of the SWAA sample. See Barrero et al. (2021b) for more information about the SWAA and Buckman et al. (2025) for a detailed discussion of how the SWAA compares to other sources of data on remote work in the United States.

Using the SWAA data, we calculate haversine distances between the centroids of home and employer worksite zip codes. We calculate the percentage of full paid days worked from home using versions of the following SWAA questions:

- **Currently (this week)** *what is your work status?*
- *For each day* **last week,** *did you* **<u>work a full day (6 or more hours)</u>***, and if so* **<u>where?</u>**

Respondents answer the second question for each day last week. The response options are (i) "Worked from home," (ii) "Worked at employer or client site," and (iii) "Did not work 6 or more hours." For each employee, we compute the WFH share of full paid workdays as days with response (i) divided by days with responses (i) or (ii).

Figure 1 presents a binscatter that relates WFH intensity (percent of paid workdays) to home-worksite distances for full-time workers, aged 20 to 64, with prior-year earnings of at least $10,000. The underlying data run from January 2022 to May 2024, and the fitted relationship is

[2] The attention checks are "what is 3+4", "what color is grass?" where green or yellow are taken as correct answers, "how many big cities have you lived in during your life. Please answer 33 if you are paying attention" where 33 is the right answer, and a consistency check that relies on an age question at the beginning of the survey and a birth-year question at the end.

net of controls for education, earnings, age, and sex.[3] The figure shows a positive relationship between WFH intensity and home-worksite distances for distances above 25 miles. This figure underscores the potential for the rise in WFH to facilitate employee relocation and the spatial diffusion of employer-level workforces and to thereby reshape the geography of labor markets. It also aligns with evidence in Coskun et al. (2024), who study the impact of WFH on commuting distances in Germany.

3. Home-Employer Distances Over Time

We turn now to our Gusto data for a balanced panel of employers to examine the distribution of home-employer distances. The left panel in Figure 2 shows that mean distance rose sharply from 2019 to 2024. In computing these means, we winsorize the individual-level distances at 250 miles. The right panel presents information about the prevalence of distant employees. Before the pandemic struck, fewer than 4% of employees lived more than 50 miles from their employers. That figure rises sharply in reaction to the pandemic, more than doubling by 2023. Figure A2 shows that the rise in home-employer distances since 2020 is modest at the median but much greater in the upper percentiles of the distance distribution.

Figure 3 shows that the rising share of distant employees mainly reflects the nature of hiring after the COVID-19 pandemic struck. As of 2024, 12% of employees hired after March 2020 live more than 50 miles from their employers. For employees hired before March 2020, only 5% live more than 50 miles from their employers in 2024. Thus, the rise in home-worksite distances documented in Figure 2 happens mainly on the hiring margin. This figure also shows directly that employers have expanded their employee recruitment and catchment areas since March 2020. The obvious, but important, implication is that home-employer distances will, in all likelihood, continue rising beyond 2024 as employer-level workforces turn over.

Figure 4 reveals an interesting shift in the prevalence of distant employees by age group. Before the pandemic, the percent of employees living more than 50 miles from their employers is highest for the youngest and oldest employees, and the overall relationship to age exhibits a mild U-shape. This relationship inverted sharply after the pandemic. As of 2024, employees in their 30s

[3] The full set of controls include education bins (less than high school, high school, some college, college, graduate), earnings bins ($10k to $20k, $20k to $50k, $50k to $100k, $100k to $150k, $150k+), age bins (20 to 29, 30 to 39, 40 to 49, 50 to 64), and sex. We follow Cattaneo et al. (2024) in estimating the nonparametric relationship and computing standard error bands.

and early 40s exhibit the highest rates of distant employees, which aligns with survey evidence that people residing with children have the strongest desires to work from home part of the week (Aksoy et al. (2022) and Buckman et al. (2025)). That might be because WFH makes childcare easier, or because living farther from employers facilitates access to cheaper housing or better schooling. The youngest and oldest workers have the lowest rates of distant employees in 2024 and the smallest rise since 2019.

The incidence of distant employees rose more sharply for high earners, as shown in the left panel of Figure 5. Before the pandemic, about 8% of employees with annualized earnings greater than $200,000 resided more than 50 miles from their employers. By 2024, 20% of them did so. Less than 7% of those earning $100,000 to $200,000 resided more than 50 miles away in 2019, but 18% did so by 2024. Those with lower earnings saw more modest rises in the incidence of distant employees. The right panel of Figure 5 shows that the shift to distant employees is highly pronounced in the Information sector, Professional & Business Services, and Finance & Insurance. As of 2024, 30% of employees in the Information sector reside more than 50 miles away from their employer worksites, and 20% do so in Professional & Business Services. At the other end of the spectrum, distant employees remain rare in Accommodation & Food Services, Construction, Retail Trade, Healthcare, and Manufacturing. These patterns in the incidence of distant employees are similar to industry patterns for job vacancy postings in Hansen et al. (202) and WFH intensity measures in Barrero et al. (2021b).

4. Tax rates, housing costs, and relocation

The new geography of labor markets intersects with tax policy and living costs in important ways. It's now easier for employees in remote-suitable jobs to flee high-tax states and high-cost cities like New York and San Francisco. See Bick et al. (2024) for evidence that WFH led to a rise in interstate migration after the pandemic hit. As our Figure 5 makes clear, the ability to relocate while retaining the same job is greatest for highly compensated employees. The loss (or gain) of these high-earning employees also has more potent fiscal consequences for states and localities.

A. Tax Rates and the Pattern of Net Migration Across States

We now provide evidence on the pattern of net migration across states. Here, we work with our full Gusto dataset and focus on employees who stay with the same employer from December of year Y-1 to December of year Y for Y = 2017, 2018, 2019, 2020, 2021, 2022, 2023 and 2024. If a continuing employee switches his state of residence from Y-1 to Y, we compute the implied net change (percentage points) in the individual's state-level effective income tax rate. We use the NBER's TAXSIM program to impute the effective tax rate based on the individual's earnings, age, new and old residences, and calendar year.[4] If someone does not move between states from Y-1 to Y, we set the net tax rate change to zero. Next, we regress the individual-level net tax rate change on a full set of year dummies from 2017 to 2024. The coefficients on the year dummies quantify the pattern *and* extent of net migration between states with respect to differences in state-level tax rates. To explore whether and how net migration varies with earnings, we fit this regression separately for eight distinct earnings bins.

Figure 6 presents the results, showing coefficients on year dummies for each earnings group and the corresponding 95 percent confidence intervals. Net migration rates across states that differ in their top tax rates are small and statistically indistinguishable from zero in 2017 and 2018. A similar pattern prevails in 2019, but there is evidence of modest net migration from high-tax to low-tax states for high earners. The pattern shifts dramatically in 2020, with clear evidence of net migration from high-tax to low-tax states. Moreover, the extent of net migration from high-tax to low-tax states in 2020 rises almost monotonically with earnings. This pattern is even stronger in 2021, and a milder version of the same pattern continues into 2022, 2023 and 2024.

To get a sense of the implications for tax revenues, consider employees with annualized earnings of at least $250,000. For this earnings group, Figure 6 reports net tax rate reductions due to relocation between states of 8 basis points in 2020, 9 basis points in 2021, and another 9 basis points over the next three years. That yields a cumulative reduction in the effective state-level tax rate of 26 basis points for this group. Tax filers with adjusted gross income (AGI) of $250,000 or more account for 26% of total AGI in the 2023 tax year.[5] Total personal income in 2023 is $23.4 trillion.[6] Hence, taken together, these observations imply that the extent and pattern of net migration reduced aggregate state-level income tax collections from high earners by $1.6 billion per year, as of 2023. Repeating this calculation for all earnings groups and summing across groups yields an aggregate loss of state-level income tax collections of $2.6 billion per year, as of 2023.

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[4] The details of the tax calculator are available at https://taxsim.nber.org/taxsim35/. We assume the individual is married, filing jointly, with no dependents.

[5] Using data from Table 1 of the 2024 "Filing season statistics" reported by the U.S. Internal Revenue Service at https://www.irs.gov/statistics/filing-season-statistics. This source apportions various types of income by AGI brackets.

[6] Table B.16, Economic Report of the President (2025).

Judging from Figure 6, net outmigration from high-tax states is not fully played out by 2024. Perhaps more important, relocation between states is probably more common among persons who switch employers as compared to those who remain with the same employer from one year to the next. For this reason, Figure 6 likely understates the intensity of net migration from high-tax to low-tax states after the pandemic.[7] For the same reason, our calculations probably understate the extent to which WFH-fueled migration has reduced state-level income tax collections.

Our accounting calculations also have other potentially important limitations. First, they capture only one channel through which rising WFH can affect state-level tax revenues. For example, the rise of WFH may lead to greater labor force participation and higher earnings among disabled persons (Bloom et al., 2024) and mothers with young children (Harrington and Kahn, 2025). Effects of this sort raise taxable earnings. Second, the rise of WFH leads to a gross reallocation of taxpayers and taxable income across states. In particular, the greater locational flexibility associated with WFH presents more acute challenges for states that rely heavily on income tax collections from high earners.

Summing up, our evidence suggests that the rise of WFH since 2020 – and the new-found flexibility it offers with respect to residential location – has lowered aggregate state-level income tax revenues by about $3 billion per year and perhaps a good deal more. It does so by facilitating the migration of workers with remote-suitable jobs from high-tax to low-tax states. In this regard, our analysis is a first effort to quantify the fiscal ramifications of expanded WFH opportunities.

B. Housing Costs and Net Migration Across Local Areas

In addition to relief from high tax rates, employees may relocate to escape high living costs or local disamenities. We focus here on the relationship of housing costs to net migration patterns. We take the same approach as with tax rates, except we now consider employees who move between residential zip codes while staying with the same employer from one December to the next. To do so, we merge data on zip-code-level home value indices from Zillow, averaged over the period from January 2017 to December 2024. If a continuing employee switches residential zip codes from Y-1 to Y, we compute the implied percent change in the 2017-2024 average of local home prices. If the person continues residing at the same address (or zip code), we set this

[7] Assessing this issue in full will require access to comprehensive employer-employee matched data with residential and employer worksite locations. Government data sources that meet these requirements typically become available with a lag of several years.

change value to zero. As before, we regress these individual-level values on year effects and consider separate regressions for each earnings bin.

Figure 7 reports the results. It shows no discernible net migration pattern with respect to housing costs in 2017, 2018 or 2019. Starting in 2020, however, and continuing through 2024, we see a strong pattern of net migration from zip codes with high housing costs to those with lower housing costs. Every group except those with annualized earnings less than $20,000 shows net movements to areas with cheaper housing from 2020 through 2022. Net migration intensity is stronger for groups with higher earnings. For employees with annualized earnings of at least $150,000, net outmigration reduced their average housing costs by about 1.5% in 2020 alone, with additional cost savings in the years from 2021 to 2024. Since the Zillow index captures total home values, Figure 7 understates the impact on price per square foot, as homes tend to be larger where space is cheaper.

In part, the net migration patterns in Figure 7 reflect the intentions of (some) employees to escape high housing costs by moving away from expensive city centers to suburbs and exurbs. These within-metro migration patterns align with the "Donut effect" of WFH on home prices (Ramani et al., 2024). That said, our evidence does not identify why employees move. For example, Figure 6 suggests that some employees switched states to escape high tax rates. Those same people necessarily switched residential zip codes. Even when mainly motivated by desires to escape high state-level tax rates, their relocations may also bring benefits in the form of lower housing costs. Thus, we cannot directly observe why someone moves between states or zip codes. Nevertheless, the timing of the net migration patterns in Figures 6 and 7 strongly suggests that the pandemic-initiated rise in WFH gave many workers an opportunity to re-optimize over where to live, and enough of them did so to materially reduce overall income taxes and housing costs.

C. Individual-Level Gains from Relocation

Thus far, our discussion of migration patterns considers their net effects on effective tax rates and housing costs when aggregating over those who switched residential locations and those who did not. It's also insightful to quantify the effects on the switchers. To do so, we construct a version of Figure 6 that conditions on switching states from one year to the next and a version of Figure 7 that conditions on moving between zip codes. See Figures A7 and A8.

As these figures reveal, the individual-level gains from residential relocation are sizable. Among continuing employees with annualized earnings of at least $250,000, those who switched states in 2020 reduced their effective state-level tax rates by 2.4 percentage points (Figure A7). Continuing employees in this earnings group who moved in 2021, 2022, 2023 and 2024 also saw material reductions in their effective tax rates as a result. The corresponding tax rate savings for switchers with annualized earnings of $100,000 to $200,000 are somewhat less than half as large.

Among continuing employees with annualized earnings of at least $150,000, those who moved between zip codes experienced large drops in their local housing costs. For example, persons in this group who switched zip codes in 2020 enjoyed a 16% reduction in local-area housing costs. Continuing employees with lower earnings also enjoyed sizable reductions in local-area housing costs when they moved between zip codes.

These results are important for at least three reasons. First, they show that the locational flexibility afforded by WFH yields large individual-level welfare gains even when abstracting from any WFH effects on productivity, commuting costs, personal autonomy, and flexibility in time use over the day. Second, the results show that Americans who work remotely, part or all of the week, benefit directly when they relocate to areas with lower housing costs. By reducing land scarcity and housing costs in and around city centers, their relocation response also benefits renters in such areas who cannot work remotely. Third, these findings help explain why many employees are highly resistant to return-to-office mandates. Once they've relocated to areas with lower tax rates and cheaper housing, it takes a large pay hike to offset the tax savings and lower housing costs hey must forego if they move back.

5. Hires and Separations: Near versus Far Employees

We turn now to the following question: As firms expand and contract, do they treat far and near employees differently with respect to employment adjustments? To see the motivation for this question, consider why a firm might vary its treatment of far and near employees as its growth rate varies. When a firm rapidly expands employment, it draws down the local supply of suitable jobseekers. In turn, this more rapid drawdown encourages the firm to cast a wider net and expend more effort to recruit and hire far employees.[8] Thus, we hypothesize that the hiring rate is more sensitive to the firm-level expansion rate for far as compared to near employees. Alternatively, when firms rapidly contract employment, the effects may fall more heavily on far employees

[8] This conclusion fits with evidence on firm-level recruiting behavior. In particular, Davis et al. (2013), Lochner et al. (2021), Carrillo-Tudela et al. (2023), and Mongey and Violante (2025) find that recruiting intensity per vacancy rises with employer-level hiring rates in the cross section. Geographic reach is one margin of recruiting intensity.

because employers see them as less connected to the organization or easier to replace. Far employees may also be more likely to quit from shrinking firms, if they have a broader set of outside options.[9] Thus, we hypothesize that the separation rate of far employees is more sensitive to the firm-level contraction rate than the separation rate of near employees. In this section, we develop novel evidence that lets us assess these hypotheses.

A. A Nonparametric Examination of Firm-Level Employment Adjustments

To do so, we relate gross hiring and separation rates to firm-level employment growth rates in a nonparametric, graphical manner. As before, "far" employees reside more than 50 miles from their employers. Our empirical approach extends the method of Davis et al. (2012) to allow for multiple employee types. An attractive feature of their method is that it uncovers the firm-level behavior of hires and separations without imposing functional forms on the data. As it turns out, hiring and separation rates exhibit highly nonlinear relationships to firm-level growth, confirming the value of a nonparametric approach.

Following Davis and Haltiwanger (1992), define the firm-level employment growth rate at time t as $g_{ct} = \frac{e_{ct} - e_{c,t-1}}{\left(\frac{e_{ct} + e_{c,t-1}}{2}\right)}$, where e_{ct} denotes firm c employment at t. Let e_{ct}^{far} and e_{ct}^{near} denote the numbers of far and near employees, where $e_{ct}^{far} + e_{ct}^{near} = e_{ct}$. We recognize that entry and exit in the Gusto dataset need not reflect birth and death. Hence, we drop observations for which g_{ct} equals 2 or -2, since those values obtain when a firm enters or exits the dataset.

Let $HIRES_{ct}^{far}$ and $HIRES_{ct}^{near}$ denote, respectively, the number of far and near employees hired by firm c at t. Here, "hired" at t means the employee appears on the firm's payroll in t but not in $t-1$. Using these quantities, we compute the firm-level gross hiring rate of far employees as $H_{ct}^{far} = 2HIRES_{ct}^{far}/(e_{ct}^{far} + e_{c,t-1}^{far})$ and the gross hiring rate of near employees as $H_{ct}^{near} = 2HIRES_{ct}^{near}/(e_{ct}^{near} + e_{c,t-1}^{near})$. Symmetrically, an employee separates in month t if he or she appears on the firm's payroll in $t-1$ but not in t. We compute firm-level gross separation rates for far and near employees in an analogous manner and denote them as S_{ct}^{far} and S_{ct}^{near}.

To aggregate across firms and over far and near employees, we need weights that yield consistent aggregation.[10] To that end, we compute firm-level weights at t as $\omega_{ct} = \frac{e_{ct} + e_{c,t-1}}{E_t' + E_{t-1}}$,

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[9] Quit rates rise with the employer-level rate of contraction in the cross section. See Davis et al. (2012).

[10] See Section 2.3 in Davis and Haltiwanger (1999) on this point.

where E_{t-1} denotes the aggregate employment of all firms in the sample at time $t-1$ except those with no employment at t, and E'_t denotes the aggregate employment of all firms at t except those with no employment at $t-1$. The corresponding far-employee and near-employee weights for firm c at t are $\omega_{ct}^{far} = \omega_{ct}\left(\frac{e_{ct}^{far}+e_{c,t-1}^{far}}{e_{ct}+e_{c,t-1}}\right)$ and $\omega_{ct}^{near} = \omega_{ct}\left(\frac{e_{ct}^{near}+e_{c,t-1}^{near}}{e_{ct}+e_{c,t-1}}\right)$, respectively.

To characterize how hiring and separation rates vary with firm-level growth rates, we first sort the g_{ct} observations into interval bins that are symmetric around 0, allowing for a mass point at 0 in the distribution of g_{ct} values.[11] Next, we separately regress the hiring and separation rates of far and near employees (H_{ct}^{far}, H_{ct}^{near}, S_{ct}^{far}, and S_{ct}^{near}) on a full set of indicators for the interval bins. When fitting these regressions, we weight the monthly firm-level, type-specific observations using ω_{ct}^{far} and ω_{ct}^{near}. We suppress the intercept term in each regression, so that we can read the relationships of interest directly from the bin-specific regression coefficients.

Figure 8 presents the results. Among expanding firms, hiring rates for distant employees are greater *and* more sensitive to the firm's expansion rate. This result confirms the hypothesis that firms shift the mix of their hires to more distant employees when growing more rapidly. For example, the gap between H_{ct}^{far} and H_{ct}^{near} is 0.7 percent of employment for firms in the [.01,.02) growth rate interval as compared to 2.2 in the [.09,.10) interval and 3.0 percent in the [.14,.15) interval. Among shrinking firms, separation rates are higher for employees who live more than 50 miles away *and* more responsive to the firm's contraction rate. This result confirms the view that separation rates rise more strongly for far employees as firms shrink more rapidly. For example, the gap between S_{ct}^{far} and S_{ct}^{near} is 0.2 percent of employment for firms in the [-.01,-.02) growth rate interval as compared to 1.9 percent in the [-.09,-.10) interval and 3.3 percent in the [-.14,-.15) interval. More generally, Figure 8 supports the view that firms treat far employees function as a more flexible margin of employment adjustment.

[11] Moving away from 0 in the rightward direction, we specify interval bins for (0,0.005), [0.005,0.01), [0.01,0.02), [0.02,0.03), [0.02,0.03),…,[0.30,0.31) and then wider bins to fully partition the right half of the support. We partition the left half of the support in a symmetric manner. When showing results, we restrict attention to bins for g_{ct} values in (-0.31,0.31), which encompass 95% of the monthly firm-level g_{ct} observations. The data are much thinner outside this interval.

B. A Nonparametric Examination of Individual-Level Separations

It's possible that far employees have other attributes – beyond distance from employer – that could lead firms to treat them differently. This concern is especially salient on the separations margin in our context. Recall from Section 3 that far employees are more common among persons hired after March 2020. As a result, far employees tend to have shorter job tenures in our sample. Shorter job tenures, rather than greater home-employer distances, could lead employers to treat far employees as more expendable or far employees feel less attached to the firm.

To address this concern, we turn to a nonparametric analysis of separations at the individual level. For each person employed in month $t-1$, we set the separation value to 1 if he or she no longer works for the same firm in month t, and 0 otherwise. We again pool the data over months and distinguish far and near employees. We regress the separations value on the same exhaustive set of interval dummies for firm-level growth rates at t. As before, we read the relationships of interest from the bin-specific regression coefficients. The advantage of this individual-level regression is that we can easily add individual-level controls for job tenure and other observable characteristics of persons.

We implement this analysis and report the results in Appendix Figure A9. It shows how the separation rate varies with firm-level growth rates when we include controls for individual-level job tenure, age, and sex. Since separation rates are known to fall nonlinearly with job tenure, we control for job tenure in a nonparametric manner. As it turns out the pattern in Figure A9 is very similar to the one in Figure 8. In other words, separation rates of far employees are more sensitive to firm-level contraction rates even when controlling for individual-level job tenure, age, and sex. This evidence supports the conclusion that far-employee separation rates are more sensitive to firm-level contraction rates because they reside farther from their employers.

6. Concluding Remarks

The rise of remote and hybrid working arrangements is reshaping the geography of U.S. labor markets. Mean distance from employee home to the employer's nearest worksite location rose from 15 miles in 2019 to 26 miles in 2024 in our balanced panel of employers. The share of employees living more than fifty miles from their employer rose from roughly 4 to 9 percent over the same period, and to 12 percent among those hired since March 2020. These developments are concentrated among higher earners, employees in their 30s and 40s, and in industry sectors like Finance & Insurance, Information, and Professional & Business Services. Thirty percent of employees in the Information sector reside more than 50 miles from their employers as of 2024, and 20 percent do so in Professional & Business Services.

These developments have wide-ranging implications for states, cities, employers, and households. For example, we show that employees tend to migrate to states with lower tax rates and to areas with less expensive housing. These migration patterns greatly intensified in 2020, especially among high earners, and they continued to unfold through 2024. Outmigration pressures are most acute for cities with high housing costs that are situated in high-tax states, especially cities that also have high employment shares in industries with remote-suitable jobs.

Migration responses to the rise in WFH matter for state-level income tax collections. Our evidence suggests that net migration from high-tax to low-tax states reduced state-level income tax collections by about $3 billion per year as of 2023. Of course, these fiscal effects are uneven, with high-tax states losing tax revenues and low-tax states benefiting from an influx of high earners. Because new hires exhibit more locational flexibility than incumbent employees hired before the pandemic, these fiscal effects may mount in the years ahead as workforces turn over.

We also find large gains for workers who relocated. Employees with annual earnings greater than $250,000 who moved between states in 2020 (while staying with the same employer) lowered their effective state-level tax rates by 2.4 percentage points, on average. Employees with annual earnings greater than $150,000 who moved to a new zip code in 2020 saw a 16% reduction in local housing costs, on average. Savings in taxes and housing costs are also sizable for high earners who moved in 2021, 2022, 2023 and 2024. Employees in the middle of the earnings distribution had smaller benefits from relocating to areas with lower taxes and housing costs. These results help explain why many employees are highly resistant to return-to-office mandates.

Finally, we show that separation and hiring behavior differs between far and near employees. Among growing firms, hiring rates of far employees are greater *and* more sensitive to the firm's expansion rate. Among shrinking firms, separation rates are greater for employees who live more than 50 miles away *and* more sensitive to the firm's contraction rate. In short, distant employees function as a more flexible margin of firm-level employment adjustments.

Employer-level workforces have also become more geographically dispersed since the pandemic struck. For two reasons – greater geographic dispersion of employer-level workforces, and the greater responsiveness of far employees – the labor market footprint of the average firm has become geographically diffused after the pandemic. This spatial diffusion of firm-level footprints will continue to develop in the years ahead as workforces turn over, because new hires reside farther from their employer's worksite than those hired before the pandemic.

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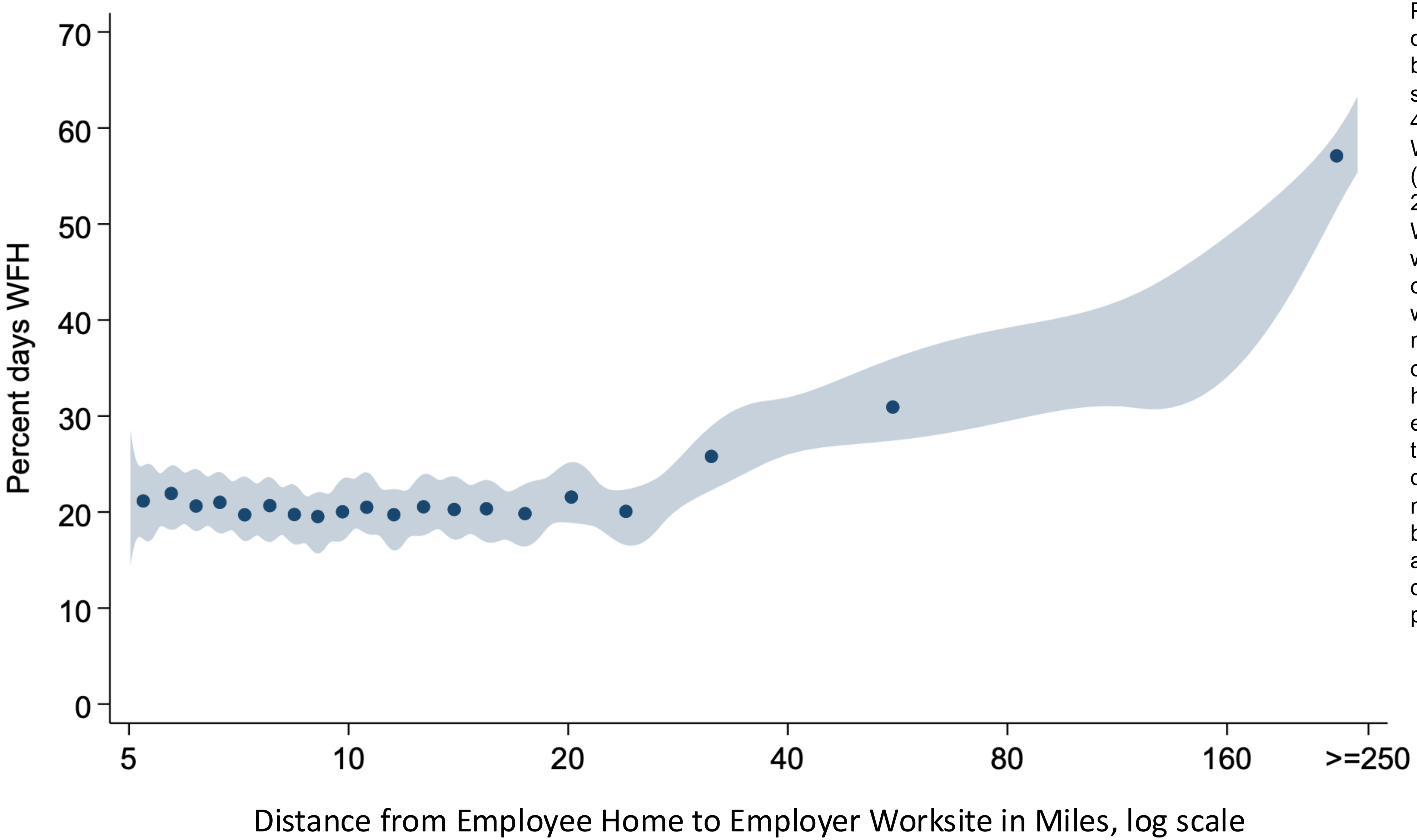
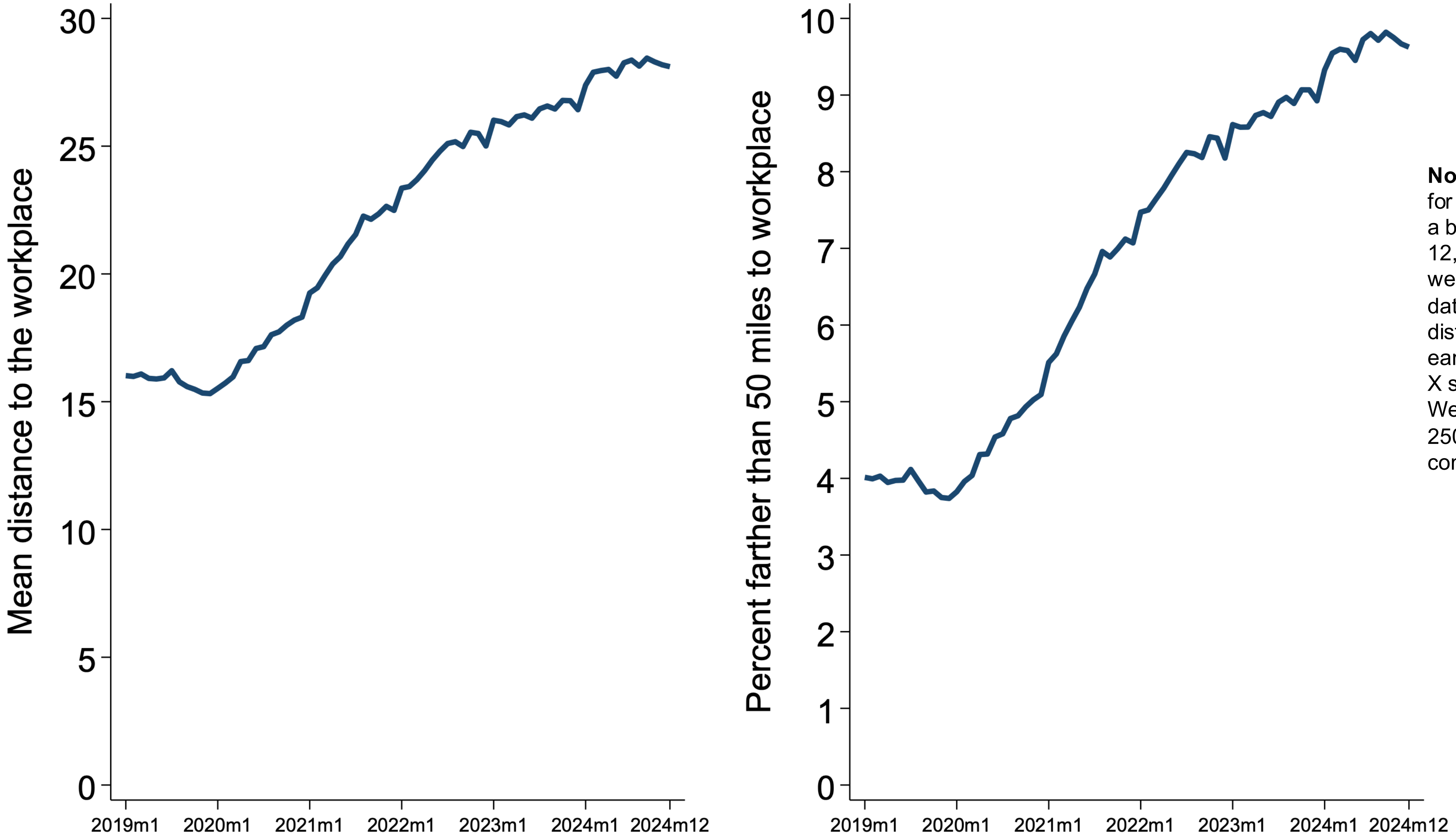
Figure 1: Work from home intensity rises with distance to employer



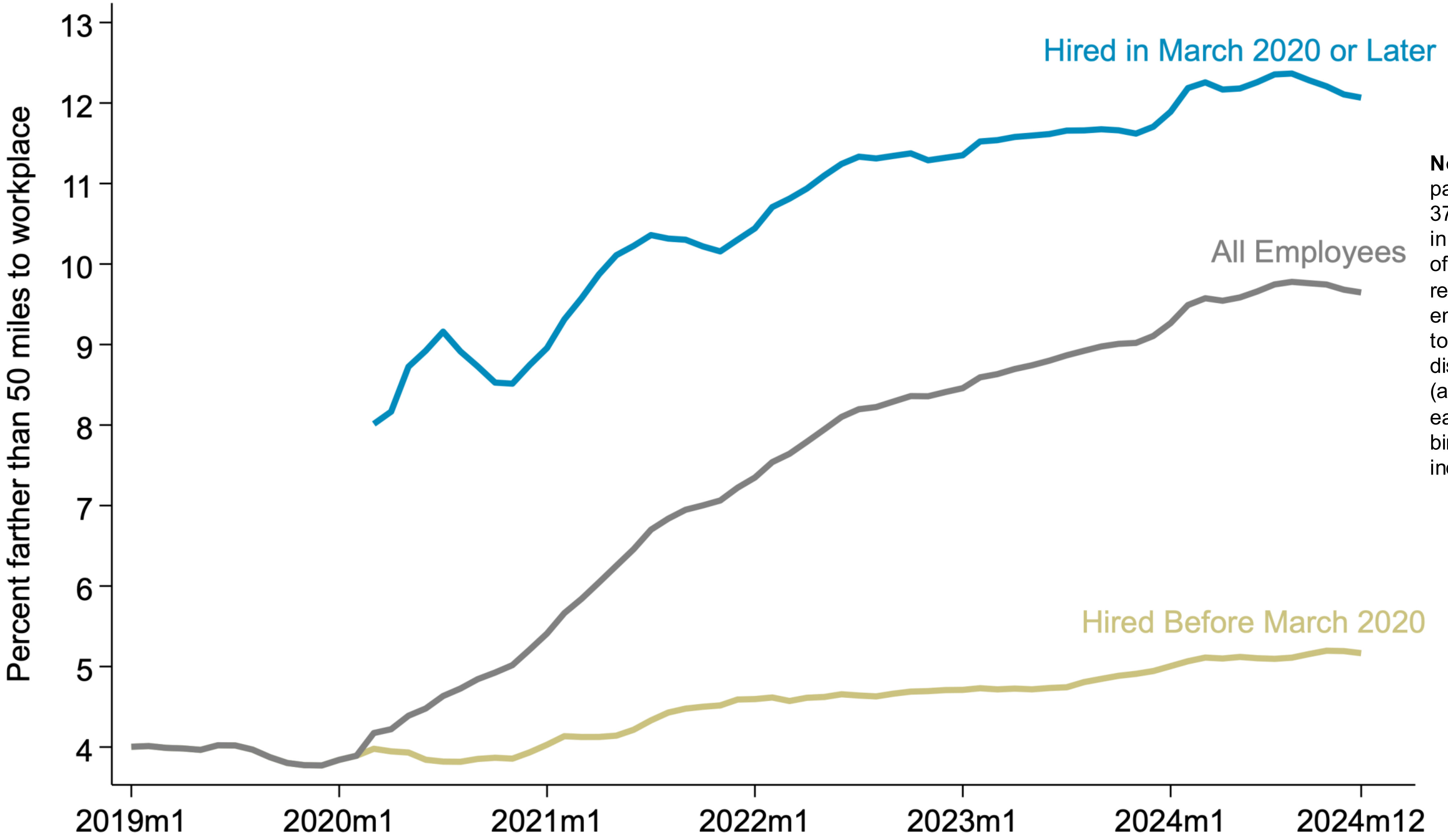
Notes: This chart plots the fitted relationship from a regression of Percent Days WFH on home-worksite distance with controls for education bins, earnings bins, age bins, and sex. We fit the regression to data on 44,110 respondents in the Survey of Working Arrangements and Attitudes (SWAA) from January 2022 to May 2024. We measure Percent Days WFH as the WFH percent of full paid workdays in the week. Our sample contains persons 20-64 years of age with prior-year earnings of $10,000 or more. We compute the haversine distance between the employee's home zip code centroid and the employer's worksite zip code centroid to obtain our distance measure. We drop employees who live within five miles of the employer's worksite because our measure is too coarse to accurately distinguish among short distances. Shaded regions denote 95 percent confidence bands.

Figure 2: Americans now live farther from their employers than in 2019



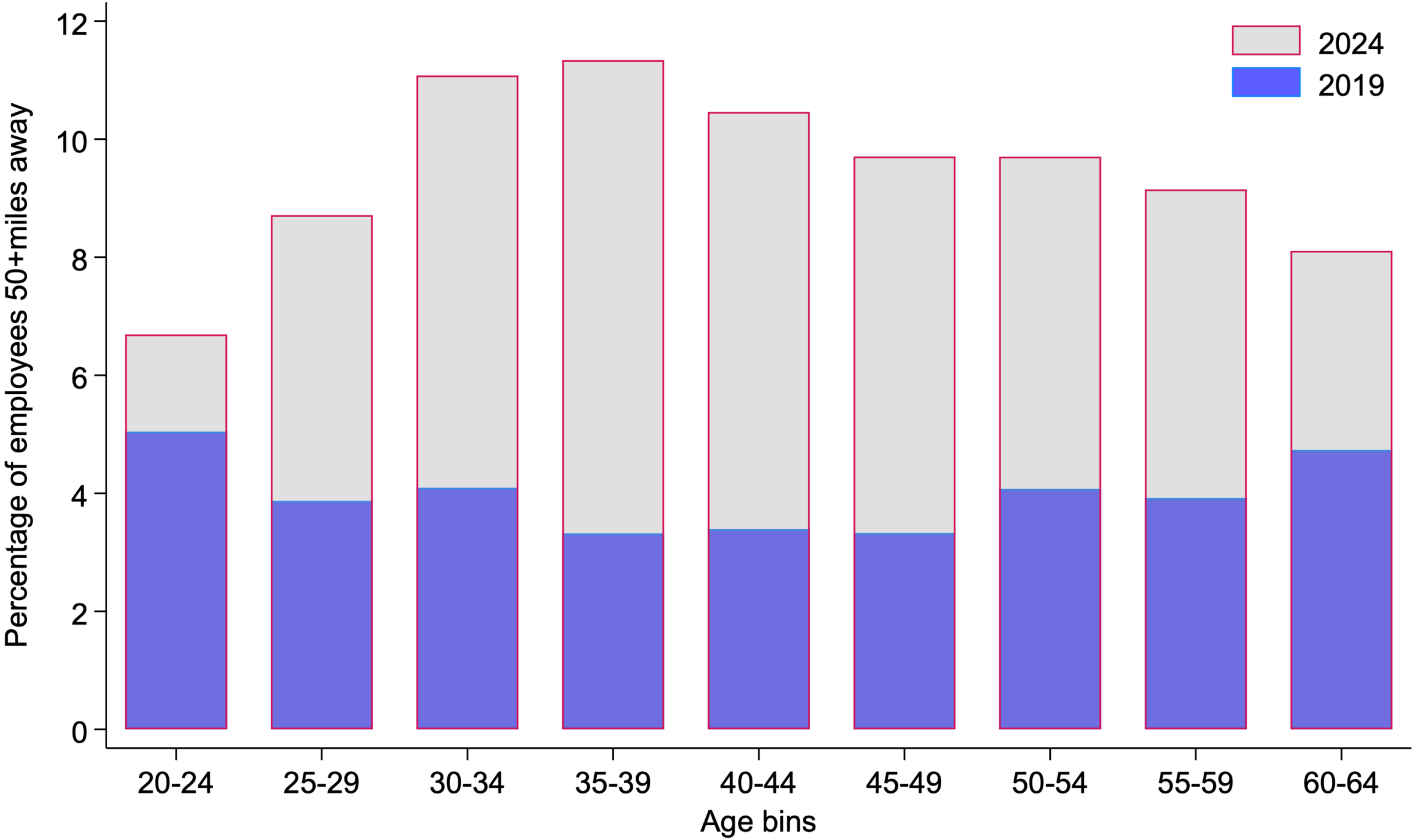
Notes: Gusto payroll data for 371,849 employees in a balanced panel of 12,454 firms. We re-weight the employee-level data to match the CPS distribution by (annualized earnings bin) X (age bin) X sex X major industry. We winsorize distance at 250 miles when computing mean distance.

Figure 3: New hires since March 2020 account for the rise in distant employees



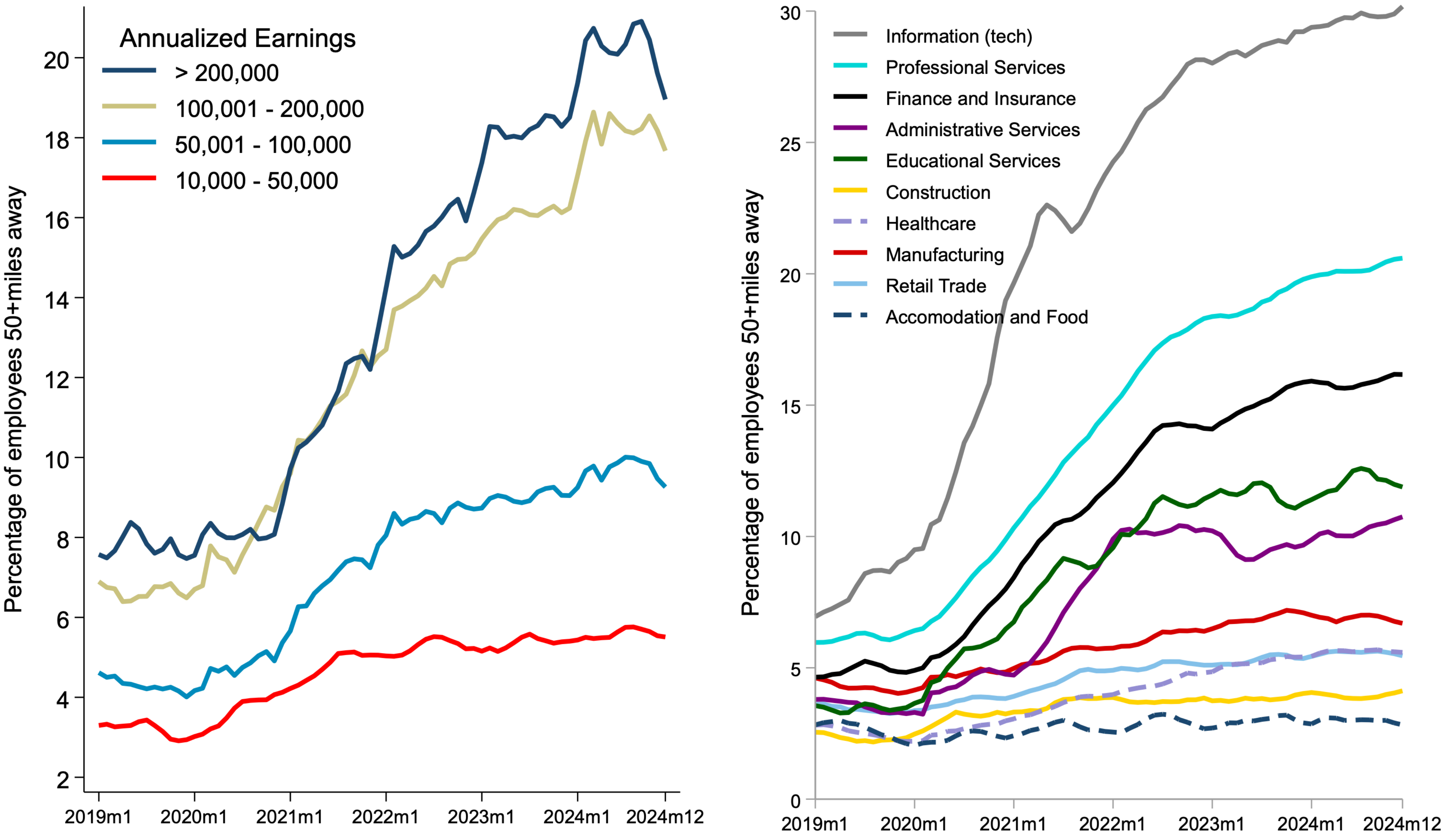
Notes: Gusto payroll data for 371,849 employees in a balanced panel of 12,454 firms. We re-weight the employee-level data to match the CPS distribution by (annualized earnings bin) X (age bin) X sex X major industry.

Figure 4: Employees in their 30s and 40s have the largest increase in distance to employer



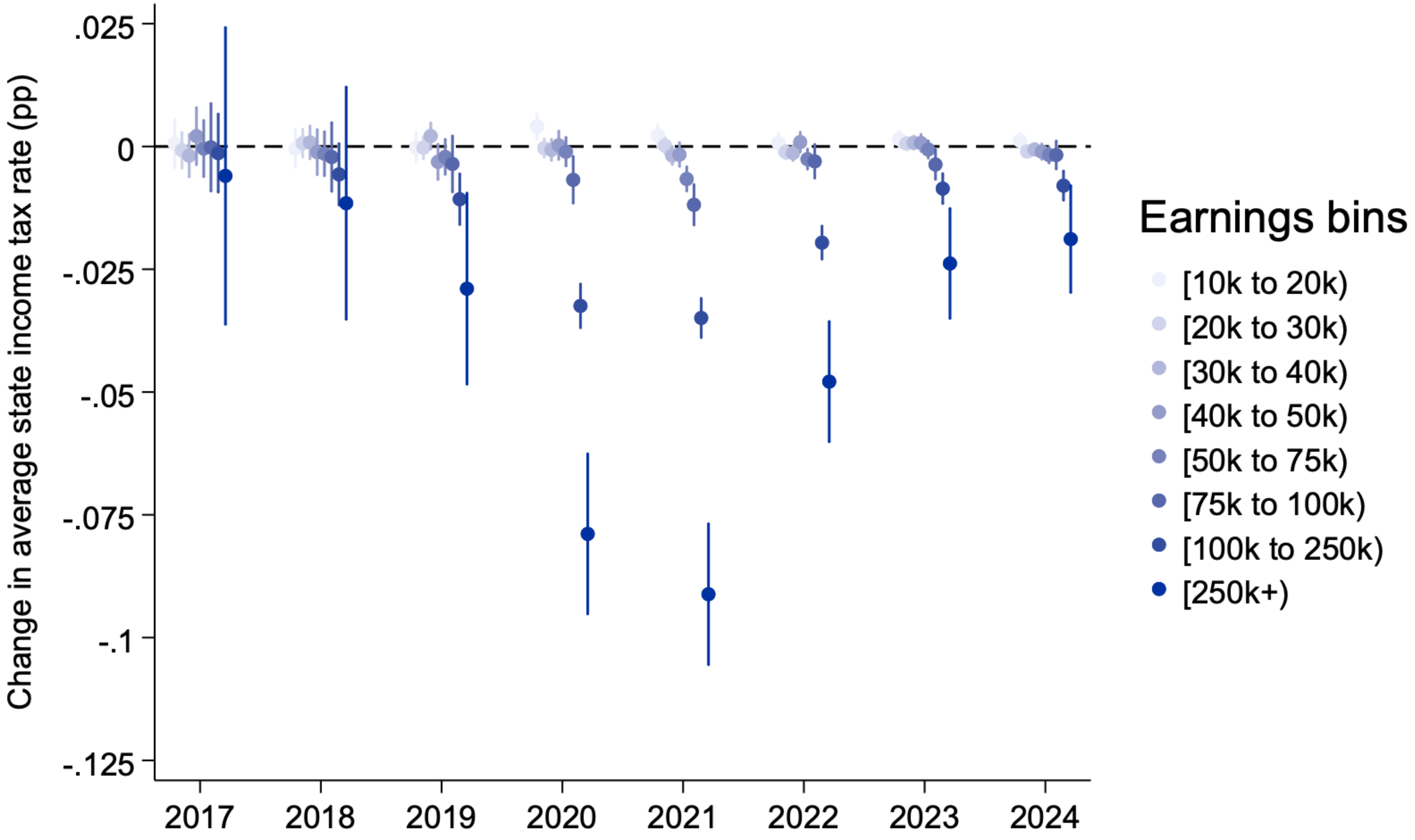
Notes: Gusto payroll data for 371,849 employees in a balanced panel of 12,454 firms. We re-weight the employee-level data to match the CPS distribution by (annualized earnings bin) X (age bin) X sex X major industry.

Figure 5: High earners in Information, Professional Services, and Finance saw the greatest increases in distance to the workplace



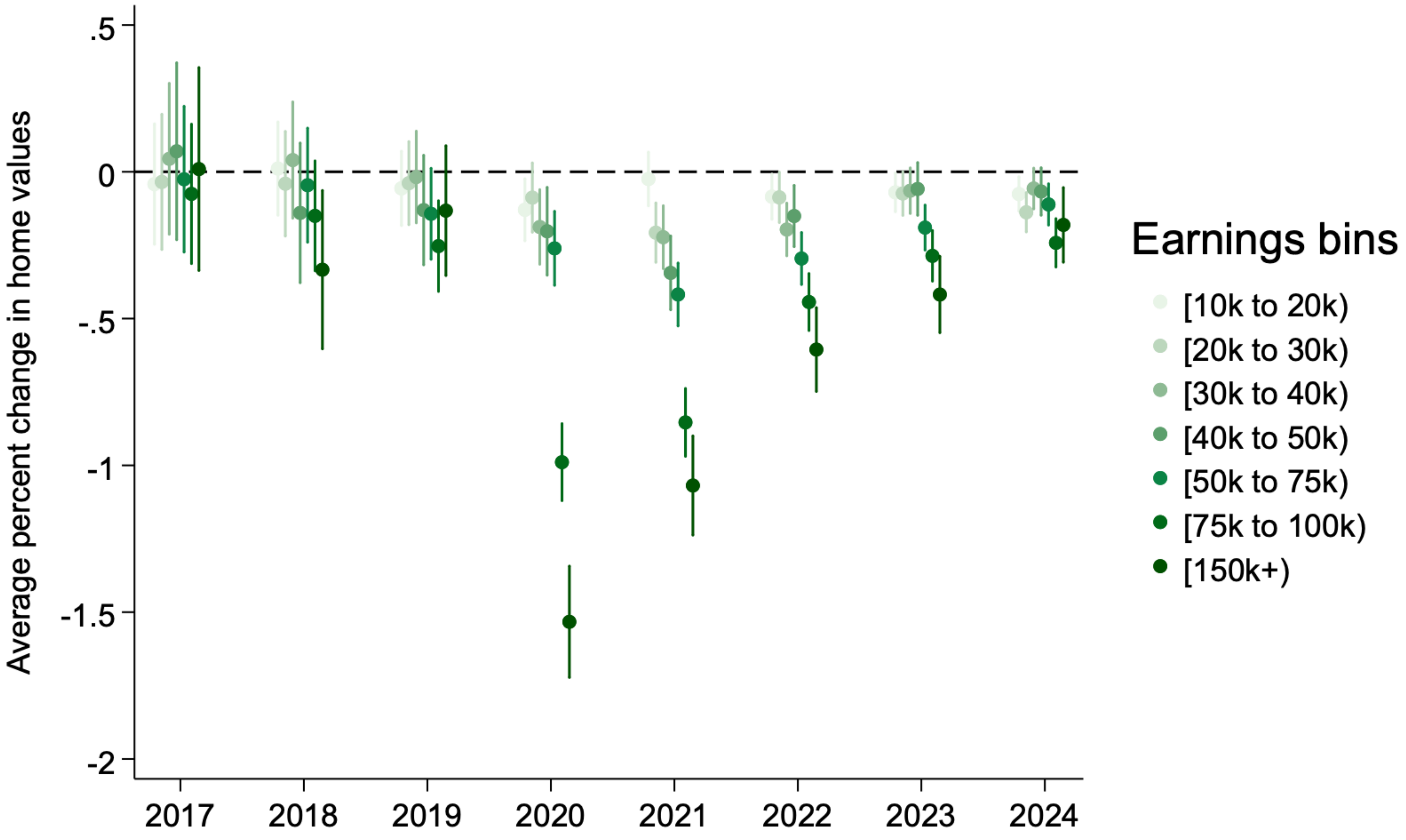
Notes: Gusto payroll data for 371,849 employees in a balanced panel of 12,454 firms. We re-weight the employee-level data to match the CPS distribution by (annualized earnings bin) X (age bin) X sex X major industry.

Figure 6: Continuing employees moved to states with lower tax rates after the pandemic struck, with stronger migration responses for higher earners



Notes: This chart reports the mean net change in the average state-level labor income tax rate among 1.3 million employees who remained with the same employer from December of Year Y-1 to December of Y, where Y is reported on the horizontal scale. Depending on the year, 52 to 64% of employees in the Gusto data set remain with their employer from December of Y-1 to December of Y. The vertical lines depict 95% confidence intervals. See Figure A.7 for a chart that reports corresponding changes in average tax rates conditional on moving between states.

Figure 7: Continuing employees moved to areas with cheaper housing after the pandemic struck, with stronger migration responses for higher earners



Notes: This chart reports the mean net change in zip-code level home values among 1.3 million employees who stayed with the same employer from December of Year Y-1 to December of Y, where Y is reported on the horizontal scale. We set zip-code level home values to the average monthly Zillow Home Value Index for each zip code from January 2017 to December 2024. The vertical lines depict 95% confidence intervals.
See Figure A8 for a chart that reports the corresponding percent change in local home prices conditional on moving between zip codes.

Figure 8: Separation and hiring rates are greater, and more responsive to employer growth, for distant employees

Notes: Gusto payroll data of a sample of about 4.85 million employees and 171 thousand companies from 2017 to 2024. We obtain these plots from nonparametric least-squares regressions of separation and hiring rates on monthly employer-level growth rate bins. There are four separate regressions: two for the hiring rates of far and near employees, and two for the hiring rates of far and near employees.

Figure A1: Sample reweighted to match Current Population Survey by gender, earnings, industry, and age

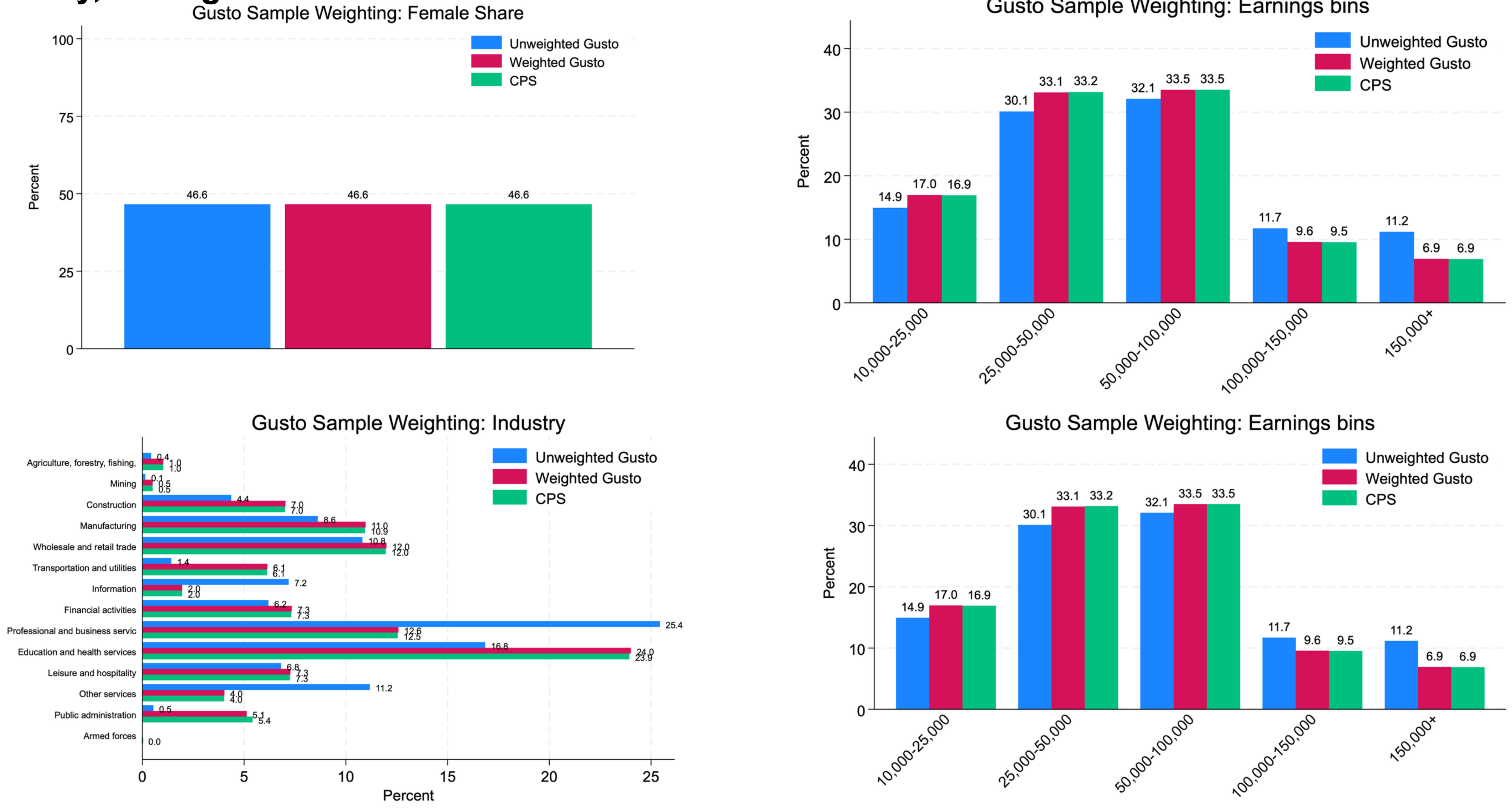
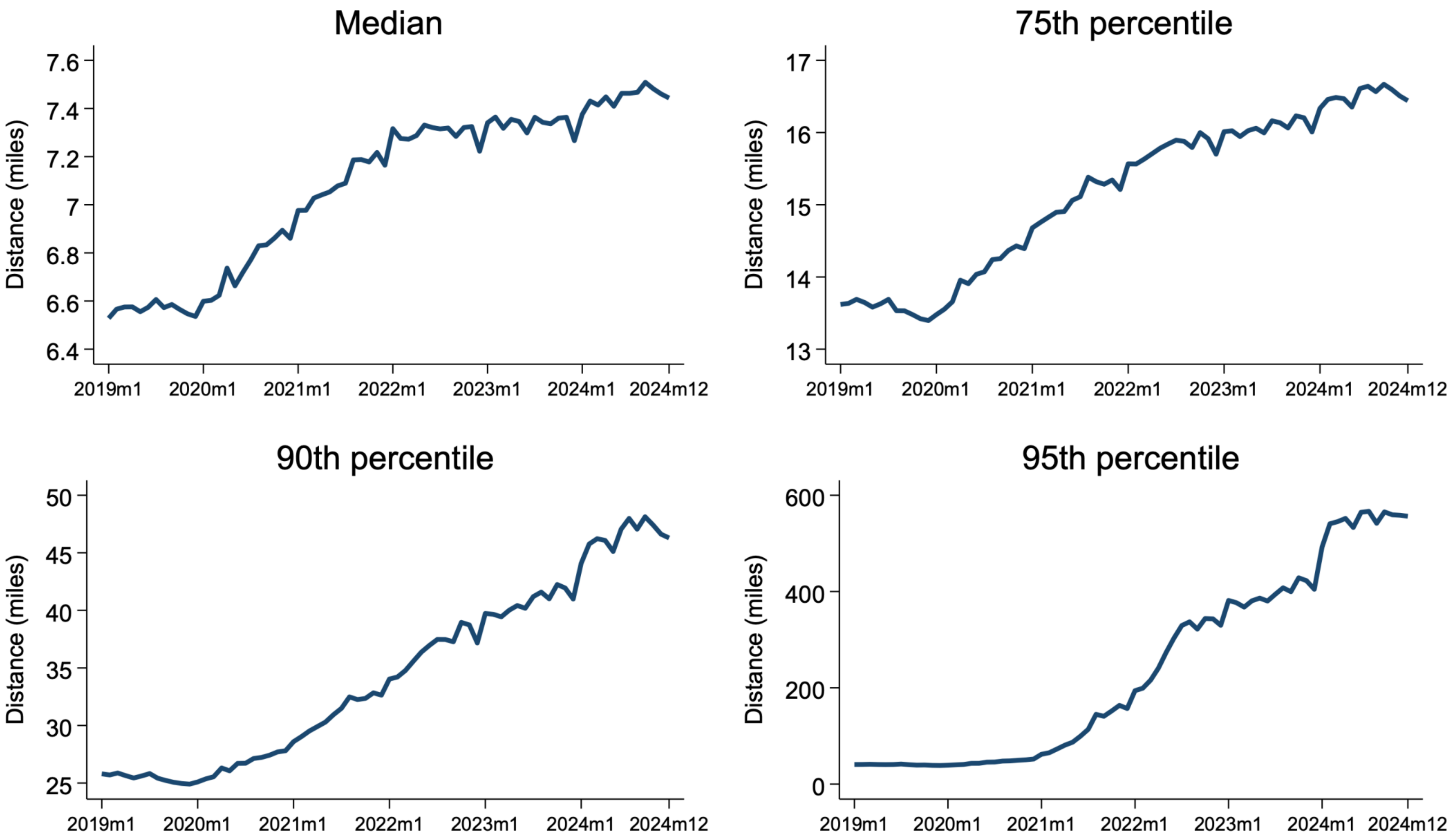
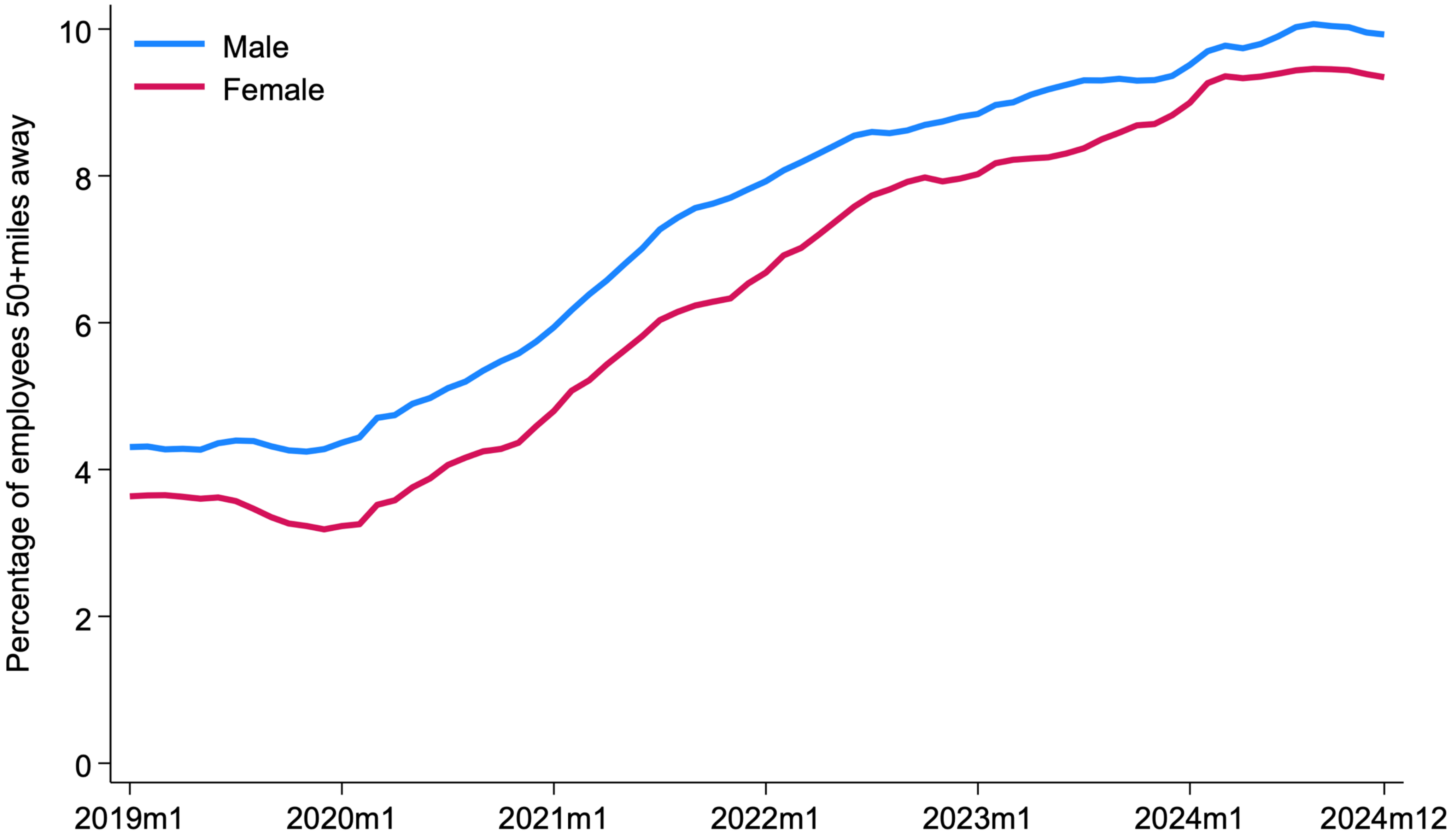


Figure A2: Distance to employer rose across the entire distribution after the pandemic struck



Notes: See notes to Figure 2.

Figure A3: The share of distant employees rose for men and women after the pandemic



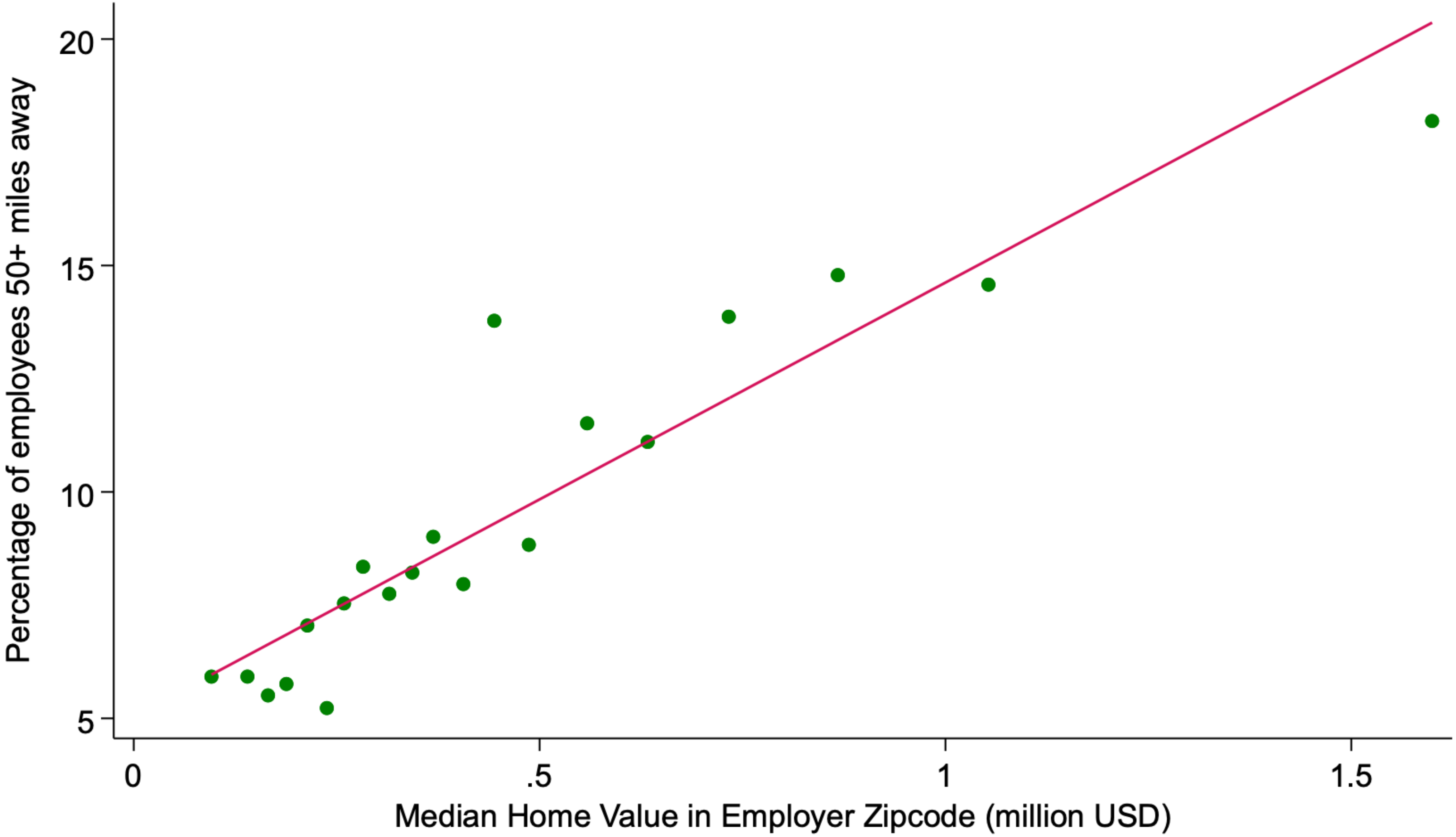
Notes: See notes to Figure 2.

Figure A4: Percent of employees 50+ miles away rose in every major industry sector but much more so among new hires in Information, Finance & Insurance, and Professional Services

	All Employees		Hired Before March 2020	Hired After March 2020
	2019	2024	2024	2024
Accommodation and Food Services (72)	2.6	3.0	2.2	3.2
Retail Trade (44-45)	3.4	5.6	4.4	6.1
Health Care and Social Assistance (62)	2.5	5.6	3.0	7.0
Manufacturing (31-33)	4.2	6.9	4.0	8.3
Educational Services (61)	3.4	12.1	5.5	15.0
Administrative Services (56)	3.5	10.3	5.9	11.8
Professional Services (54)	6.1	20.2	9.7	26.1
Finance and Insurance (52)	4.9	15.9	9.2	20.4
Information (51)	8.1	29.7	13.7	37.4

Notes: See Figure 2 notes

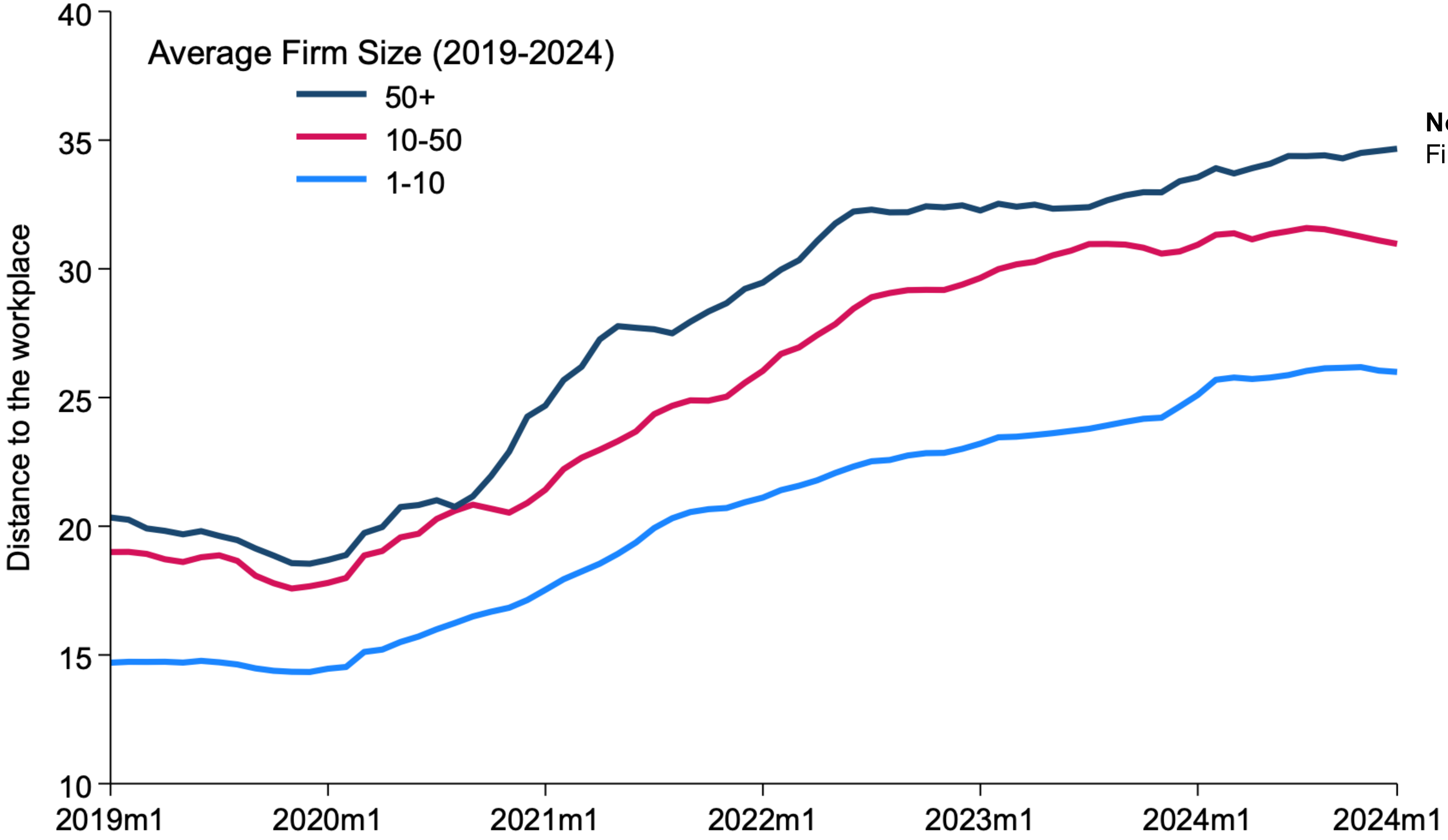
Figure A5: Employers in areas with high housing prices have a much greater share of distant employees



Notes: Gusto payroll data in 2024. Employee-level data are reweighted to match the CPS distribution by (annualized earnings bin) X (age bin) X sex X major industry.

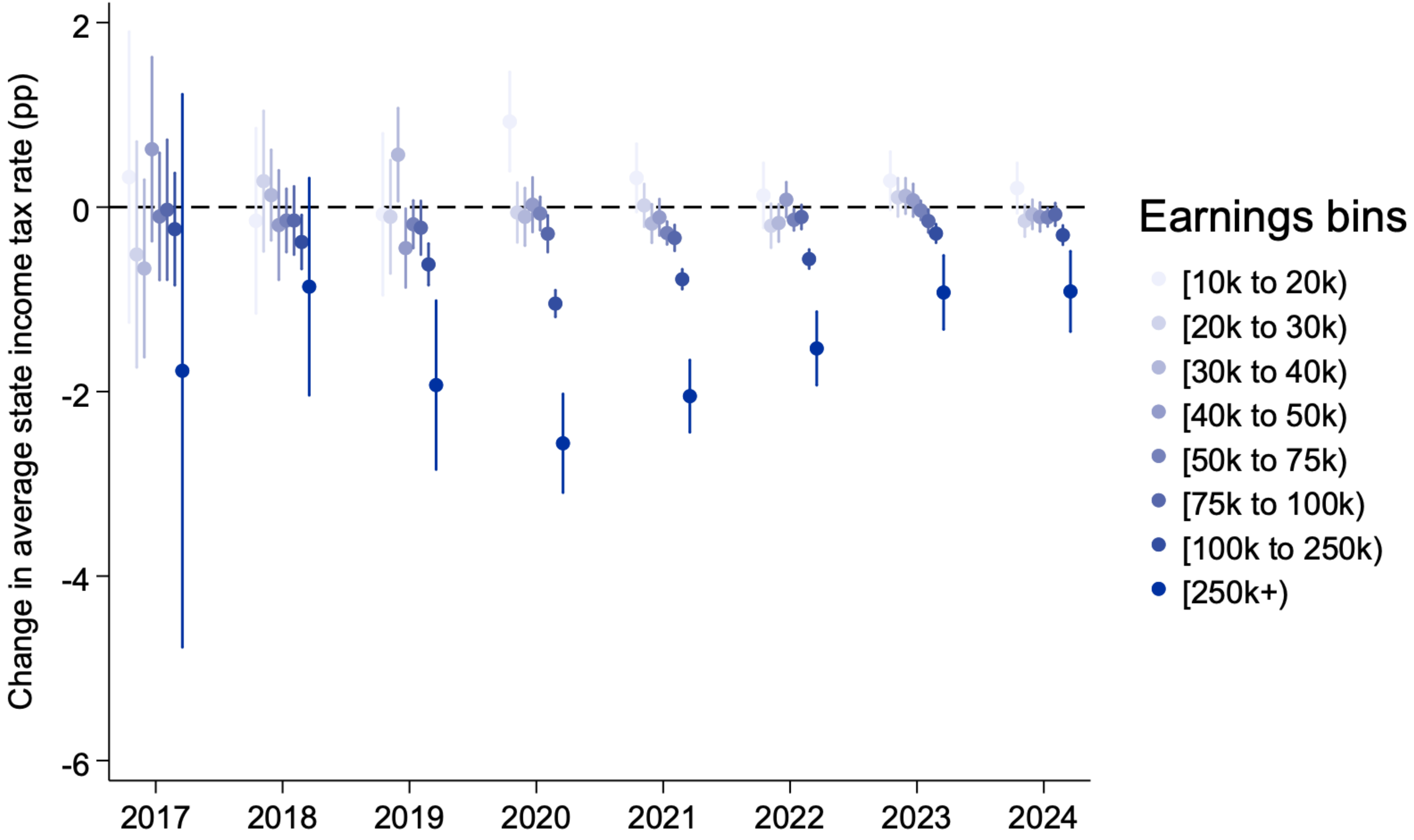
N= 1,465,067 Coef: 13.2 Clustered SE: (.267)

Figure A6: Distant employees became more common across the employer size distribution after the pandemic struck



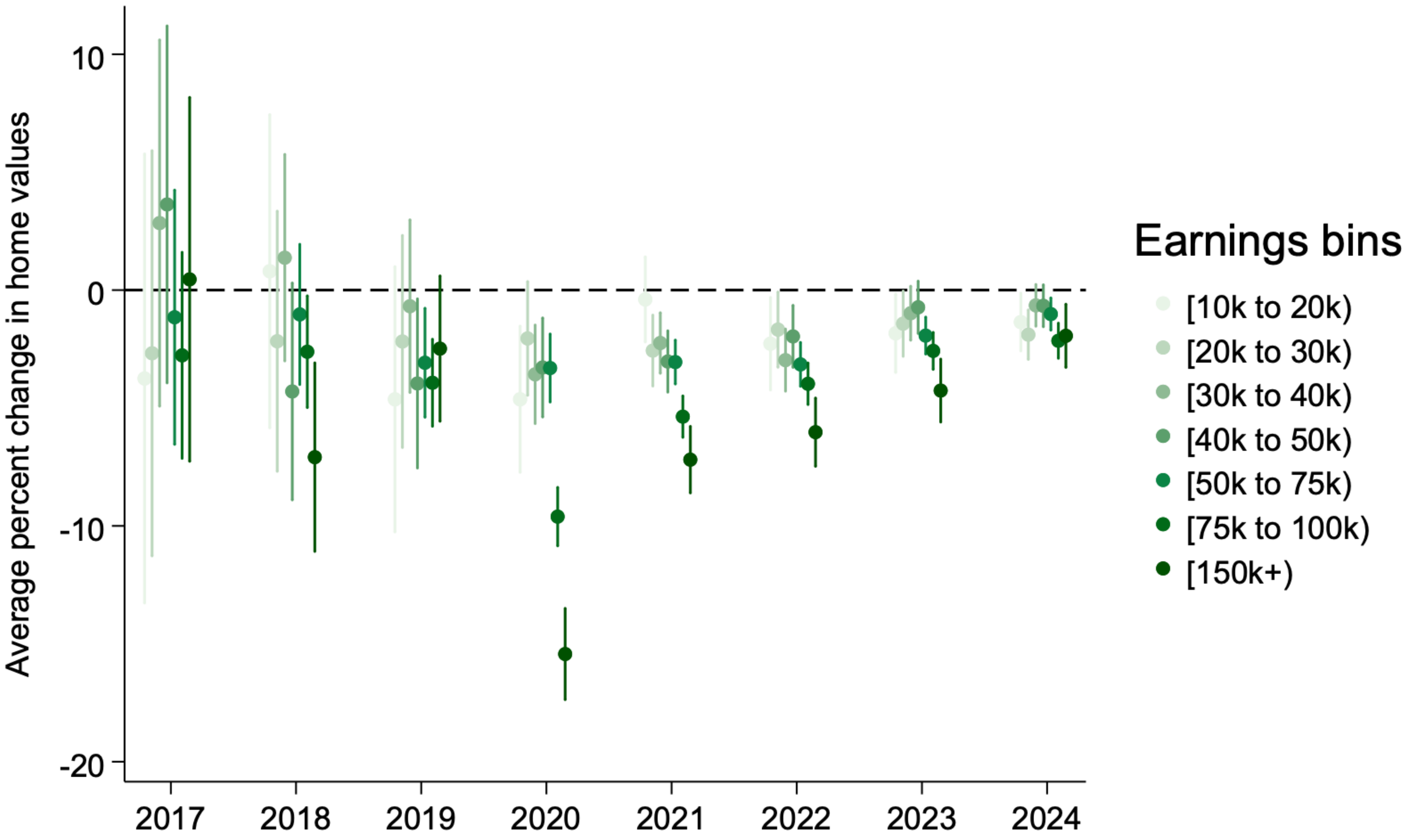
Notes: See notes to Figure 2.

Figure A7: Mean changes in tax rates, continuing employees who move between states



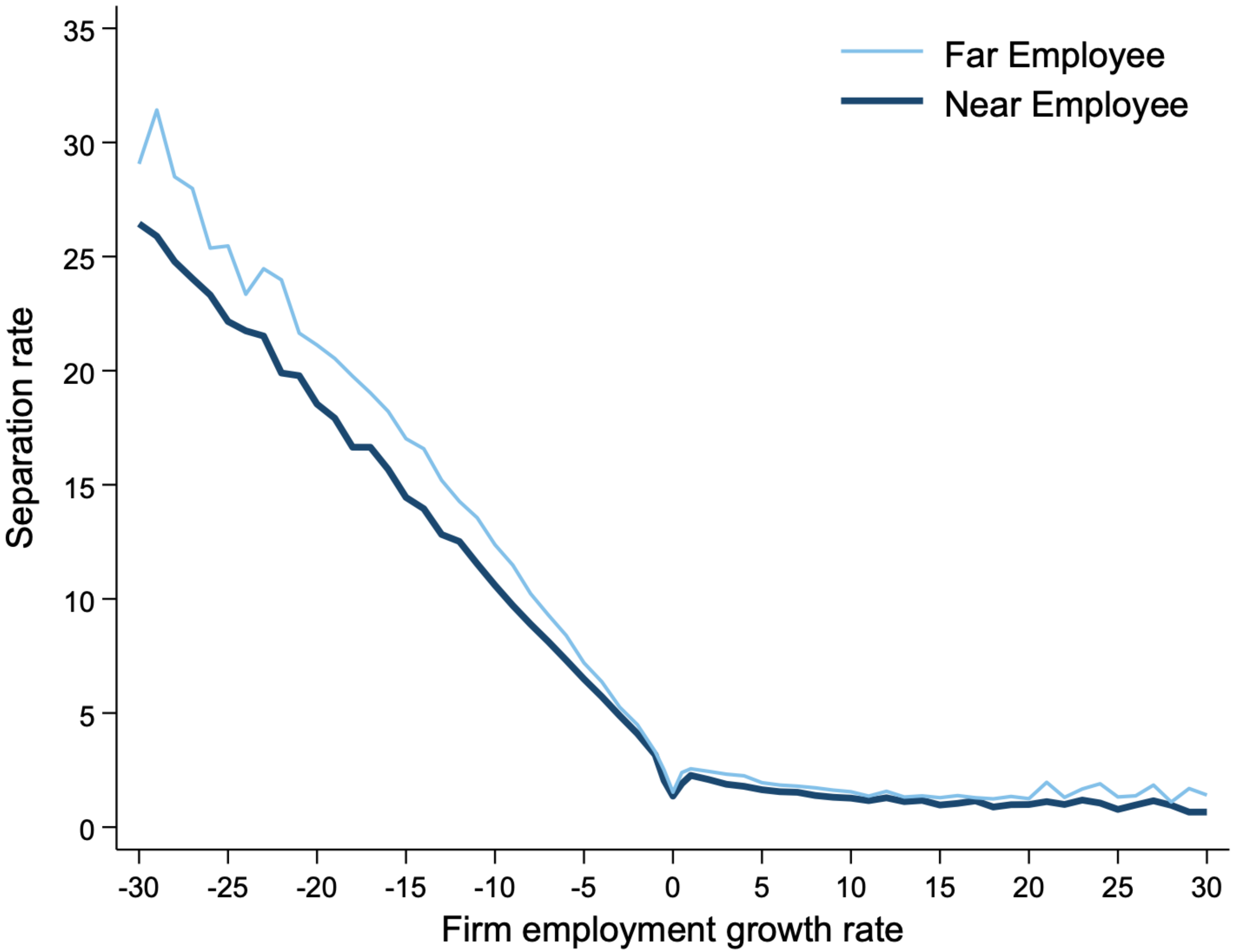
Notes: We construct this chart using the same approach as in Figure 6 in the main text, except that we now restrict attention to continuing employees who switched their state of residence from Year Y-1 to Year Y.

Figure A8: Mean percent changes in local home prices, continuing employees who moved between zip codes



Notes: We construct this chart using the same approach as in Figure 7 in the main text, except that we now restrict attention to continuing employees who moved between between zip codes from Year Y-1 to Year Y.

Figure A9: Separation rates remain more responsive to firm-level growth for far employees when controlling for individual-level job tenure, age, and sex



Notes: We obtain these plots from nonparametric least-squares regressions of individual-level monthly separation values on monthly employer-level growth rate bins and controls for job tenure, age, and sex of the employee. For each person employed in month $t-1$, we set the separation value to 1 if he or she longer works for the same firm in month t, and 0 otherwise. We pool the data over months from 2017 to 2023 and distinguish far and near employees. We fit separate regressions for far and near employees. In each case, we regress the individual-level separations value on an exhaustive set of interval dummies for firm-level growth rates at t (using the same set of interval dummies as in Figure 8), an exhaustive set of dummies for the individual's current tenure with the firm (one month, two months, three months,…), an exhaustive set of dummies for the individual's age, and the individual's sex. As in Figure 8, we read the plotted relationships directly from the coefficients on the interval dummies for firm-level growth rates. The near-employee sample contains 46.9 million individual-level observations, and the far-employee sample contains 5.8 million observations.