Work-from-Home and Wage Convergence Across Cities: An Exploration

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April 2025

Abstract

This paper provides evidence on a WFH-related hypothesis that has not previously been tested empirically. The hypothesis is that the presence of fully remote workers, for whom residence and work locations are decoupled, should create a tendency toward wage convergence across cities within teleworkable occupations. The reason is that, since fully remote workers can work anywhere, local wages must match those available in other cities for employers to attract any of these workers. By combining occupational wage data with data on which occupations are teleworkable, the paper attempts to test the wage-convergence hypothesis. The results are mixed, but some evidence does emerge in favor of the hypothesis.

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1. Introduction

After surging during the pandemic, work-from-home has upended real-estate markets, leading to greater residential decentralization as commuting costs have fallen, while also hollowing out downtown areas via higher office vacancy rates and lower patronization of service establishments in city centers. In addition, an increase in demand for home-office space has evidently contributed to the post-pandemic escalation of home prices. A vibrant literature studies these effects of work-from-home (WFH).[1]

The present paper contributes instead to a smaller set of studies on WFH's wage impacts. Liu and Su (2024) study the urban wage premium for the purpose of gauging WFH's impact on urban agglomeration economies, while Arntz, Yahmed and Berlingieri (2022) study a variety of labor-market outcomes, including individual wage changes resulting from WFH. By contrast, we focus on the dispersion of wages, rather than their levels. Our goal is to test a central prediction of WFH models that allow fully remote work, where a worker can live and work in different cities.

The prediction is that, within an occupation, wages should converge across cities (becoming equal) when WFH is fully remote. The logic is simple: since residential and work locations are decoupled when work is fully remote, workers in equilibrium must be indifferent to where they work, and thus indifferent among the cities that offer jobs in their occupation. For such indifference to hold, the occupation's wages must be equalized across cities. Otherwise, a city

[‡] We thank Kangoh Lee and Yichen Su for helpful comments. The usual disclaimer applies.

[1] For evidence on the relocation impacts of WFH and on the effects of WFH-induced decentralization on the spatial patterns of house prices, see Gupta et al. (2022), Brueckner, Kahn and Lin (2023), Bloom and Ramani (2022), and Akan et al. (2025). For evidence on the home-office-space effect on housing demand, see Stanton and Tiwari (2021), Mondragon and Wieland (2022), and Gamber, Graham and Yadav (2023). For remote work's office-market impacts, see Gupta, Mittal and Van Nieuwerburgh (2022), and for its effects on downtown service workers, see Gokan et al. (2024).

offering a lower wage will fail to attract any employees, who (being fully remote) can simply accept a job elsewhere without altering residential locations. We illustrate this idea using a model drawn from Brueckner, Kahn and Lin (BKL, 2023).

We cannot take this prediction too literally, however, in studying the real-world economy. The reason is that WFH is most commonly hybrid in nature, with workers being employed in the city where they live but working from home part of the week. Hybrid WFH thus does not involve the decoupling of residential and work locations achieved under fully remote work, which means that predictions of a fully remote model need not strictly apply.

However, the size of the fully remote workforce is appreciable, suggesting that those predictions may have some relevance nevertheless. Many media stories have provided anecdotal evidence on the extent of fully remote work,[2] but hard evidence has been more difficult to amass. The substantial survey dataset collected by Barrero, Bloom and Davis (2021) (updated to the October 24-January 2025 period)[3] shows that, among fully employed workers, 13% are fully remote while 26% have a hybrid WFH arrangement. Separate evidence comes from the *2025 Economic Report of the President*, chapter 2, which shows very similar but slightly lower percentages for both groups. Therefore, despite being overshadowed by hybrid WFH, the fully remote workforce is appreciable in size, and its presence may generate a force toward wage convergence in the occupations it covers. Looking empirically for such convergence is thus a highly worthwhile undertaking.

We use MSA-level data from the Occupational Employment and Wage Statistics (OEWS) database of the US Bureau of Labor Statistics. The database gives various measures of the annual wage for hundreds of occupations at the MSA level along with occupational MSA employment. Using these data, we construct a variety of occupation-specific measures of wage dispersion across MSAs. Some of the measures involve a variance-style format, being the employment-weighted squared or absolute deviations across MSAs around the occupation's national mean wage. Other measures rely on ratios of wages at various percentiles of the occupation's wage disribution across MSAs.

[2] See, for example, Bindley (2020, 2021), Buhayar (2020), Coy (2021), Dillon (2021), Kamp (2021).

[3] See their website at `https://wfhresearch.com/`.

The OEWS data are combined with information from Dingel and Neiman (2020) showing which occupations are "teleworkable," which we use to construct a dummy variable indicating that the work in the occupation can be done remotely. We expect that teleworkable occupations will exhibit wage convergence following the surge in remote work associated with the pandemic. Our empirical approach is to first run a difference-in-differences regression for the pre- and post-pandemic years of 2019 and 2023, with the dependent variable being one of the wage-dispersion measures. We expect a negative coefficient for the interaction of the teleworkable dummy and a year-2023 indicator, showing lower wage dispersion for teleworkable occupations in 2023. To check for pre-trends, we run an event-study regression across the years from 2015 to 2023, where the teleworkable dummy is interacted with year-specific indicators. While our results show mixed evidence of wage convergence for teleworkable occupations, the emergence of some favorable results suggests that hypothesis may have merit.

We also contribute to the literature on spatial inequality resulting from wage differences across regions. This literature shows that in the US and Europe, wages were converging across space until about the 1980s or 1990s, with wages then starting to diverge (Ganong and Shoag, 2017; Klienman, Liu and Redding, 2023; Gaubert, Kline, Vergara, and Yagan, 2021; Diamond and Suárez Serrato 2025). This increasing divergence has been coupled with dramatic variation in house price growth across space (Howard and Liebersohn, 2023). Such regional wage differences can result in large spatial inequities that governments attempt to address via place-based policies. Telework then may act as a market-based equalizer, reducing income inequality in the same way that spatially targeted transfers would.

The plan of the paper is as follows. Section 2 presents a model to motivation the empirics, section 3 discusses the data, empirical specifications, and construction of the wage-dispersion measures. Section 4 presents the empirical results, and section 5 offers conclusions.

2. Illustrative model

As in BKL, the economy for simplicity has just two cities with fixed unitary residential land areas and endogenous populations N_c, $c = 1, 2$, where $N_1 + N_2 = \overline{N}$, the fixed total population. Suppose initially that each city's production uses workers in just a single occupation. The endogenous employment levels in the two cities are L_c, $c = 1, 2$, and they must also sum to the total population: $L_1 + L_2 = \overline{N}$. When remote work is possible, a city's population need not equal its employment level, but otherwise $L_c = N_c$ must hold.[4]

Workers employed in city c earn a wage of $w_c(L_c)$, with the underlying production function given by $f_c(L_c)$. Productivity and hence the wage is assumed to be the same for resident and remote workers.[5] The cities could produce different goods, thus having different production functions, or the c subscript could alternatively capture different endowments of an immobile fixed factor used in the production of the same good. The wage function is then given by $w_c = p_c f_c'$ and $w_c' = p_c f_c'' < 0$, where p_c is city c's exogenous output price, with $p_1 = p_2 = 1$ holding after normalization if the same good is produced in both cities. Also, intercity relocation is costless, a standard assumption in models with multiple jurisdictions. Along with a productivity difference, the cities also differ in amenity levels, which are denoted A_c, $c = 1, 2$.

As in BKL, suppose for simplicity that the workers' common utility function is quasi-linear and depends on land consumption q, nonland consumption e, and amenities, being given by $U(e, q, A) = A + e + v(q)$, with $v' > 0$ and $v'' < 0$. Letting r_c denote a city's land price, the budget constraint is $e_c = w_c(L_c) - r_c q_c$, and the first-order condition for q_c is $v'(q_c) = r_c$. In addition, clearing of the city's land market requires $N_c q_c = 1$, implying $q_c = 1/N_c$. Then, net housing utility, equal to $v(q_c) - r_c q_c$, can be written as $v(1/N_c) - v'(1/N_c)(1/N_c) \equiv H(N_c)$, where $H' < 0$. Net housing utility therefore decreases with population, a consequence of the resulting upward pressure on the land price. Utility in city c can then be written as $A_c + w_c(L_c) + H(N_c)$, thus depending on both population and employment.

Suppose that fully remote work is infeasible, in which case a city's employment level must equal its population, with $L_c = N_c$. Then, the equilibrium populations of the two cities are

[4] BKL's focus on fully remote work is shared by Brueckner and Sayantani (2023) and to some extent by the models of Delventhal, Kwon and Parkhomenko (2022), Delventhal and Parkhomenko (2024), Lee (2024), and Gokan et al. (2024), which allow a mixture of hybrid and fully remote work. Other theoretical papers focusing solely on hybrid WFH include Kyriakopoulou and Picard (2023), Behrens, Kickho and Thisse (2024), Davis, Ghent and Gregory (2024), and Brueckner (2025). For surveys of the WFH literature, see Duranton and Handbury (2023) and Van Nieuwerburgh (2024).

[5] The evidence on WFH productivity is mixed, with some studies showing lower productivity at home and some showing no difference. See Bloom et al. (2015), Gibbs Mengel and Siemroth (2023), Harrington and Emanuel (2024), and Bloom, Han and Liang (2024).

determined by equalization of utilities between them, or

$$A_1 \ + \ w_1(N_1) \ + \ H(N_1) \ \ = \ \ A_2 \ + \ w_2(N_2) \ + \ H(N_2), \tag{1}$$

along with the population constraint $N_1 + N_2 = \overline{N}$. The population difference between the cities in equilibrium depends on the intercity amenity difference and the difference in the wage functions. An equilibrium condition like (1) is familiar from Roback (1982) and Rosen (1979).

When fully remote work is possible, residential and work locations are decoupled, and a city's population and employment no longer need to be equal. Two equilibrium conditions must then hold.[6] First, since workers can work in either city regardless of their place of residence, they must be indifferent between workplaces in an equilibrium where both cities have jobs. This indifference requires equal wages in the two cities, or

$$w_1(L_1) \ \ = \ \ w_2(L_2). \tag{2}$$

Satisfaction of this equilibrium condition is achieved by shifts in employment, with workers switching to jobs in the initially high-wage city until wages under WFH are equalized.

In addition, workers must be indifferent to their place of residence, which requires satisfaction of a modified version of (1), with the employment levels L_c replacing populations N_c in the wage functions. Since the wages cancel from this equation given the wage equalization in (2), the residential-indifference condition reduces to

$$A_1 \ + \ H(N_1) \ \ = \ \ A_2 \ + \ H(N_2). \tag{3}$$

The adding-up conditions $N_1 + N_2 = \overline{N}$ and $L_1 + L_2 = \overline{N}$ must also be satisfied.

Wages will generally differ between the cities in the absence of WFH, but wage convergence occurs when WFH is introduced. The directions of this convergence in the two cities depend

[6] Individuals also have two equal-utility conditions in the case of interstate commuting within a shared metro area (Agrawal and Hoyt, 2018).

on how the initial pre-WFH wage levels differ. Although these convergence directions cannot be determined in general, BKL show that determinate results can be stated when the cities differ either in amenity levels or productivity levels, but not both.

In the first case, the amenity difference can be written as $A_1 > A_2$, and equality of productivities means that the c subscript disappears from the wage function. BKL then show that pre-WFH wages satisfy $w_1 = w(N_1) < w_2 = w(N_2)$, a consequence of $N_1 > N_2$. Under WFH, wage equality implies an equal division of employment between the cities, so that $w_1 = w_2 = w(\overline{N}/2)$, with employment in each city equal to half the population.[7] Since the common wage lies between the pre-WFH wages, wage convergence under WFH thus yields a wage increase in the high-amenity city and a wage decrease in the low-amenity city.

Suppose instead that amenities are equal across the cities while productivity is higher in city 1, implying that $w_1(L) > w_2(L)$ holds for a common L. BKL then show that pre-WFH wages satisfy $w_1(N_1) > w_2(N_2)$ even though N_1 is larger than N_2. The common WFH wage again lies between the pre-WFH wages, so that wage convergence under WFH thus yields a wage decrease in the high-productivity city and a wage increase in the low-productivity city, directions that are reversed relative to the differential-amenity case.[8]

If both amenity and productivity differences coexist, the directions of the wage movements in the two cities under WFH are ambiguous. But it remains true that wages converge to a common value across cities, so that (2) is satisfied.

When multiple occupation groups exist, all of the previous claims continue to hold provided that a city's wage in a given occupation is independent of wages in the other occupations, which requires additive separability of the production function across occupations. However, even in the absence of this separability, the same key conclusion still holds: an occupation's wages must be equalized across cities in equilibrium, so that workplace indifference holds for workers in that occupation. The directions of an occupation's wage convergence may then be harder to analyze, but convergence still occurs under WFH.[9]

[7] City 1's employment thus falls under WFH, while BKL show that its population rises.

[8] BKL show that city 1's employment rises under WFH, while population falls ($N_1 = N_2$ from (3) when $A_1 = A_2$), changes that are the reverse of those in the differential-amenity case

[9] In a variant of the BKL model with a second group of workers in jobs that cannot be done remotely,

Wage convergence also occurs when state income taxes are added to the model, as in Agrawal and Brueckner (2025).[10] Most US states use the residence-taxation principle in taxing remote workers, which means that taxes on income earned from firms in cities located in other states are paid to the state of residence, not the state of employment. For a worker living in city 1 (located in state 1) to be indifferent between working locally and working remotely in city 2 (located in state 2), after-tax wages must be equal, or $(1-t_1)w_1(L_1) = (1-t_1)w_2(L_2)$, where t_1 is state 1's income-tax rate (applied regardless of where the income is earned). Since $1-t_1$ cancels in this condition, workplace indifference again reduces to the wage-equalization condition in (2).[11] While WFH under residence taxation again leads to wage convergence across cities, the conclusion is different under "source" taxation, where taxes on income from remote work are paid to the state of employment, not the state of residence (an uncommon arrangement). The workplace-indifference condition from above is then written as $(1-t_1)w_1(L_1) = (1-t_2)w_2(L_2)$. Since the tax terms no longer cancel, convergence occurs in after-tax, not pre-tax, wages. Note that, even with residence taxation, after-tax rather than pre-tax wages may be relevant when the tax system is progressive rather than proportional, in which case effective tax rates would depend on the level of the wage and would not cancel in the workplace indifference condition. We allow for this possibility in our empirical exploration.

3. Data sources, empirical specifications, and dispersion measures

3.1. Data sources

The wage data used in the paper are drawn from the Occupational Employment and Wage Statistics (OEWS) database of the US Bureau of Labor Statistics. The database provides employment levels and various wage measures for hundreds of different occupations at several

Brueckner and Sayantani (2023) show that, under WFH, non-remote wages remarkably *also* converge across cities along with remote-workers wages. However, this conclusion assumes identical preferences for the remote and non-remote groups along with their presence in the same city housing market rather than in different markets segmented by quality. As a result, convergence of non-remote wages may not be a realistic conclusion.

[10] For other papers on taxes and remote/nonresident work, see Agrawal and Stark (2022) and Agrawal and Tester (2024).

[11] In Agrawal and Brueckner (2025), tax revenue is used to provide a public good, which enters the utility function and thus affects the residential-indifference condition. But this change has no effect on the conclusion that wages converge under WFH.

levels of aggregation. Our analysis relies on the MSA-level OEWS data, focusing on both the mean and median occupational wages for the MSA to capture wage levels. Using the data, we compute various measures of wage dispersion across MSAs, doing so annually, for use in testing our wage-convergence hypothesis.

The occupational wages reported in the OEWS for a given year are based on six employer surveys that extend back over three years, being done every six months. The most recent survey is from May of the given year, which is preceded by a survey in November of the preceding year, and so on. According to OEWS documentation, multiple surveys are required to generate adequate employer coverage. Wages from the earlier surveys are adjusted to the reporting year to reflect any national wage trend for the occupation. The data collected from the surveys are further used to impute data values for survey nonrespondents and employers not surveyed.

Given this backward-looking method, the BLS cautions against using their occupational wage data in time-series analysis, recognizing that actual intertemporal wage changes will only emerge slowly in the data. While this reservation could impede a test of the wage convergence hypothesis, our simple difference-in-differences analysis should be mostly unaffected by the issue. That analysis is based on the pre- and post-pandemic years of 2019 and 2023, and the resulting four-year gap should allow changes in wage dispersion to be captured despite the backward-looking nature of the wage data. Our full data set, which is used in an event-study analysis, includes more than just those two years, ranging from 2015 to 2023. With that analysis relying on successive years of data (rather having the gap seen in the DiD analysis), the backward-looking collection method could be more of an issue. Other prominent papers, however, have recently used the OEWS data to study temporal issues (Haltiwanger, Hyatt, and Spletzer, 2024).

Several additional features of the data deserve note. First, starting with the 2021 data year, the BLS implemented a new methodology for generating imputed data for nonrespondents and non-surveyed employers. Since implications of this change are technical in nature, it is hard to judge the effect (if any) on comparability of the data before and after the change. Second, starting with the 2022 data year, the surveys began to ask respondents to give actual employee wage numbers rather than just identifying which of twelve wage bins contains a given wage. Since annual wages in the top bin are high (above $239,000), the old bin structure appeared to accurately capture most wages, suggesting that the switch would not significantly affect comparability of the wages before and after it. Third, the BLS reports that the pandemic impeded data collection, reducing the amount of information gathered for 2020 and 2021. The effect (if any) of this change on the reliability of the data is unclear, however. Figure 1 tends to discount each of these concerns regarding data availability and comparability across years. The figure shows, for each year of our data, mean and median wages across occupations and MSAs. Given the smooth nature of the curves, any effects from the issues just described are not evident.

Testing the hypothesis that wages converge across cities in teleworkable occupations requires knowing which occupations can be done remotely. For that information, we rely on the categorization done by Dingel and Neiman (2020). For hundreds of occupations, they assign a 1 versus 0 value to indicate that the occupation is teleworkable. In relatively few cases, an occupation may be divided into subtypes where teleworkable status differs, in which case a weighted average takes the place of the 1-0 value. Since the resulting fractional values are inappropriate for our DiD analysis, we set them equal to 0 in our analysis, so that an occupation where not all subtypes can be done remotely is considered non-teleworkable.

The great majority of occupations are present in both the Dingel-Neiman data and in the OEWS data across all of our sample years. Focusing on a balanced panel of occupations that excludes occupations that are in less than two metro areas, we arrive at a sample containing 595 occupations across each of the nine sample years from 2015 to 2023, for a total of 5355 year-occupation observations. The data for our DiD regressions, which rely on just the years 2019 and 2023, contain 631 occupations.

3.2. Empirical specifications

Construction of the wage-dispersion measures is discussed in the next subsection, but our empirical specifications can be presented in advance. Accordingly, let D_{it} be the wage-dispersion measure for occupation i in year t, let α_i be a set of occupation fixed effects, and let $post_t$ be a dummy variable that equals 1 in the post-pandemic year 2023 and 0 in the pre-pandemic year 2019. In addition, let $teleworkable_i$ be a dummy variable indicating that occupation i is teleworkable. Then, for $t = 2019,\ 2023$, the DiD regression is

$$D_{it} \;\; = \;\; \alpha_i \; + \; \beta \, post_t \; + \; \gamma \, post_t \times teleworkable_i \; + \; u_{it}, \tag{4}$$

where u_{it} is the error term. Note that use of occupation fixed effects means that the teleworkable dummy need not enter the regression separately.

The identifying assumption for our results to be causal is that any trends in teleworkable and non-teleworkable wage dispersion across metro areas are parallel. Identification does not require the levels of wages, nor their dispersion, to be similar. Obviously the pandemic affected labor markets in ways other than through telework, and these other channels may have affected the wage levels rather than wage dispersion. Nonetheless, identification requires any pandemic-related effects on wage dispersion not manifesting through the teleworkable channel to be similar for teleworkable and non-teleworkable occupations, thus differencing out in the empirical design.

To explore the plausibility of the identifying assumption, we also estimate an event-study regression across all the years from 2015 to 2023. Letting θ_t denote year fixed effects, this regression takes the form

$$D_{it} \;\; = \;\; \alpha_i \; + \; \theta_t \; + \; \sum_{y \neq 2019} \delta_y \; 1_t(t = y) \times teleworkable_i \; + \; v_{it}, \tag{5}$$

where $1_t(t = y)$ are indicators for each event year that equal 1 if $t = y$ and 0 otherwise and v_{it} is the error term. This specification has year-specific coefficients δ_y for the interaction with the teleworkable variable, allowing the dispersion effects of an occupation's teleworkable status to be tracked across individual years relative to the omitted year, 2019.

In estimating (4) and (5), the regressions are weighted by US employment for the occupation across the sample MSAs (denoted $us\_occ\_emp_{it}$ for occupation i in year t). The logic is that, when total occupational employment is higher, more wage observations underlie the dispersion measure D. Then, analogous to standard heteroscedasticity weighting when a dependent variable is equal to a mean from different-size populations across observations, weighting by *us_occ_emp* seems appropriate in our context. In addition, the standard errors are clustered by occupation.

In one specifications, to illustrate the separate trends in teleworkable and non-teleworkable occupations, we estimate a variant of (5) separately for both groups with only unit and time fixed effects. We then plot θ_t to show the disaggregated yearly evolution of the teleworkable and nonteleworkable wages relative to 2019.

3.3. Wage-dispersion measures

Two of our wage-dispersion measures are similar to measures of variance. Both are based on MSA annual occupational wages, measured in thousands of dollars, and we separately use the mean and median annual wages in different regressions. Let w_{imt} denote the mean (alternately median) wage for occupation i in MSA m in year t and $\overline{w}_{it}$ denote the simple mean across all MSAs of w_{imt} in the occupation in year t. The first wage-dispersion measure is the square root of the weighted sum of squared wage deviations from the occupational mean, written as

$$sum\_wgt\_sq\_devs_{\,it} \;=\; \left[\sum_m emp\_shr_{im2019}\,(w_{imt} \;-\; \overline{w}_{it})^2\right]^{1/2}, \tag{6}$$

where the weighting factor emp_shr_{im2019} is MSA m's share of occupation i's national employment in the base year 2019. Weights are held fixed to exploit only wage changes. The second measure follows (3) but uses absolute instead of squared deviations:

$$sum\_wgt\_abs\_devs_{\,it} \;=\; \sum_m emp\_shr_{im2019}\,|w_{imt} \;-\; \overline{w}_{it}|, \tag{7}$$

Wage convergence would correspond to a decline in (6) or (7) over time.

To avoid false conclusions about changes in wage dispersion due to changes over time in the levels of occupational wages, normalization is required. The wages w_{imt} in (6) and (7) are deflated to 2019 values through the transformations $w_{imt} = \widetilde{w}_{imt} * (\overline{w}_{2019}/\overline{w}_t)$, where $\widetilde{w}_{imt}$ is the original, unnormalized wage and $\overline{w}_t$ is the BLS national wage index for year t. In addition, for each occupation, we calculate the dispersion measures over a balanced panel of metro areas. If a metro area does not appear for all years in a particular occupation, that occupation is dropped so that the dispersion measures do not capture compositional shifts in MSA representation.

Our other wage-dispersion measures use the percentiles of an occupation's inter-MSA wage distribution in a given year, again relying alternately on the mean and median wages for a given MSA. The measures create ratios of the percentiles, for example the 90th divided by the 10th percentile of the distribution. Formally, the variables are

$$(X/Y)_{it} \quad = \quad \frac{X^{th}\text{-percentile wage for occupation } i \text{ in year } t}{Y^{th}\text{-percentile wage for occupation } i \text{ in year } t}, \tag{8}$$

so that the variable using the wages at 90th and 10th percentiles would be written $(90/10)_{it}$. Wage convergence would correspond to a decline in 90/10 over time. Numerous studies in labor economics use percentile-based wage ratios to study earnings inequality over time (see Fortin, Lemieux and Firpo, 2011).

While our baseline measures use pre-tax wages, wage convergence should occur in after-tax wages under progressive taxation, as noted above. Following the procedure described in Online Appendix A.1, we use NBER TAXSIM to calculate after-tax wages for a representative single taxpayer using the occupation's wage in the city to construct income. As a robustness check, we then construct our dispersion measures accounting for taxes.

Summary statistics for 2019 values of the data are provided in Table 1. The table shows that 33% of occupations are teleworkable, while showing broad ranges for both variance-based dispersion measures (the measures shown are based on mean wages). The first two percentile ratio variables (90/10, 75/25) capture the overall dispersion in an occupation's wage distribution across MSAs, while the 50/10 and 60/10 ratios capture dispersion in the lower part of the wage distribution, with the 90/50 and 90/40 ratios capturing dispersion in the upper part of the distribution. The mean of *us_occ_emp* is almost 1.07 million.

4. Regression results

4.1. DiD regressions

Panel A of Table 2 shows the results of estimating the DiD regression in (4) using the variance-based measures, *sum_wgt_sq_devs* and *sum_wgt_abs_devs*. Columns 1 and 2 show the results based on the mean occupational wage in an MSA, while the columns 3 and 4 show the results based on an MSA's median wage. Each of the *post* coefficients is significant, showing that non-teleworkable occupations experienced wage convergence over the 2019-2023 period. Although the focal *teleworkable* $\times$ *post* interaction coefficient has the expected negative sign in all the regressions, only one of coefficients is statistically significant, and then only at the 10% level. Therefore, using the variance-based measures, wage convergence appears to be no more rapid for teleworkable than for non-teleworable occupations.

Results are more favorable to our hypothesis, however, using the percentile-ratio dispersion measures. Panel B of Table 2 shows the DiD results for the percentile measures based on mean MSA wages. While the 90/50 and 90/40 regressions have insignificant *teleworkable* $\times$ *post* coefficients, those coefficients are negative and significant in the 90/10, 75/25, 50/10, and 60/10 regressions, although significance is only at the 10% level in the 90/10 regression. The *post* coefficients are negative and significant except in the 90/40 regression.

The implication is wage convergence is seen for most of the dispersion measures, but that convergence is faster for teleworkable occupations than for non-teleworkable occupations, supporting the main hypothesis of this paper. However, given that the interaction coefficients are insignificant in the 90/50 and 90/40 regressions but significant in the 50/10 and 60/10 regressions, it appears that convergence occurs mostly among cities in the lower part of the wage distribution. This pattern of teleworkable wage convergence could be generated by newly mobile workers abandoning jobs in lower-wage MSAs in favor of other cities, putting upward pressure on those wages. Even though new workers are arriving, wages in high-wage metro areas may not fall if market frictions prevent wage reductions.

Given the magnitudes of the *post* and interaction coefficients in the 50/10 and 60/10 regressions, convergence in the lower part of the wage distribution was about three times as fast for teleworkable than for non-teleworkable occupations ($-(0.021 + 0.011) = -0.032$ vs.

-0.011 in the 50/10 case). Compared to the 50/10 and 60/10 means of about 1.2 from Table 1, the teleworkable ratios fell by about by 2.7% of their mean values over the 2019-2023 period ($= 0.032/1.2$).

A question is why the percentile approach gives favorable results when the variance-based measures do not. One possibility is that the latter approach is sensitive to outlier MSAs, which lie above the 90th or below the 10th percentiles of the inter-MSA occupational wage distribution, while the percentile approach is not sensitive. Another possibility is that convergence only occurs in a portion of the distribution, rather than over the entire distribution.

Panel C of Table 2 repeats the regressions of Panel B using the median, rather than mean, MSA wages to generate the percentile ratios. As can be seen, the results are somewhat less favorable to the wage-convergence hypothesis than those in Panel B. The $teleworkable \times post$ coefficients remain negative and significant in the 50/10 and 60/10 regressions, but significance is only at the 10% level in the first case. This extent of convergence in the lower part of the teleworkable wage distribution is not strong enough to generate significantly negative interaction coefficients for the broader 90/10 and 75/25 dispersion measures, as occurred in Panel B. While the reason for this difference in results is unclear, it could be that the mean wage better captures compensation for an MSA's high-paid remote jobs, where wage convergence might be most expected.

4.2. Event-study specification

As usual, it is important to check for parallel trends in validating the DiD results. Accordingly, we ran event-study regressions over the period 2015-2023 for all the percentile ratios based on mean wages, and Figure 2 plots estimated teleworkable coefficients by year and their confidence intervals. Panel A shows the results for the broad 90/10 and 75/25 dispersion measures. Reflecting the marginal significance of the $teleworkable \times post$ coefficient in Panel B of Table 2, both the 90/10 and 75/25 confidence intervals for the pandemic and post-pandemic years of 2020-2023 show negative teleworkable effects only in 2020 and 2021 (only 2021 in the latter case). In addition, the graph shows evidence of a pre-trend for the 75/25 ratio. The 90/10 series has a similar pre-trend but the pre-2019 coefficients are not significant.

Panel B of Figure 2 shows the event-study results for the 60/10 and 50/10 percentile ratios. Mirroring the Panel-B results from Table 2, the confidence intervals for 2021, 2022, 2023 show significant negative teleworkable effects, with no evidence of pre-trends for either ratio variable. Therefore, the event-study results confirm Table 2's conclusion of faster wage convergence for teleworkable jobs after 2019 and help to provide support for the parallel trends assumption for these two variables.

As a robustness check, Panel C of Figure 2 shows event-study results using 60/10 and 50/10 percentile ratios based on after-tax rather than pre-tax wages. The results are very similar to those in Panel B, again with limited evidence of any pre-trends. Interestingly, the fall in the 60/10 series is closer to that of the 50/10 series after accounting for taxes, perhaps because progressive federal taxes dampen the wage ratios higher in the distribution. Accounting for the progressivity of the tax system, which means that a focus solely on pre-tax wages may be misleading, has little effect on the conclusion of wage convergence in the bottom half of teleworkable wage distribution.

The data patterns underlying these results are illustrated in Figure 3, which shows the coefficients and confidence intervals from separate regressions of the percentile ratios for teleworkable and non-teleworkable occupations on year dummies. Panel A gives the results for the 50/10 percentile ratio, showing that both types of occupations saw wage convergence over the bottom half of wage distribution after 2020, but that convergence was faster for teleworkable occuptions. Pre-trends are absent for both types of occupations.

Panel B of Figure 3 gives the results for the 90/10 ratio. While the ratio dropped after 2020 for both teleworkable and non-teleworkable occupations, the overlapping confidence intervals for the two types of occupations mirror the marginal significance on the $teleworkable \times post$ coefficient in Panel B of Table 2, indicating little difference in the post-2020 patterns.

These figures are consistent with the significant negative *post* coefficients in table 2, and they suggest that the pandemic affected the occupational wage distribution across cities in ways unrelated to WFH. Non-teleworkable wages converged due to post-pandemic factors other than WFH, but since these effects difference out in our empirical design, the larger convergence impact among teleworkable jobs identifies the pure effect of WFH.

Figure A.1 in the online appendix shows event studies for the variance-based measures, which indicate clear trend breaks but also some pre-trends that reinforce the generally insignificant effects of Panel A in Table 2. Figure A.2 in the appendix, which repeats Panels A and B of Figure 3 using percentile ratios based on the median wage, is less favorable to our hypothesis than Figure 3. The 60/10 and 50/10 coefficients are only marginally significant for the years 2022 and 2023, mirroring the results in Table 2, and the graph shows evidence of pre-trends for both percentile ratios. Event-study results for the remaining 90/50 and 90/40 wage-dispersion measures show insignificant results and are thus not reported.

The more-favorable performance of the percentile ratios based on mean wages, in both the DiD and event-study regressions, could reflect the better suitability of the mean versus the median in capturing wage convergence, as noted above. But fact that the mean and median approaches, which could be viewed as almost equivalent, perform differently may also sound a note of caution in judging whether our results fully support the wage-convergence hypothesis.

Another cautionary note arises from the pattern of the pandemic impacts on the percentile ratios. As seen Figure 2, an immediate impact on the percentile ratios for teleworkable occupations appears in the first year of pandemic reporting, 2021, staying roughly constant thereafter. Given the backward-looking nature of the BLS data, this one-year impact might be viewed as surprising, with wage-convergence instead expected to emerge more slowly after 2020. On the other hand, given the relatively small magnitude of the relative drop in the percentile ratio for teleworkable jobs (on the order of 2%)—and the fact that WFH increased most in this year—it could well be capturable by the BLS data despite its backward-looking nature. Most importantly though, the mean results do show that the percentile ratios responded to the onset of WFH *differently for teleworkable occupations*, an outcome that would be hard to explain without the help of our hypothesis.

5. Conclusion

This paper has provided evidence on a WFH-related hypothesis that has not previously been analyzed with data. The hypothesis is that the appreciable presence of fully remote workers in the post-pandemic economy, for whom residence and work locations are decoupled, should create a tendency toward wage convergence across cities within teleworkable occupations. The reason is that, since fully remote workers can work anywhere, local wages must match those available in other cities for employers to attract any of these workers. By combining occupational wage data from the Bureau of Labor Statistics with data from Dingel and Neiman (2020) on which occupations are teleworkable, the paper has attempted to test the wage-convergence hypothesis. The results are mixed, but some evidence does emerge in favor the hypothesis. Since the wage-convergence hypothesis is new and important if true, further work in investigating its validity using individual microdata that overcomes some of the data limitations in our paper deserves high priority.

Table 1: Summary statistics

Variable	*Mean*	*Std. Dev.*	*Min*	*Max*
teleworkable	0.330	0.471	0.000	1.000
sum_wgt_sq_devs	9.540	8.028	1.311	45.517
sum_wgt_abs_devs	7.425	6.399	1.135	37.668
90_10	1.446	0.147	1.059	3.502
75_25	1.212	0.070	1.028	2.296
50_10	1.187	0.062	1.023	2.242
60_10	1.230	0.075	1.027	2.419
90_50	1.216	0.073	1.029	1.907
90_40	1.188	0.097	1.006	1.855
us_occ_emp	1,069,362	1,064,011	180	3,839,010

(occupations = 631, year = 2019)

Table 2: Difference-in-differences regressions using wage dispersion measures

Panel A: Variance-based measures

VARIABLES	(1) sum_wgt_sq_devs (mean)	(2) sum_wgt_abs_devs (mean)	(3) sum_wgt_sq_devs (median)	(4) sum_wgt_abs_devs (median)
post	-0.311***	-0.285***	-0.349***	-0.315***
	(0.102)	(0.092)	(0.107)	(0.091)
teleworkable × post	-0.321	-0.609*	-0.251	-0.600
	(0.368)	(0.321)	(0.359)	(0.400)
Constant	9.540***	7.425***	7.886***	7.063***
	(0.068)	(0.059)	(0.067)	(0.071)
Observations	1,262	1,262	1,262	1,262
R^2	0.989	0.989	0.983	0.984

Panel B: Percentile ratios using mean wage

VARIABLES	(1) 90/10	(2) 75/25	(3) 50/10	(4) 60/10	(5) 90/50	(6) 90/40
post	-0.028***	-0.014***	-0.011**	-0.013**	-0.013***	-0.004
	(0.009)	(0.004)	(0.005)	(0.006)	(0.003)	(0.006)
teleworkable × post	-0.024*	-0.013**	-0.021***	-0.025***	0.002	-0.007
	(0.013)	(0.006)	(0.007)	(0.008)	(0.007)	(0.009)
Constant	1.446***	1.212***	1.187***	1.230***	1.216***	1.188***
	(0.003)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)
Observations	1,262	1,262	1,262	1,262	1,262	1,262
R^2	0.935	0.936	0.891	0.907	0.926	0.930

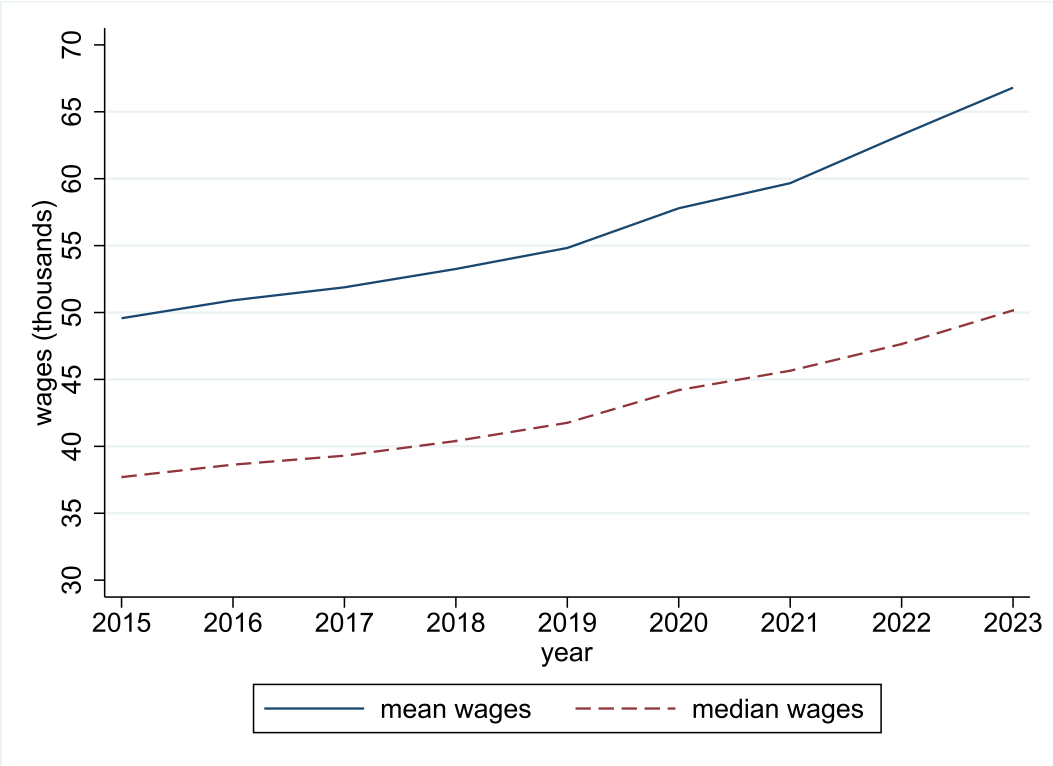
Panel C: Percentile ratios using median wage

VARIABLES	(1) 90/10	(2) 75/25	(3) 50/10	(4) 60/10	(5) 90/50	(6) 90/40
post	-0.035**	-0.015*	-0.003	-0.009	-0.027***	-0.031***
	(0.017)	(0.009)	(0.013)	(0.013)	(0.006)	(0.006)
teleworkable × post	-0.015	-0.009	-0.025*	-0.029**	0.014	0.012
	(0.021)	(0.011)	(0.015)	(0.015)	(0.009)	(0.008)
Constant	1.467***	1.221***	1.195***	1.241***	1.225***	1.272***
	(0.006)	(0.003)	(0.005)	(0.005)	(0.002)	(0.002)
Observations	1,262	1,262	1,262	1,262	1,262	1,262
R^2	0.878	0.867	0.741	0.795	0.879	0.917

Standard errors clustered by occupation in parentheses

*** p<0.01, ** p<0.05, * p<0.1

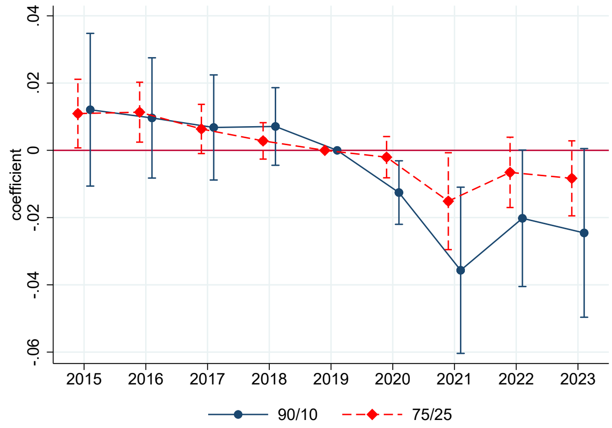
Figure 1: Wage trends



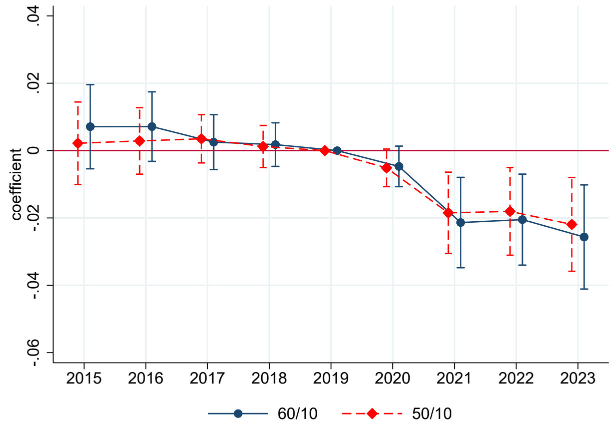
This figure shows the trend in mean and median wages over time. To construct this figure, we use wage data series for "all occupations." We aggregate the metropolitan data for this series to the national level by weighting the wage by total employment in each metropolitan area.

Figure 2: Event studies for wage-percentile ratios

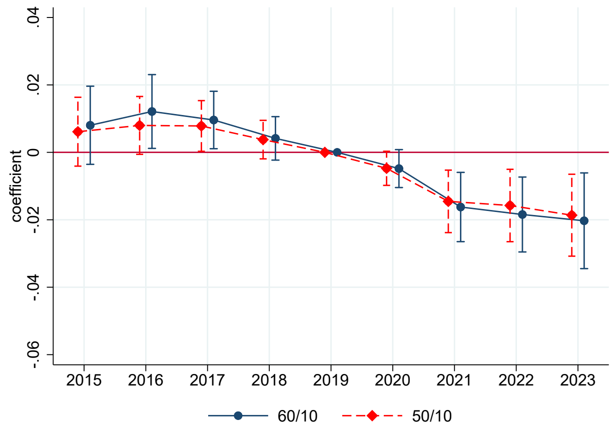
Panel A: 90/10 and 75/25 percentile ratios



Panel B: 60/10 and 50/10 percentile ratios



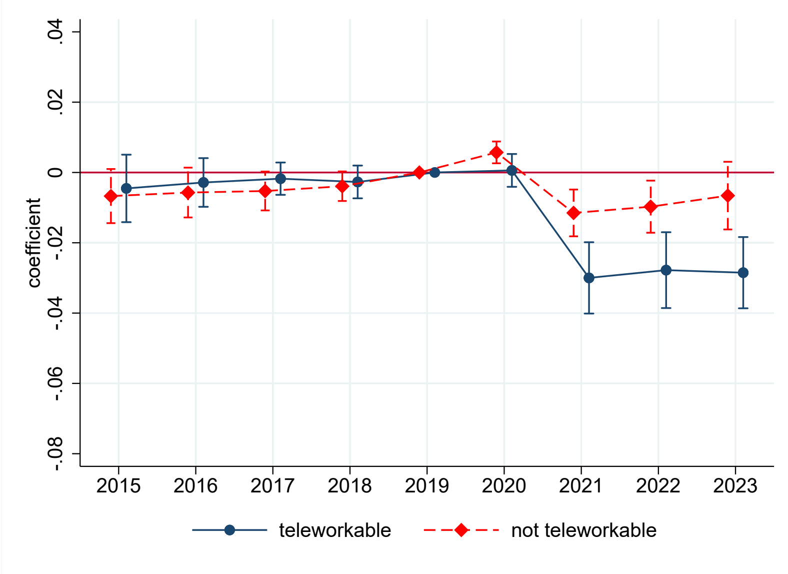
Panel C: Tax-adjusted 60/10 and 50/10 percentile ratios



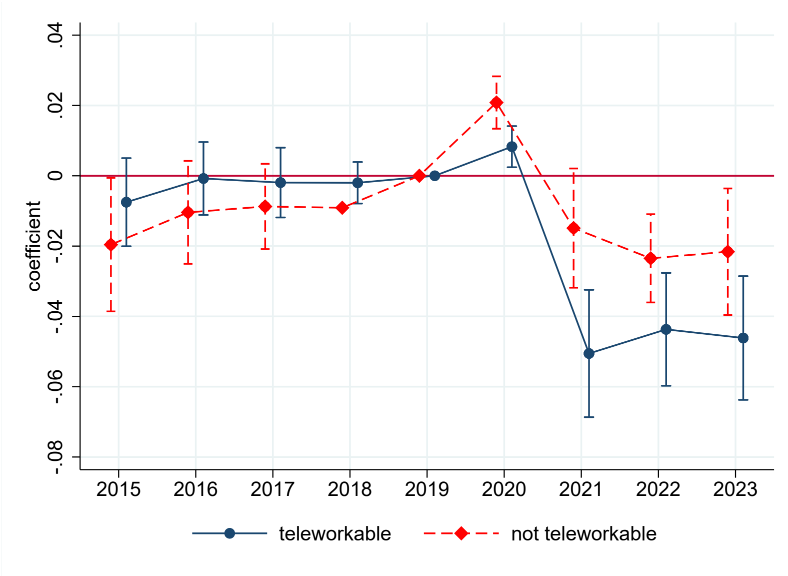
This figure shows event studies using various percentile wage percentile ratios. Standard errors are clustered by occupation, with 95% confidence intervals shown.

Figure 3: Separate trends in teleworkable and non-teleworkable percentile ratios

Panel A: 50/10 percentile ratio



Panel B: 90/10 percentile ratio



This figure shows separate trends in the percentile ratios for teleworkable and non-teleworkable occupations. Standard errors are clustered by occupation, with 95% confidence intervals shown.

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Online Appendix for

"Work-from-Home and Wage Convergence Across Cities: An Exploration"

David R. Agrawal and Jan K. Brueckner

A.1. Tax methodology

In the model of Agrawal and Brueckner (2024), if taxes are residence-based, marginal tax rates cancel from the wage-equalization condition. However, this cancellation follows from the assumption tax income taxes have a single flat rate. If taxes are progressive, convergence should occur in after tax wages, $w - T(w)$ where $T(w)$ are taxes paid as a function of income. This tax adjustment is also important because higher wages in a high-wage area imply higher tax rates than in a low-wage area. This differences arises even in the absence of state tax differentials simply due to progressivity of the federal income tax (Albouy, 2009).

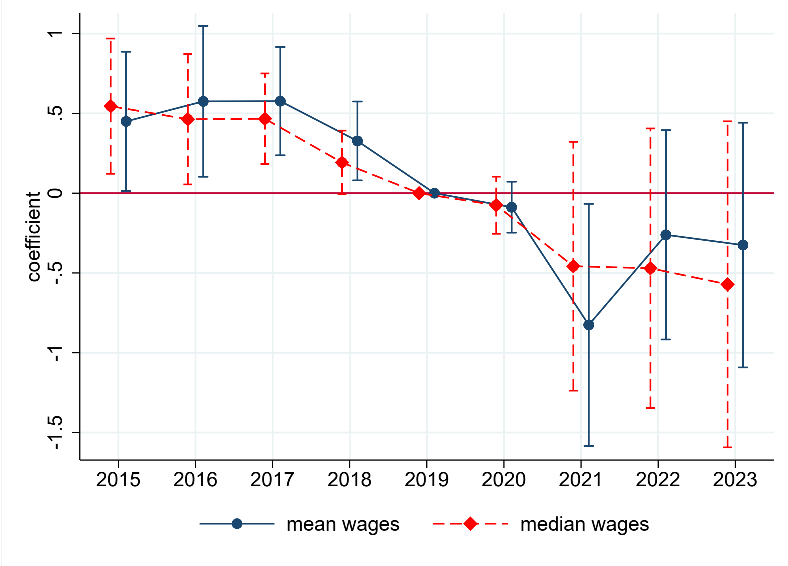
To adjust wages for tax rates, we use NBER TAXSIM (Feenberg and Coutts, 1993), version 35.9. The occupational wage data do not contain any other elements of taxable income, and for this reason, we simulate tax rates for a representative worker. We assume the representative worker is single and age 45. In addition, the individual earns some capital income from dividends and interest that is proportional to wage income (dividends are 6% and interest income is 2%). A deductible property tax is assumed to equal $100 + 0.02E$ and the mortgage deduction is $200+.08*E$, where E is labor income. These imputations follow NBER TAXSIM's construction of representative tax rates, where they note that "These ratios are not intended to be typical or average, merely not unreasonable."

With respect to state tax rates, most states tax teleworkers according to the residence principle, though several states tax based source principle. As the data we have includes wages from teleworkers and individuals working in-person, we use the tax rate of the state where the metro area is located. In cases of cross-border MSAs, we use the primary state. The assumption on the state where taxes are paid is reasonable given that most workers in the data series work in-person.

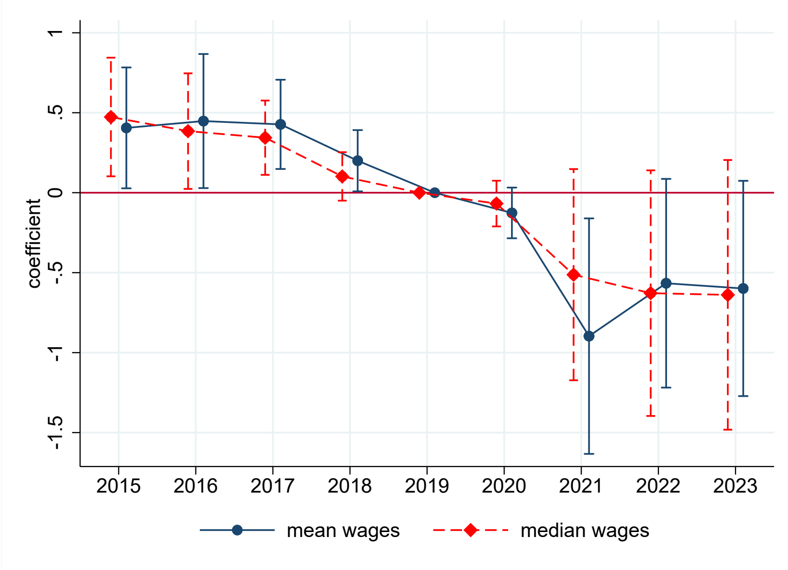
We then construct after-tax wages as the wage data minus federal income taxes, state income taxes, and the taxpayer's FICA contribution.

Figure A.1: Event studies based on deviations

Panel A: Standard deviation in wages



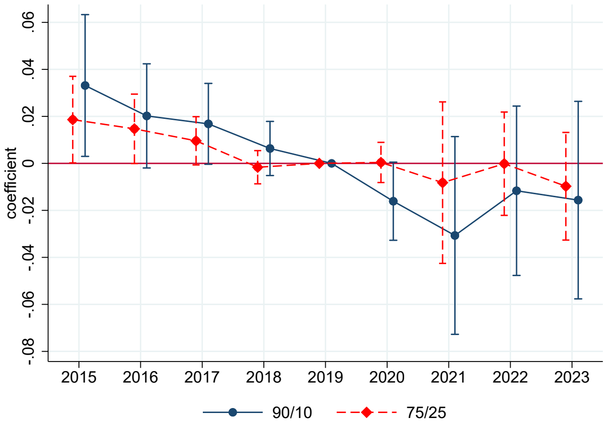
Panel B: Absolute deviation in wages



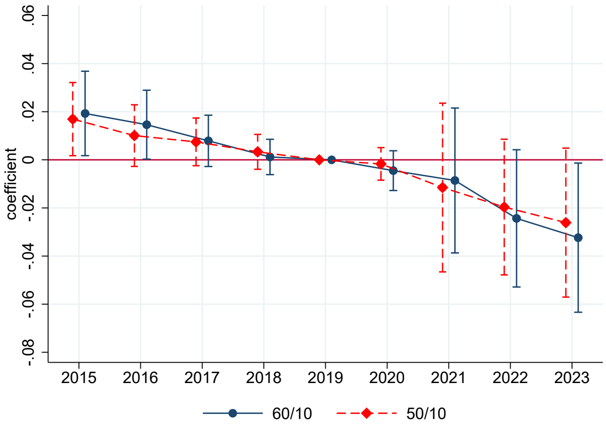
This figure shows event studies using standard deviations and absolute deviations. Standard errors are clustered by occupation, with 95% confidence intervals shown.

Figure A.2: Event studies based on median wage-percentile ratios

Panel A: 90/10 and 75/25 percentile ratios



Panel B: 60/10 and 50/10 percentile ratios



This figure shows event studies for wage ratios using median wages (the main text uses mean wages) to construct the ratios. Standard errors are clustered by occupation, with 95% confidence intervals shown.