The Effect of Working from Home on the Agglomeration Economies of Cities: Evidence from Advertised Wages

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Abstract

Using job posting wage data, we find a substantial decrease in the urban wage premium for occupations with high working-from-home (WFH) adoption following the COVID-19 pandemic. This decline is accompanied by an employment shift away from large employment centers. Through the lens of a stylized model, our empirical findings suggest that WFH adoption weakens the agglomeration economies of cities. A decomposition exercise reveals that the urban wage premium drop is partly driven by reduced wage returns for interpersonal skills in large cities, suggesting that the weakening of the agglomeration effect stems partially from reduced interactive activities.

Keywords: Agglomeration, Productivity, Spillover, Urban Wage Premium, Working from Home, Remote, Virtual, WFH, Wages, Job Posting, COVID-19, Pandemic

JEL Codes: R12, R23, J24, J31

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1 Introduction

It is well documented that productivity and wages tend to be higher in large and densely populated cities compared with smaller cities or rural areas (Ciccone and Hall, 1996; Glaeser and Mare, 2001; Baum-Snow and Pavan, 2012; Moretti, 2013; Diamond, 2016). The elevated productivity in large cities is primarily attributed to the "agglomeration effect" resulting from the geographical clustering of workers and firms. Increased interaction and proximity among workers in large cities enables easier knowledge transfer and skill acquisition, which elevates local productivity (Glaeser, 1999; Wheaton and Lewis, 2002; Jaffe et al., 2003; Charlot and Duranton, 2004; Kerr and Kominers, 2010; Akcigit et al., 2018; Davis and Dingel, 2019; Baum-Snow et al., 2021; Jarosch et al., 2021; Emanuel et al., 2023). Additionally, the co-agglomeration of firms and industries facilitates professional networking and the establishment of new business relationships, which further boosts productivity within these large urban areas and industry clusters (Ellison et al., 2010).

This paper studies the impact of working from home (WFH) on the agglomeration economies of cities and its aggregate productivity implication. On the upside, WFH enhances job flexibility, which has been shown to boost productivity for certain workers (Bloom et al., 2015; Barrero et al., 2021; Emanuel and Harrington, 2022). It also allows workers to access high-productivity firms in large cities without incurring the high costs of urban living. This could increase the labor supply to these large-city firms, potentially driving up aggregate productivity, wages, and output.

Conversely, WFH could dilute the positive productivity spillovers arising from spontaneous in-person interactions. The lack of informal "coffee talks" could limit the exchange of knowledge and ideas, both within and between firms clustered in large cities. Furthermore, the decrease in physical presence may undermine the role of large cities in fostering professional networks and facilitating complex business relationships. If WFH weakens the agglomeration effect, it could negatively impact productivity and wages in large-city firms, potentially causing workers to shift to smaller-city firms. This could not only reduce the urban wage premium but also lead to a decline in aggregate productivity, wages, and output.

We present a highly stylized spatial equilibrium model to illustrate the competing forces through which WFH affects the strength of agglomeration economies, the urban wage premium, and aggregate economic output. The model assumes that the agglomeration effect is fueled by the productivity externalities generated by onsite workers. The model predicts that the adoption of WFH reduces the wage premium in large cities, regardless of whether WFH weakens the agglomeration effect in large cities. Specifically, if the agglomeration effect remains strong despite a reduction in onsite workers, WFH adoption could increase the labor supply for firms in large cities. This increase would result in more workers servicing large-city firms while residing in smaller cities, which enables broader access to these firms' high productivity and thus elevates aggregate productivity, wages, and output. In contrast, if the switch from onsite to remote work significantly weakens agglomeration economies in large cities, this could lead to diminished productivity in large cities. In such a scenario, workers might be incentivized to switch to firms in smaller cities. The decreased productivity in large cities and the equilibrium reallocation of workers could lead to lower aggregate productivity, wages, and output.

Based on our model, we derive two empirical predictions to validate the model and to examine whether the adoption of WFH weakens the agglomeration economies. First, the urban wage premium should decrease with the advent of WFH, *regardless of* whether agglomeration economies in large cities are weakened. Second, the direction of employment shift between cities depends on the primary driver of the reduced urban wage premium. If the decrease is primarily due to a weakened agglomeration effect in large cities, employment (based on employers' locations) should move from large to small cities. However, if an increased labor supply to large cities is the main cause, employment should shift from small to large cities.[1]

To empirically assess whether the adoption of WFH affects local productivity and whether the effect is due to a decrease in agglomeration economies, we use the COVID-19 pandemic as an exogenous shock to the prevalence of WFH. The pandemic forced many employers across various occupations to suddenly and unexpectedly shift to a WFH model, while other occupations, due to the nature of their work, were unable to do so (Bartik et al., 2020; Bick et al., 2022; Brynjolfsson et al., 2020). These differential levels of WFH adoption provide an empirical setting to examine the effects of WFH on economic outcomes such as wages and employment in large cities compared with smaller cities.

Our empirical method assumes that shocks unrelated to the WFH adoption during the pandemic did not *disproportionately* affect wages of jobs located in large cities within high-WFH-adoption occupations. We are aware that other pandemic shocks unrelated to WFH adoption could have distinct impacts on high- and low-WFH-adoption occupations. However, if the effects operate at the occupational level, they should not alter the urban wage premium or employment growth differently by city size. Similarly, other pandemic

[1]It is worth noting that observing an increase in employment in large cities does not necessarily contradict a decrease in the agglomeration effect. This is because the surge in labor supply might outweigh the reduced agglomeration effect. Conversely, a disproportionate decrease in both employment and the wage premium in large cities would provide compelling evidence for the decline of agglomeration economies in large cities.

shocks might have affected wages and employment differently in large and small cities. However, our conclusion should hold as long as these city-specific effects do not differ systematically by occupations' level of WFH adoption.[2]

We test our model's urban wage premium prediction using data on advertised wages from Emsi Burning Glass (now Lightcast). Our findings indicate a significant decrease in urban wage premium for jobs in occupations that heavily adopted WFH after the pandemic shock. This decrease was observed for both college-degree-required and non-degree jobs. Furthermore, the reduced urban wage premium in high-WFH-adoption occupations did not bounce back post-2020 and remained well below pre-pandemic levels as of mid-2023. Conversely, for occupations with low WFH adoption, the urban wage premium remained mostly unchanged after the pandemic shock. These findings validate our model's first prediction.

One potential concern is that our results might be influenced by spatial sorting of skill supply or demand during and post-pandemic, potentially reflecting changes in skill sorting rather than an actual urban wage premium reduction. To mitigate the concern, we show that even after controlling for jobs' observable skill needs, there is a significant decrease in the urban wage premium within high-WFH-adoption occupations. Additionally, to rule out any confounding effects due to geographical changes in job postings, we examine the location-specific industry-level average weekly earnings from the Quarterly Census of Employment and Wages (QCEW). We find a similarly disproportionate drop in the urban wage premium in high-WFH-adoption industries over the three years following the pandemic.

Another potential concern is that the decrease in the urban wage premium within high-WFH-adoption occupations might simply be a mechanical result of larger cities offering a greater share of WFH-compatible jobs. If WFH functions as a job amenity that provides compensating wage differentials, a disproportionate increase in WFH-compatible jobs offered by large-city firms could automatically reduce the urban wage premium without any decrease in agglomeration economies or increase in labor supply in large cities. To demonstrate that the drop in the urban wage premium is not mechanically driven by a higher WFH adoption in large cities, we show that the urban wage premium decreased among both WFH-compatible and non-compatible jobs within high-WFH-adoption occupations. For added robustness, we use the latest American Community Survey (ACS) and find that hourly wages reported by *onsite* workers in high-WFH-adoption occupations witnessed a significant urban wage premium drop in 2021, compared with 2018 and 2019.

[2]It is noteworthy that this paper does not intend to analyze the short- or long-run effect of the pandemic per se, such as predicting the extent to which on-site work will return in the long term or whether large cities will make a come-back eventually. The pandemic is used as the *empirical setting* of the study, not the subject.

We next explore whether the decreased urban wage premium among jobs in high-WFH-adoption occupations was mainly driven by diminished agglomeration effects in large cities or by an increased labor supply (of remote workers) in these cities. We use the QCEW to analyze the location-specific employment growth. Since the QCEW reports employment by industry (not by occupation), we examine whether employment growth in high-WFH-adoption industries was faster in larger employment clusters compared with smaller ones post-pandemic. Our finding suggests a disproportionate decline in employment (based on employers' locations) in high-WFH-adoption industries in larger cities compared to smaller cities relative to the pre-pandemic period. In other words, high-WFH-adoption industries in large cities not only experienced a relative wage decrease but also saw an outward employment shift. According to our model, this finding implies that the decreased relative wage in large cities is likely attributable, at least partially, to weakened agglomeration economies in these cities.[3]

Lastly, we move away from empirical model tests and shift our focus to indirectly evaluating the weakening of agglomeration economies using an alternative approach. We employ a Gelbach decomposition exercise, drawing from Gelbach (2016), to identify which *skills* listed in posted jobs contribute the most to the overall decline in the urban wage premium within high-WFH-adoption occupations. Our hypothesis is that if labor supply to large cities increased due to WFH adoption, we should observe disproportionate decreases in the urban wage premium of skills that are specifically complementary to remote work, such as information technology skills. In contrast, if the weakening of agglomeration economies in large cities plays a more important role, we should anticipate disproportionate decreases in the urban wage premium of skills supportive of knowledge spillovers, network building, or fostering business relationships.

Our decomposition results suggest that several skill cluster families, including "Marketing and Public Relations," "Customer and Client Support," "Building Relationship," "Communications," "Business Management," and "Information Technology," play a crucial role in the decline of the urban wage premium. Notably, skills related to "Marketing and Public Relations," "Customer and Client Support," "Building Relationship," and "Communications" tend to be particularly productive in interactive activities (Deming, 2017; Deming and Kahn, 2018). The relative decline in wage returns to these skills in large cities suggests that

[3] Some studies have found higher or unexpectedly high productivity for remote workers compared with onsite workers (Bloom et al., 2015; Barrero et al., 2021; Emanuel and Harrington, 2022). Our findings do not dispute these results. Specifically, we are not comparing the productivity of remote and onsite workers, holding all other factors equal. Rather, our results suggest that WFH adoption may have disproportionately affected the relative productivity of jobs based in larger cities. The productivity reduction could affect both onsite and remote workers because fewer onsite workers due to WFH could decrease the degree of knowledge spillovers for all workers.

there has likely been a decrease in the frequency of productive interactive activities requiring these skills in firms located in large cities. In addition to the decrease in the urban wage premium for these skills, we also observe a decline in the frequency that these skills are listed in job postings in large cities compared with smaller ones, further suggesting reduced demand for these skills in large-city workplaces. These findings constitute indirect evidence that large cities saw their agglomeration economies weakened due to reduced productive interactions.

In contrast, "Information Technology" skills typically involve using electronic tools and applications, which complement the feasibility of remote work. These skills also saw a significant decrease in the urban wage premium. This finding suggests that the decline in the urban wage premium could also be partially attributed to an increase in the labor supply of remote workers to large cities.

Our paper contributes to several strands of literature. First, we add to the ongoing discussions surrounding the impact of the pandemic-induced rise in WFH on cities and productivity. Many studies have highlighted a shift in housing demand from city centers to suburbs and from larger to smaller cities due to the increasing prevalence of WFH (Gupta et al., 2021; Liu and Su, 2021; Ramani and Bloom, 2021; Althoff et al., 2022; Delventhal et al., 2022; Li and Su, 2022; Howard et al., 2023; Monte et al., 2023). Other studies explore how the endogenous change in productivity brought about by the WFH shock affects the well-being and inequality of the U.S. population (Behrens et al., 2021; Davis et al., 2021; Delventhal and Parkhomenko, 2022). Especially relevant to our paper, Brueckner et al. (2021) present a spatial equilibrium model with WFH and show that remote work is likely to equalize wages across regions. We further demonstrate that both the weakening of agglomeration economies in large cities and the increased labor pool accessible to firms in these cities are likely important drivers behind the diminished wage differentials across space.

In addition, our paper complements the extensive body of research exploring the agglomeration economies of cities and the urban productivity premium. This literature seeks to unravel why workers and firms in larger cities tend to be more productive. Prior studies provide evidence that the productivity advantage in large cities arises from both the effect of sorting of more productive firms and workers into these areas and the productivity-boosting effect of the large cities themselves (Combes et al., 2008; D'Costa and Overman, 2014; Gaubert, 2018; Martellini, 2022). Notably, research by Glaeser and Mare (2001), De La Roca and Puga (2017), and Eckert et al. (2022) demonstrates that experience in large cities not only increases workers' productivity and wages but also bolsters wage growth even after individuals leave these areas. Our paper offers additional insight into the mechanisms behind cities' agglomeration effects. Previous research has established micro-foundations and provided evidence for various mechanisms that drive agglomeration economies, with knowledge spillovers, input-output linkages, and labor pooling being the most prominent (Rosenthal and Strange, 2003; Duranton and Puga, 2004; Bleakley and Lin, 2012). Our paper adds to this literature by studying the effect of the removal of in-person interactions on agglomeration effects.

The rest of the paper is organized as follows. Section 2 presents a stylized model and its predictions. Section 3 describes the data. Section 4 presents the empirical results that test the model predictions. Section 5 presents additional skill-level analyses to further shed light on the mechanism behind the weakened agglomeration effect. Section 6 concludes.

2 Stylized Model of Working from Home and Agglomeration

To demonstrate how increased WFH adoption could affect agglomeration economies, the urban wage premium, and productivity, we introduce a stylized model, which captures the key mechanisms at work and summarizes the main implications of WFH in the presence of local agglomeration externalities.

Assume there are two locations: H and L. H represents a large or high-density city, and L represents a small or low-density city. People who work for firms in H can either be onsite by living in location H or work remotely by living in location L.[4] However, if they live and work in different locations, they incur a long-distance cost ϕ. We assume that people who work for firms in location L must also live in L.[5] All workers are identical. The total number of workers in the economy sums up to 1.

Notation-wise, let N_{HH} be the number of workers who work for firms in H and live in H; let N_{HL} be the number of workers who work remotely for firms in H and live in L; let N_{LL} be the number of workers who work for firms in L and live in L.

[4] Note that our model assumes that remote workers of firms in H can only live in location L. Without the presence of amenities, if location H has higher housing costs, any workers who work from home would choose to live in L in equilibrium, even if they could opt to live in H. In Appendix A3, we present an alternative model allowing workers employed by firms in H to choose between living in H or L while WFH, effectively separating the concepts of WFH and remote work. We show that the core insights from our baseline model persist even with this additional feature.

[5] We assume away the margin between WFH and onsite work in L for simplicity. The assumption is consistent with the fact that agglomeration economies are largely a large-city phenomenon. Moreover, even if WFH is modeled in L, under the assumption of perfect mobility and that rent is higher in H, workers who work in L will all choose to live in L.

2.1 Production

Large/High-Density City H: The production function in the large and high-density location H is given by the following equation:

$$F_H(B_H, N_{HH}, N_{HL}) = B_H(N_{HH} + N_{HL})^{\gamma},$$

where B_H is the productivity level in location H, which firms in H take as given. Given the level of B_H, firms use labor, either provided onsite N_{HH} or remotely N_{HL}, as the input for production. Beyond each firm's control, the presence of onsite workers generates productivity externalities. Specifically, $B_H = B_H(N_{HH})$ is a function of the number of onsite workers located in H:

$$B_H(N_{HH}) = B_{0H} N_{HH}^{\theta},$$

where $\theta > 0$, which represents the intensity of productivity externalities, influenced by the agglomeration effect of workers in location H. This can be interpreted as externalities resulting from spontaneous physical interactions and the ease of building relationships in large and densely populated areas.

Firms' profit-maximization problem implies that the wage is equal to the marginal product of labor:

$$W_H = \gamma B_{0H} N_{HH}^{\theta}(N_{HH} + N_{HL})^{\gamma-1}.$$

We can see that the wage level of location H decreases as the labor supply increases due to the diminishing marginal return of labor. However, owing to the production externality term, a greater number of onsite workers can boost wages due to the agglomeration effect.

Small/Low-Density City L: The production function in the small and low-density location L is simpler, as only onsite workers are used in production:

$$F_L(B_L, N_{LL}) = B_L N_{LL}^{\gamma}.$$

We assume that the productivity level in location L only contains an exogenous component B_L, which is equivalent to assuming $\theta = 0$. We believe this is a reasonable assumption because production externalities are usually facilitated by intense communication and knowledge exchanges, which are more common in large cities and industry clusters. In addition, previous research suggests that the strength of agglomeration tends to exhibit some degree of convexity with respect to city size (Moretti, 2021).

Firms' profit-maximizing problem yields that the wage level in location L is

$$W_L = \gamma B_L N_{LL}^{\gamma-1}.$$

2.2 Housing Market

Local housing costs adjust based on local housing demand, varying according to the local housing supply elasticity. The housing demand in location j, $j \in \{H, L\}$, is the sum of the population who chooses to *live* in location j regardless of the location of their labor supply.

The rent of local housing services in location H is

$$r_H = \pi_{0H} + \pi_H \ln(N_{HH}).$$

The housing demand in H is the number of workers who work and live in H. The rent in location L is

$$r_L = \pi_{0L} + \pi_L \ln(N_{HL} + N_{LL}).$$

Slightly different from location H, the housing demand in L is the sum of workers who supply labor remotely for firms in H while living in L and workers who work and live in L.

2.3 Workers' Location Choice

Workers can make one of the following choices: (i) working and living in H: HH, (ii) working in H and living in L: HL, or (iii) working and living in L: LL. We use an exogenous cost of remote work, denoted by ϕ, to model the shock of WFH adoption—the cost decreases exogenously when WFH becomes prevalent. We then examine the impact of WFH on the equilibrium outcomes by evaluating the comparative statics of a decrease in ϕ.[6] Appendix A2 presents an alternative setup where workers adopt WFH as a result of both an

[6]Our model of WFH is more simplified compared with some other studies that explore the impact of WFH on productivity, such as Davis et al. (2021) and Delventhal and Parkhomenko (2022). In our baseline model, we assume the marginal productivity of remote and onsite workers is identical; we use the cost of WFH (ϕ) to induce a shift in the fraction of remote workers. A decrease in ϕ can be viewed as a reduced-form way to account for both the relative productivity increase of WFH as described by Davis et al.

exogenous decrease in the cost of WFH and an exogenous increase in the productivity of remote workers. We show that ϕ can capture both sources of exogenous shocks in a reduced-form way.

Workers can attain the following utility levels based on their work and residential location choices:

$$U_{HH} = w_H - \beta r_H,$$

$$U_{HL} = w_H - \beta r_L - \phi,$$

$$U_{LL} = w_L - \beta r_L,$$

where w_H and w_L are the log wages in H and L, respectively; r_H and r_H are log rents in H and L, respectively; ϕ is the cost of working remotely from another city.

Since all workers are assumed to be identical, in equilibrium, all three levels of utility must equalize (assuming we are not in a corner solution where U_{HL} is too low such that no one works remotely):

$$\bar{U} = w_H - \beta r_H = w_H - \beta r_L - \phi = w_L - \beta r_L.$$

The equalization property of the homogeneity assumption allows for easy comparative statics.

2.4 Effect of WFH in Equilibrium

Urban Wage Premium From the equalized utility levels, it is evident that a decrease in ϕ would narrow the spatial gaps in both rents and wages. Specifically, taking the difference between the first and second equations, we can see that the rent premium between H and L is a function of ϕ:

$$r_H - r_L = \frac{\phi}{\beta}.$$

Taking the difference between the third and second equations, we can see that the wage premium between H and L is exactly ϕ:

$$w_H - w_L = \phi.$$

(2021) and the shift in social norms as described by Delventhal and Parkhomenko (2022). Our analysis does not require explicit assumptions on these factors. In addition, our stylized model abstracts away from commuting and hybrid arrangement. While our model simplifies many aspects of the work environment, it is designed with the specific aim of illustrating how WFH can affect agglomeration economies. As such, we intentionally streamline other forces to present a focused picture.

Thus, when the cost of WFH (ϕ) decreases, the urban wage premium also decreases. However, this condition alone does not directly indicate how much the aggregate wages and output levels are impacted by the decrease of ϕ. Below, we analyze these effects.

Agglomeration and Aggregate Productivity To examine the effect of a reduction in ϕ on equilibrium productivity, wages, and output, we totally differentiate the sum of production in both locations with respect to ϕ. This allows us to understand the mechanisms through which ϕ affects output. Since we assume a constant and equal labor share (γ) in both H and L, and the total population is normalized to one, the direction of change for output aligns with the direction of change in wages and productivity.

The effect of a decrease in ϕ on the aggregate output is

$$\frac{\partial(F_H + F_L)}{\partial(-\phi)} = \underbrace{\theta B_{0H} N_{HH}^{\theta-1} \frac{\partial N_{HH}}{\partial(-\phi)} (N_{HH} + N_{HL})^{\gamma}}_{\substack{\text{Weakening of Agglomeration Economies} \\ <0}} + \underbrace{(W_H - W_L) \frac{\partial(N_{HH} + N_{HL})}{\partial(-\phi)}}_{\substack{\text{Reallocation of Labor from } L \text{ to } H \\ <0 \text{ or } >0}}. \tag{1}$$

The effect can be decomposed into two components: (i) a decrease in the aggregate output due to weakened agglomeration economies in H and (ii) a change in the output due to the reallocation of labor between L and H (in terms of job location). Below, we show that the first component is definitively negative if $\theta > 0$. However, the second component's sign depends on the direction of labor reallocation between H and L, which is not definitive. The intuition of Equation 1 is as follows: The rise in WFH reduces the number of onsite workers, thereby lowering the agglomeration effect in H and the output. The extent of this effect depends on the sensitivity of productivity in H with respect to the number of onsite workers, i.e., θ. If the reduction in H's agglomeration effect is minimal and WFH allows a sufficient number of workers to remotely supply their labor to the high-productivity location H while residing in L, the gains from such reallocation could compensate for the productivity loss from a weakened agglomeration effect. However, if the reduction in H's agglomeration effect is so significant that it drives workers to relocate from H to L, the aggregate output will definitively decrease. It is important to note that a scenario exists where there is a net increase of workers moving to firms in H, but the weakened agglomeration economies still result in a net loss of output.

To analyze the sign of each component in Equation 1, we need to know the direction of changes in the number of onsite workers $\frac{\partial N_{HH}}{\partial(-\phi)}$ and the reallocation of labor $\frac{\partial(N_{HH}+N_{HL})}{\partial(-\phi)}$. Appendix A1 presents the derivation. Here, we show the effect of a decrease in ϕ on the numbers of onsite and remote workers servicing firms in H:

$$\frac{\partial N_{HH}}{\partial(-\phi)} = -\frac{1}{\beta\left(\frac{\pi_L}{1-N_{HH}} + \frac{\pi_H}{N_{HH}}\right)} < 0; \tag{2}$$

$$\frac{\partial N_{HL}}{\partial(-\phi)} = \frac{1}{\beta\left(\frac{\pi_L}{1-N_{HH}} + \frac{\pi_H}{N_{HH}}\right)} + \frac{\beta\left(\frac{\pi_L}{1-N_{HH}} + \frac{\pi_H}{N_{HH}}\right) - \frac{\theta}{N_{HH}}}{\beta\left(\frac{\pi_L}{1-N_{HH}} + \frac{\pi_H}{N_{HH}}\right)\left(\frac{1-\gamma}{N_{LL}} + \frac{1-\gamma}{N_{HH}+N_{HL}}\right)}. \tag{3}$$

In line with the discussed intuition, we demonstrate that reducing the cost of WFH decreases the number of onsite workers (N_{HH}). However, the effect on the total labor supply for production in H is not certain:

$$\frac{\partial(N_{HH} + N_{HL})}{\partial(-\phi)} = \frac{\beta\left(\frac{\pi_L}{1-N_{HH}} + \frac{\pi_H}{N_{HH}}\right) - \frac{\theta}{N_{HH}}}{\beta\left(\frac{\pi_L}{1-N_{HH}} + \frac{\pi_H}{N_{HH}}\right)\left(\frac{1-\gamma}{N_{LL}} + \frac{1-\gamma}{N_{HH}+N_{HL}}\right)}. \tag{4}$$

Interestingly, the impact of a decrease in the cost of WFH on labor supply to location H can be either positive or negative, depending on the intensity of agglomeration, θ. If $\theta = 0$ (no externality spillovers), a reduction in ϕ will definitely increase the total labor supply to location H. The intuition is that before WFH adoption, workers employed by firms in H have to bear the cost of housing in H, thereby limiting the number of workers who can take advantage of the productivity offered in H. The adoption of WFH allows more workers to relocate to L while still working for firms in H, effectively relieving the congestion problem associated with working in H.

Conversely, if $\theta > 0$ (where agglomeration externalities exist), the positive effect of reducing ϕ on the total labor supply to H diminishes and could even reverse if θ is large enough. This happens because as more workers switch from onsite to remote work, the productivity spillover from onsite workers decreases, which lowers the marginal product of *both* onsite and remote workers. Since these externalities are not internalized in firms' profit maximization problem and hence not priced in wages, the number of onsite workers and the total number of workers at firms in H will decrease and will fall below the optimal level.

Model Predictions In sum, our model predicts that the rise of WFH (a decrease in ϕ) will invariably reduce the urban wage premium, irrespective of potential weakening in agglomeration economies of large cities. This can be attributed to WFH expanding the labor pool available to firms in these large cities, which could also drive down the urban wage premium.

To further test whether agglomeration economies have declined in large cities, we need to assess whether

$\frac{\partial(N_{HH}+N_{HL})}{\partial(-\phi)} < 0$. If we observe not only a reduced urban wage premium but also a *decline* in employment by firms in large cities due to WFH, this would suggest a drop in productivity in these cities so that workers are encouraged to switch to firms in smaller cities. In this scenario, the weakened agglomeration economies in large cities would reduce aggregate productivity, output, and wages.

2.5 Empirical Tests in the Context of the COVID-19 Pandemic

We use the sudden and unprecedented surge in WFH prevalence during the COVID-19 pandemic as an empirical setting. The adoption of WFH during this period varied widely across occupations. To test our model predictions, we examine changes in the spatial patterns of wages and employment separately for occupations with different levels of WFH adoption.

Occupations with High WFH Adoption Figure 1a illustrates how the labor demand and supply curves would theoretically shift during the pandemic in large cities for high-WFH-adoption occupations and the effects on the equilibrium wage and employment. For high-WFH-adoption occupations, the model predicts that the reduced number of onsite workers in large cities during the pandemic may lower productivity due to weakened agglomeration economies, which could lead to decreased labor demand. Meanwhile, the labor supply of remote workers for high-WFH-adoption occupations may increase in large cities as they remotely work for large-city jobs due to the increased prevalence of WFH. The reduced labor demand and expanded labor supply in large cities will lower the wage level ($w \rightarrow w'''$) and thus reduce the urban wage premium within high-WFH-adoption occupations.[7] Crucially, if we observe a decrease in employment within high-WFH-adoption occupations in large cities post-pandemic, this implies that the labor demand in large cities *must* have shifted downward (because the labor supply curve moves upward due to the advent of WFH).

Occupations with Low WFH Adoption We now turn to the local labor markets for occupations with low WFH adoption. It is noteworthy that the COVID-19 pandemic, besides increasing WFH adoption, also sparked a surge in migration from large cities to smaller ones. This was not only fueled by the shift away from locations of employers due to the prevalence of WFH but also driven by the pandemic-induced decline in urban amenities and activities. This migration away from large cities likely shrunk the local labor *supply* in large cities for onsite positions while having less impact on occupations with high WFH adoption.

[7] In smaller cities, labor supply is likely to shift downward due to the reallocation of labor, resulting in higher wages. This could further reduce the urban wage premium.

In addition, the migration would naturally redistribute demand for local services, like restaurants, from large to smaller cities. This shift would likely decrease local labor *demand* in local service sectors of large cities, which predominantly require the onsite presence of workers. In contrast, high-WFH-adoption occupations, usually in professional services, are less impacted by local service demand shift (Eckert et al., 2022).

Figure 1b illustrates the potential impact of these labor demand and supply shifts on equilibrium wage and employment in large cities for low-WFH-adoption occupations. The concurrent downward shifts could reduce employment in these occupations within large cities ($M \rightarrow M'$). However, equilibrium wages might not shift definitively in any direction. Thus, the urban wage premium for low-WFH-adoption occupations may remain relatively stable if the demand and supply effects offset each other.

Table 1 summarizes the expected changes in the urban wage premium and employment in large and small cities separately for occupations with high and low WFH adoption and the underlying economic forces.

Identifying Assumption The key assumption behind our empirical approach of using the pandemic shock to identify the effect of WFH adoption is that other pandemic shocks unrelated to WFH adoption did not *disproportionately* affect wages and employment for jobs in high-WFH-adoption occupations in large cities. Given this assumption, if we observe a decrease in the urban wage premium for high-WFH-adoption occupations post-pandemic, while it remains largely unchanged for low-WFH-adoption occupations, we can attribute the decline in urban wage premium to WFH adoption, thereby validating our model's prediction.

It is important to acknowledge that during the pandemic, other shocks unrelated to WFH adoption, such as the exacerbated labor shortage in the low-skilled market, could have affected high- and low-WFH-adoption occupations differently. However, as long as these effects did not vary systematically by city size, we would not expect to see a disproportionate change in the urban wage premium for high-WFH-adoption occupations. Similarly, other pandemic-driven shifts, such as altered preferences for low-density housing and changes in urban amenities, may have affected the labor supply of large and small cities differently, subsequently affecting wage levels in these cities differently. While these factors could potentially induce changes in the urban wage premium, they are not expected to cause a disproportionate shift in high-WFH-adoption occupations.[8]

[8] One could argue that workers in high-WFH occupations were leading the suburbanization wave, which may have decreased the total labor supply in these occupations to large cities instead of increasing it. If this were the case, it should have led to an *increase* in the urban wage premium. Under this scenario, the observed decline in the urban wage premium among high-WFH

3 Data

3.1 Advertised Wages by Occupation and Geography: Burning Glass (Lightcast)

We use data from various sources to test the model's predictions. Our main wage data come from Lightcast, formerly known as Burning Glass Technologies, which we will refer to as Burning Glass data henceforth. Burning Glass is a company that scrapes and cleans job postings from about 40,000 online job boards and company websites across the U.S. The aim is to capture the universe of job postings in the U.S. A de-duplication algorithm is used to avoid repetition. We use the Burning Glass data from January 2018 to May 2023. The dataset represents approximately 70% of U.S. vacancies (Carnevale et al., 2014).[9] Around 20% of the postings in the Burning Glass data contain wage information, including total and hourly salary provided as a range (maximum and minimum value). We calculate a job's wage by taking the mid-point between the maximum and minimum hourly salary for the job (Hazell et al., 2022).

Notably, the job postings include highly detailed occupation codes (SOC) and industry codes (three-digit NAICS), which are generated by Burning Glass based on the text within each job listing. Additionally, the data include the county associated with each job posting, which we take as the primary job location.[10]

The job postings also offer various job-level details such as minimum degree requirement, full-/part-time status, salary types, tax terms, and an extensive array of skill requirements.[11] These detailed job characteristics enable us to study changes in the urban wage premium controlling for job characteristics. With the specific skill requirements, we can distinguish between changes in the composition of workers or local skill demand and shifts in local wage premium, holding constant skill demand. The absence of such information in most datasets, including government administrative data, makes Burning Glass data a unique resource for our analysis.

For the sake of computational efficiency, we randomly sample 10% of the raw Burning Glass data for

occupations could only be explained by a significant decrease in productivity in large cities.

[9]Carnevale et al. (2014) show that online job ads can overrepresent higher-skilled, white-collar positions, a potential bias in the Burning Glass data. However, we do not use the Burning Glass data to study the overall job number or local composition. Instead, we use the wage information of the posted jobs to analyze how local wage changes vary across different occupations.

[10]Some might question whether the location associated with each job posting truly reflects the primary job location or the firm's location, rather than the location of workers targeted by the job ads. Given that Burning Glass scrapes online job postings, there is no direct method to confirm whether the location information indeed represents the actual job or firm location. We indirectly verify this by comparing the local industry shares in the Burning Glass data with the those in the Quarterly Census of Employment and Wages (QCEW), which is based on employer locations. We compute the 3-digit NAICS industry shares in each metropolitan statistical area (MSA) using both datasets. Figure A1 shows the binned scatterplot of the shares, separately for January 2020 (pre-pandemic) and July 2020 (during the pandemic). The industry compositions in the Burning Glass data closely correspond with those derived from employers' locations in the QCEW, both before and after the pandemic began.

[11]Salary types include base pay, bonus, commission, and shift premium. Tax terms include employee and contractor.

our statistical analysis, including binned scatterplots and regression analyses.

3.2 Spatial Patterns of Employment

Our employment data are from the Quarterly Census of Employment and Wages (QCEW). The data provide quarterly employment counts, covering over 95% of all U.S. jobs, across industries defined by NAICS codes. Nevertheless, the QCEW data do not provide breakdowns in employment numbers by occupation.

Our primary measure of the relevant local labor market size for each job is the employment size of the job's occupation and metropolitan statistical area (MSA). Thus, we need to impute employment size by occupation and MSA. To do so, we use the Burning Glass data to generate a crosswalk between the three-digit NAICS code and the SOC occupation code. Since each job posting in the Burning Glass data is assigned a three-digit NAICS code and SOC code, we calculate the empirical distribution of the NAICS conditional on each SOC code. Using the probabilistic crosswalk, we impute employment by SOC occupation and county. We then use a county-MSA crosswalk to compute the employment size by occupation and MSA.

However, to analyze differential employment growth across MSAs, we directly use *industry*-level employment data from the QCEW. We use industry-level employment data rather than the imputed occupation-level data for employment analysis because the imputation process using the NAICS-SOC crosswalk can mute a substantial amount of variations in cross-industry employment growth found in the raw industry-level data. Therefore, to capture any variations accurately, we reply on the original industry-level data to analyze spatial patterns of employment.

Importantly, because the QCEW data are drawn from employment information reported by business establishments participating in the Unemployment Insurance programs, the employment counts reflect the locations of employers, not workers. This distinction is crucial for analyzing how the rise of WFH has influenced labor supply to firms in large cities compared with smaller ones.

3.3 Measuring the Adoption of Working from Home (WFH)

Burning Glass We categorize each job as WFH-compatible or not using the original texts of job postings from 2018 to 2022. We use a dictionary approach, where we search for keywords associated with WFH or remote work. To ensure our categorization is immune to negations (e.g., employers reference WFH-related topics to indicate the lack of such options), we exclude jobs from the WFH-compatible category if any negation words appear just before or immediately following the WFH keywords. We discuss our dictionary approach in details in Appendix A4.1.

After classifying each job as WFH-compatible or not, we calculate the fraction of WFH-compatible jobs within each SOC occupation. We define an occupation's WFH adoption level as high, moderate, or low based on the post-pandemic increase in the fraction of WFH-compatible jobs. In our main analysis, occupations with high WFH adoption are defined as those that saw an over 20 percentage point increase in the national share of WFH-compatible jobs, as determined by comparing pooled data from 2018 to March 2020 with pooled data from April 2020 to May 2023 in the Burning Glass data (representing the 90th percentile of the distribution in change of WFH-compatible job share). Occupations with moderate WFH adoption saw an 11 to 20 percentage point increase in the share of WFH-compatible jobs (representing the 50th and 90th percentiles), while occupations with low WFH adoption saw less than an 11 percentage point increase.

American Community Survey (ACS) We use the ACS from 2018 to 2021 to supplement the Burning Glass data. The ACS collects information on how respondents usually commute to work in the previous week (Ruggles et al., 2022). The survey reports whether a respondent "worked from home" during the prior week. Combining this information with occupational codes (OCC2010), we compute the fraction of respondents from each occupation who worked from home each year up to 2021. Therefore, by assessing the change in the fraction of WFH workers by occupation before and after the pandemic's onset, we can also classify each occupation's WFH adoption level in the ACS data.[12] We use the levels of WFH adoption by occupation measured with the ACS data to conduct a number of robustness checks.[13]

[12] In ACS, we define an occupation's WFH adoption level based on the change in the national share of remote workers within the occupation between 2019 and 2021. We classify occupations as high-WFH-adoption occupations if they saw an over 28 percentage point increase in the national share of WFH workers, comparing data from 2019 and 2021 (representing around the 90th percentile of the distribution in the change of WFH worker share within the ACS data). Moderate-WFH-adoption occupations saw an 8 to 28 percentage point increase in the share of WFH workers (representing the 50th and 90th percentiles), while low-WFH-adoption occupations saw less than an 8 percentage point increase.

[13] For robustness checks that use the ACS to evaluate changes in the urban wage premium, we compute the occupation-level WFH adoption directly from the ACS. In other checks, we measure the level of WFH adoption by occupation using the ACS and merge the measurement with the Burning Glass data. However, a challenge arises because the ACS uses the broader Census Occupation Code (OCC2010), while the Burning Glass uses the more detailed SOC codes. Thus, a large number of SOC occupations in the Burning Glass data cannot be directly matched to OCC2010 codes. To leverage the ACS's WFH-adoption information, we combine 57 SOC-occupation-level work context characteristics from the Occupational Information Network (O*NET) data with the observed occupation-level WFH adoption in the ACS. Then using observed O*NET work contexts for *all* occupations, we impute the level of WFH adoption for all SOC occupations. Please refer to Appendix A4.2 for more details on the imputation process.

American Time Use Survey (ATUS) The ATUS provided by the Bureau of Labor Statistics is another resource for tracking WFH adoption by occupation (Hofferth et al., 2020). The ATUS measures the amount of time that respondents spend on various activities over a 24-hour period. Hence, the data allow us to calculate the fraction of working hours spent at home by occupation over time. With its annual data releases, we can compare the prevalence of WFH before and after the pandemic. However, the ATUS has its limitations as the number of respondents is often too small for occupation-level analyses. Thus, we mainly use the ATUS to validate our findings from the Burning Glass data and ACS.

Cross-Validations To ensure the credibility of our primary WFH adoption measurement from the Burning Glass data, we cross-validate it using alternative datasets. It is crucial to note that our study does not focus on the precise *level* of WFH adoption but rather the relative changes in WFH adoption levels across occupations post-pandemic. In other words, it is the *ranking* of WFH adoption across occupations that is relevant for our analysis. For validation, we compute WFH prevalence by occupation group using the ACS and ATUS data and the fraction of WFH-compatible jobs by occupation or occupation group in the Burning Glass data over the first two years of the pandemic (2020–2021). Figures 2a and 2b plot the fraction of WFH-compatible jobs by occupation group against the workers' WFH prevalence by occupation group in the ATUS and ACS data, respectively, both indicating strong correlations. Figure 2c compares our estimated shares of WFH-compatible jobs by occupation with those from Bloom et al. (2023), suggesting a high correlation with an R-squared exceeding 0.75.[14] Lastly, Figure 2d shows that the WFH prevalence measures across occupation groups using the ACS and ATUS data align closely with an R-squared close to 0.9.[15]

4 Empirical Evidence

4.1 The Adoption of WFH Arrangement

We begin our empirical analysis by documenting changes in WFH adoption over time. Using the ACS and ATUS data from 2005–2021, we first calculate the aggregate share of remote workers by year.[16] Figure 3a

[14]Bloom et al. (2023) develop a machine-learning technique to categorize WFH-compatible jobs with increased precision.

[15]For the validation of the imputed levels of WFH adoption based on the ACS and O*NET occupational characteristics, please see Appendix A4.2.

[16]For 2020, to highlight changes in WFH during the pandemic, we impute Q2-Q4 share of remote workers, assuming the Q1 2020 share is equal to the 2019 share. Specifically, assume that the 2019 share of remote workers is $share_{2019}$ and observed 2020 share is $share_{2020}$. Then the imputed share of remote workers in Q2-Q4 2020 is $share_{Q2-Q4,2020} = \frac{share_{2020} - 0.25 share_{2019}}{0.75}$.

reveals a dramatic rise in WFH adoption starting in 2020 and a high level maintained into 2021. The pattern is reflected in both ACS and ATUS.

Consistent with predictions of Dingel and Neiman (2020) and findings from other studies, we document that the level of WFH adoption varied widely across different types of workers, occupations, and industries (Barrero et al., 2021; Bick et al., 2022; Brynjolfsson et al., 2020).[17] Figure 3b shows that college-educated workers were more likely to transition to WFH in 2020 than their non-college-educated counterparts. Across occupations, Figure 3c shows a very high WFH uptake by computer and mathematical occupations, followed by business and financial occupations. In contrast, occupations related to food services and health care saw a much lower level of WFH adoption. Similarly, Figure 3d shows industry-level disparities, with finance, information, and professional and business services sectors leading in WFH adoption, contrasting with sectors such as accommodation and food services, as well as health care and social assistance.

4.2 The Effect of WFH Adoption on the Urban Wage Premium

In this section, we examine the effect of WFH adoption during the COVID-19 pandemic on the urban wage premium. Based on the empirical tests outlined in Section 2.5, we expect a decrease in the urban wage premium for occupations with high WFH adoption during the pandemic. Conversely, occupations with low or moderate WFH adoption are expected to see smaller changes.

We begin by presenting binned scatterplots of residualized log posted hourly wages against residualized log employment of each job's occupation and MSA. We use employment size by occupation and MSA as a measure of the relevant local labor market size for each job.[18] To residualize the variables, we control for dummy variables for SOC occupation code, three-digit NAICS code, job's required education level, salary type, full-/part-time status, tax terms, and the posting month. Hourly wages are from the Burning Glass data, and employment size is from the QCEW. Figure 4 presents these plots, where the *slopes* of the curves represent the urban wage premium.[19]

[17] A few recent papers use customized surveys to document differential changes in the prevalence of WFH during the pandemic—e.g., the Survey of Working Arrangements and Attitudes by Barrero et al. (2021). We do not use the survey data because our analysis requires a highly detailed occupation code, which is not available in these surveys.

[18] We also present similar binned scatterplots using total MSA employment (rather than by MSA and occupation) to measure the job's relevant local labor market size. These plots are presented in Figure A2.

[19] We validate the urban wage premium estimated from the Burning Glass data using the 2019 ACS. We use the ACS for the pre-pandemic year because estimating the urban wage premium requires the location of *jobs*, and the ACS reports the job locations only for *onsite* workers. The prevalence of WFH before the pandemic was very low, so using the ACS to measure the urban wage premium before the pandemic is unlikely to introduce significant bias. Figure A3 compares the urban wage premium estimated from the two datasets and shows that they are highly comparable.

Figure 4a presents the plot for all jobs from two periods: the pre-pandemic era (January 2018 to March 2020) and the period after the pandemic hit (April 2020 to May 2023). In a cross-sectional view, the slopes of the curves are positive, indicating that residual wages are generally higher in larger labor markets, a finding that aligns with prior empirical evidence. Following the pandemic, the urban wage premium experienced a drop, decreasing from 0.0276 to 0.0212, and the decline is statistically significant.

Figures 4b and 4c present the plots for jobs that require a college degree and those that do not, respectively. While both plots show a decrease in the urban wage premium, the decline is not statistically significant for the jobs that require a college degree.

Figures 4d and Figure 4e present the plots for jobs in occupations with high and low levels of WFH adoption, respectively. From Figure 4d, we observe a large and statistically significant decline in the urban wage premium for occupations with high WFH adoption. The drop is from 0.0417 to 0.0309, approximately a 26% decline. In contrast, for jobs in low-WFH-adoption occupations (as shown in Figure 4e), the decline in the urban wage premium is much smaller, decreasing from 0.0174 to 0.0167. This corresponds to roughly a 4% decrease from a much lower base number. This finding—i.e., a more dramatic decrease in the urban wage premium for occupations with high WFH adoption compared with those with low WFH adoption—is consistent with the prediction of our model as described in Section 2.5.[20]

Lastly, Figure 5 presents the urban wage premium annually from 2018 to 2023, separated into four groups of job postings according to their level of WFH adoption and educational requirements. Each group's urban wage premium is normalized by the 2018 estimate. We find a notable drop in the urban wage premium among occupations with high WFH adoption, regardless of whether a college degree is required. Moreover, this decrease did not rebound since the pandemic's outbreak. Conversely, the urban wage premium remained relatively stable among occupations with low WFH adoption regardless of the need for a college degree.

Spatial Sorting of Skill Demand One might be concerned that the observed decline in the urban wage premium could be due to factors other than the adoption of WFH, such as the pandemic causing an exodus of higher-wage firms from large cities for reasons unrelated to WFH. This means that the reduction in the relative wages in larger cities does not necessarily indicate a true decline in the urban wage premium for a given set of jobs but could instead be a result of higher-skill jobs leaving these large cities.

[20]Figure A4 presents binned scatterplots of changes in the urban wage premium of four selected occupation groups. To see which cities experienced wage declines most during the pandemic, in Figure A5, we present changes in residualized log posted wages for jobs in four occupation groups across various MSAs. More details are presented in Appendix A5.1.

To further investigate this possibility, we analyze the extent to which our estimates of the decline in the urban wage premium are driven by spatial sorting of skill demand and how much they are driven by a genuine decrease in the urban wage premium for a given set of worker skills. Fortunately, the Burning Glass data provide a rich array of skill requirements associated with each job posting, allowing us to perform this analysis.[21] Specifically, we estimate the following equation:

$$\begin{aligned}\ln(w_{ikjt}) = &\alpha_0 \ln M_{kj} + \alpha_1 \ln M_{kj} \times Post_t + \alpha_2 \ln M_{kj} \times Mod_k + \alpha_3 \ln M_{kj} \times Post_t \times Mod_k \\ &+ \alpha_4 \ln M_{kj} \times High_k + \alpha_5 \ln M_{kj} \times Post_t \times High_k + \alpha_6 Post_t + \alpha_7 Mod_k + \alpha_8 High_k \\ &+ \alpha_9 Post_t \times Mod_k + \alpha_{10} Post_t \times High_k + \mathbf{X}_{ikjt}\mathbf{\Theta} + \varepsilon_{ikjt},\end{aligned} \quad (5)$$

where w_{ikjt} is the posted hourly wage of job i in occupation k MSA j and time t; M_{kj} is the employment size of occupation j in MSA j (as measured in 2019 Q1); $Post_t$ is an indicator of the post-pandemic period (i.e., 1 if t is after March 2020); Mod_k is an indicator that k is an occupation with moderate WFH adoption; $High_k$ is an indicator that k is an occupation with high WFH adoption; $\mathbf{X}_{ikjt}$ is a vector of job-level characteristics, including dummy variables for SOC occupation code, three-digit NAICS code, years of education required by the job, salary type, full-/part-time status, tax terms, posting month, and required skills. The parameter α_1 represents the change in the urban wage premium post-pandemic for low-WFH-adoption occupations; $\alpha_1 + \alpha_3$ represents the change in the urban wage premium for moderate-WFH-adoption occupations; $\alpha_1 + \alpha_5$ represents the change in the urban wage premium for high-WFH-adoption occupations; α_3 (α_5) represents the differential change in the urban wage premium for moderate (high) WFH-adoption occupations compared with low-WFH-adoption occupations. We estimate the equation using the Burning Glass data from 2018–2023.

Table 2 presents the estimates of Equation 5. Column 1 includes basic job characteristics.[22] Column 2 further controls for the skill fixed effects. Both specifications show small and statistically insignificant changes in the urban wage premium for jobs in low-WFH-adoption occupations. However, for high-WFH-adoption occupations, the change in the urban wage premium is strongly negative. Even after controlling for

[21] The added complexity of the data is that some job postings specify only a few skill requirements while others list more than ten distinct skills. To simplify our computations, we focus on the first 20 skills mentioned in each job posting, ranked by the overall frequency of mentions across all postings. About 90% of the jobs in the sample mention fewer than 20 skills. In job postings with fewer than 20 skills, the remaining slots are filled as "na."

[22] The regression results are slightly different from the slopes of the binned scatterplots in Figure 4d and 4e. This is because in the figures, we residualize log hourly wage and log M separately for the sample before and after the pandemic began.

detailed skill fixed effects, the magnitude remains largely unchanged. This suggests that the considerable decline in the urban wage premium among high-WFH-adoption occupations is likely a true reflection of a decrease in the relative price of labor in larger cities, holding skills constant.

For further validation, Table A1 columns 1 and 2 present the results after controlling for the interaction between occupation fixed effects and the post-pandemic dummy, as well as the interaction between MSA fixed effects and the post-pandemic dummy. These controls aim to capture any pandemic-related changes that have affected an entire occupation or MSA. The results remain largely consistent with those in Table 2, thereby strengthening the robustness of our findings.[23]

Alternative Definitions of WFH Adoption There may be concerns that our results hinge on how we define the levels of WFH adoption. To address the concern, in Table 2 column 3, we use an alternative indicator of high WFH adoption that classifies an occupation as "high WFH adoption" if it belongs to business/finance or computer/mathematics occupation groups. As shown in Figure 3c, these two occupation groups exhibited a dramatic increase in WFH adoption from 2020 onward. When using this alternative categorization, the regression results confirm that these two occupation groups experienced a disproportionate decrease in the urban wage premium compared with other occupations, corroborating the robustness of our baseline results.

In Table A1 columns 3 and 4, we use the same baseline specification but define WFH adoption levels based on each job' three-digit NAICS industry code, rather than the SOC occupation code. The results closely align with those in Table 2 columns 1 and 2.[24]

Selection Bias Because only a subset of job postings provide wage information, there may be concerns of selection bias in our estimated regression coefficients. Specifically, if high-skilled jobs in large cities are less likely to list wages post-pandemic, this could result in a spurious decrease in our urban wage premium estimates. To address that concern, in column 4, we apply a Heckman correction to rectify the potential bias. In the first stage, we use the triple interaction between dummy variables for jobs' required years of

[23]To address concerns that changes in the urban wage premium might occur at a geographical level below the MSA, such as the county level, we perform the same regression analysis as in Equation 5, but redefine M at the occupation-county level. The estimates are reported in Table A2. Column 1 includes only job-level controls, while Column 2 further controls the interaction term of MSA fixed effects, the high-WFH-adoption dummy, and the post-pandemic dummy. The interaction term absorbs any MSA-level changes in the urban wage premium. The results suggest that the decline in the urban wage premium has occurred both within and across MSAs.

[24]In Table A3, we use the baseline specification but categorize WFH adoption levels using the *imputed* change in the fraction of WFH workers—the imputation is based on the observed change in the fraction of WFH workers in the ACS and the O*NET occupational characteristics. The results are also consistent with those in Table 2. Please see footnote 13 and Appendix A4.2 for detailed discussions of the imputation.

education, the post-pandemic period, and occupation's WFH adoption level across all job postings to predict the availability of wage information for a given posting. In the second stage, we estimate the conditional expectation of wages according to Equation 5, given that wage information is available for a job. The results in column 4 indicate that, after accounting for wage selection based on observed job characteristics, the estimated decrease in the urban wage premium for high-WFH-occupations is comparable to the baseline estimates in columns 1 and 2. Although we cannot exclude the possibility of other forms of selection, our findings suggest that the estimated decline in the urban wage premium using the Burning Glass data is unlikely to be attributed to a selection bias based on the skill level of jobs.

To further ensure that our findings are robust to selection bias from wage postings, in Table A4, we estimate changes in the urban wage premium using the average weekly earning data from the QCEW. The QCEW data offer several benefits. They provide earnings information likely free from selection bias, and the earnings information is based on employers' locations. However, some cautionary points need to be considered: First, the data do not provide hourly wage information; weekly earnings might be confounded by changes in the number of part-time workers during the pandemic. Moreover, while QCEW reflects the earnings of existing workers, Burning Glass pertains to new job postings. Despite these differences, the results in Table A4 point to a substantial and statistically significant decrease in the urban wage premium for high-WFH-adoption industries.[25] The magnitude of the decrease intensified from 2020 to 2022, possibly because wages for existing workers adjust at a slower pace compared with those for new jobs.

Mechanical Effect of Larger Cities' Disproportionate WFH Adoption Another potential concern is that the observed decrease in the urban wage premium among high-WFH-adoption occupations could be a mechanical result of larger cities' disproportionate adoption of WFH and the fact that WFH may serve as a type of amenities compensating for lower wages. If jobs based in larger cities were more likely to adopt WFH than similar jobs in smaller cities, this could have led to a greater wage reduction in large cities, creating a spurious decrease in the urban wage premium that is unrelated to weakened agglomeration or increased labor supply.

[25] Here, we estimate changes in the urban wage premium by *industries* with different WFH adoption levels rather than by occupations, because the QCEW only includes NAICS industry codes. We define high, moderate, and low WFH-adoption industries using each industry's fraction of WFH-compatible jobs in the Burning Glass data: Industries (three-digit NAICS) with high WFH adoption saw an increase of more than 20 percentage points in the national share of WFH-compatible jobs, as determined by comparing pooled data from 2018 to March 2020 with pooled data from April 2020 to May 2023. Industry with moderate WFH adoption saw an increase between 11 and 20 percentage points, while industries with low WFH adoption saw an increase of less than 11 percentage points.

To examine this concern, we delve into the WFH options at the individual job level. If the decrease in the urban wage premium among high-WFH-adoption occupations is not solely due to larger cities' increasing WFH adoption and compensating wage differentials, we should observe a decrease in the urban wage premium not just overall in high-WFH-adoption occupations but also specifically in *both* job categories that do and do not provide WFH options within these occupations. The rationale behind this is that if the decline in the urban wage premium is driven by weakened agglomeration economies and diminished knowledge spillovers, then the productivity of onsite workers could be negatively impacted if a substantial proportion of their colleagues or workers in the same occupation shifted to remote work. Moreover, if labor supply to firms based in large cities increased due to the "virtual" influx of remote workers, the wages of both remote and non-remote workers in the same local labor market may face downward pressure.

We conduct the test using both the Burning Glass data and the ACS. First, using the Burning Glass data, we estimate changes in the urban wage premium separately for jobs allowing and not allowing WFH within occupations with the same WFH adoption level. Table 3 Panel A presents these results. Columns 1 and 2 show a large and statistically significant decrease in the urban wage premium for both WFH-compatible and non-WFH-compatible jobs in high- or moderate-WFH-adoption occupations. The magnitude of the decline is even slightly larger for non-WFH-compatible jobs in high-WFH-adoption occupations. In contrast, for jobs within low-WFH-adoption occupations (column 3), although we observe a notable decrease in the urban wage premium for WFH-compatible jobs, it remained unchanged for non-WFH-compatible jobs. The findings present evidence that the decreased urban wage premium among high-WFH-adoption occupations is unlikely to have been mechanically driven by larger cities' disproportionate WFH adoption.

Second, using the ACS data from 2018 to 2021, we estimate changes in the urban wage premium by occupation's WFH adoption level among *onsite* workers.[26] We only focus on *onsite* workers because the ACS provides the MSA of workers' workplaces, which only represents the *job* location for onsite workers. In other words, using the ACS, we are not able to estimate changes in the urban wage premium based on job locations for those working remotely.[27] If the urban wage premium reduction was purely a result

[26]The sample is restricted to onsite workers aged from 25–65 who worked at least 35 hours per week. The dependent variable is a worker's log hourly wage. M is the employment size of the worker's occupation in the MSA of the workplace. The post-pandemic dummy is set to 1 for the years 2020 and 2021. Footnote 12 details the categorization of high-, moderate-, and low-WFH-adoption occupations. We control for workers' characteristics, including dummy variables for age, gender, race, Hispanic origin, marital status, educational attainment, and occupation code.

[27]One might suggest estimating changes in the urban wage premium based on workers' residential locations. Pre-pandemic, the estimates based on residential and workplace locations likely overlapped significantly. However, during the pandemic, with widespread WFH adoption and subsequent worker migration away from workplace cities, these estimates likely diverged. Jobs with the most significant drop in the urban wage premium are likely those where workers move away toward smaller cities. Therefore,

of larger cities' greater WFH adoption, we would not anticipate any changes in the urban wage premium among onsite workers. Table 3 Panel B presents the results. Consistent with the results from the Burning Glass data, the results in the ACS show a decrease in the urban wage premium among onsite workers in high-WFH-adoption occupations. While we also observe a decrease in the urban wage premium among onsite workers in low-WFH-adoption occupations, onsite workers in high- and moderate-WFH-adoption occupations saw a substantially greater decline.

Reduced Compensating Wage Differentials Lastly, a remaining alternative explanation for the decreased urban wage premium in high-WFH-adoption occupations could be that adopting WFH offers greater amenity value to workers working for employers based in large cities than they do in smaller cities. After adopting WFH, firms might pay employees less because of the reduced commuting burden they enjoy. Since commute time tends to be longer in large cities prior to the pandemic, the switch to WFH could have led to a greater reduction in commute time for jobs based in large cities, potentially leading to a more substantial wage decrease in these cities due to changing compensating differentials.

We examine the plausibility of this explanation by exploiting the idea that the reduction in commute time due to WFH adoption should be larger for workers who initially had longer commutes. If reduced commute time led to wage reductions, we would expect the largest drops in wages among workers who likely had the greatest reductions in commuting—those working in high-WFH-adoption occupations living in neighborhoods with traditionally long commutes for their occupations. Using ACS data from 2015–2021, we estimate changes in reported wages based on occupation category and the average pre-pandemic commute time for workers' residential PUMA and occupation category. Table A5 shows that workers in high-WFH-adoption occupations residing in neighborhoods with long pre-pandemic commutes experienced a greater reduction in their commute time. However, despite the gains in commuting amenities, we do not find that these workers had greater wage decreases. These findings provide some evidence that our observed reduction in the urban wage premium is unlikely solely driven by reduced compensating wage differentials in large cities. Appendix A5.2 provides more details on this analysis.

estimating the urban wage premium based on residual locations could severely underestimate the actual decrease.

4.3 The Effect of WFH on Local Employment

Our model suggests that the surge in WFH could reduce the urban wage premium, whether because of weakened agglomeration economies in large cities or increased labor supply to firms in these cities due to the surge in WFH availability. To investigate whether the agglomeration economies in large cities have been weakened, we can explore whether employment (based on firms' locations) shifted away from large cities among the high-WFH-adoption occupations. If firms in large cities employed relatively fewer workers in high-WFH-adoption occupations *and* relative wages in large cities declined, it would imply that the local productivity must have declined among these occupations.

We conduct the employment analysis using the QCEW data. Since QCEW only provides employment data by industry, not occupation, to avoid potential measurement errors from imputed occupation-level employment growth, we define jobs' WFH adoption levels based on their *industries*, rather than by occupations.[28] We use the following simple regression to examine whether employment in MSAs with large initial employment sizes increased or decreased across industries with different levels of WFH adoption:

$$\begin{aligned}\Delta \ln Emp_{kjt} = &\sum_{t=2019,2022} a_1^t \ln M_{kjt}^0 \times Low_k + \sum_{t=2019,2022} a_2^t \ln M_{kjt}^0 \times Mod_k \\ &+ \sum_{t=2019,2022} a_3^t \ln M_{kjt}^0 \times High_k + \eta_{kt} + \theta_j + e_{kjt},\end{aligned} \tag{6}$$

where $\Delta \ln Emp_{kjt}$ is the change in log employment in industry k and MSA j between the 1st quarter of 2017 and the 4th quarter of 2019 ($t = 2019$), or between the 1st quarter of 2020 and the 4th quarter 2022 ($t = 2022$); M_{kjt}^0 is the employment size at the beginning of each period; Low_k is an indicator that industry k has low WFH adoption; Mod_k is an indicator that industry k has moderate WFH adoption; $High_k$ is an indicator that industry k has high WFH adoption. Parameters a_1^{2019}, a_2^{2019}, and a_3^{2019} represent how employment changed between 2017 and 2019 by the labor market size for low-, moderate-, and high-WFH industries, respectively. Similarly, parameters a_1^{2022}, a_2^{2022}, and a_3^{2022} represent how employment changed between 2020 and 2022 by the labor market size for low-, moderate-, and high-WFH industries, respectively. We control for industry $\times$ time period fixed effects.

Table 4 presents the results. Column 1 shows that employment growth of all three industry groups was relatively slower in larger MSAs over the three years pre-pandemic—estimates of a_1^{2019}, a_2^{2019}, and a_3^{2019} all

[28] The categorization of WFH adoption levels by industry is detailed in footnote 25.

are negative, though not statistically significant for a_3^{2019}. However, with the onset of the pandemic, there was a more pronounced decline in employment in larger MSAs for both types of occupations—estimates of a_1^{2022}, a_2^{2022} and a_3^{2022} are all strongly negative, which surpass the magnitudes of a_1^{2019}, a_2^{2019}, and a_3^{2019}. In Column 2, high-WFH-adoption industries are classified as "Finance," "Information," and "Professional and Business Services." The finding remains the same.

It is worth noting that industries with low or moderate levels of WFH adoption also saw a sizable shift in employment from large to small cities post-pandemic. This finding is consistent with the predictions detailed in Section 2.5. However, the reasons for the disproportionate employment drop in large cities differ between low-/moderate-WFH-adoption industries and high-WFH-adoption industries, as elaborated in Table 1.

In conclusion, the substantial decrease in the urban wage premium for occupations and industries with high WFH adoption, combined with the disproportionate negative employment growth in larger cities for these industries, suggest that the adoption of WFH weakened the productivity advantage of large cities during the pandemic.[29]

5 Decomposition by Skill

Next, to provide additional evidence for changes in agglomeration economies and spatial labor supply due to WFH adoption, we shift our focus from directly testing the model predictions. We implement an alternative approach by examining the urban wage premium associated with specific *skills* required in posted jobs. We consider each job as a package of required skills, and the wage return for each job can be considered as the sum of the wage returns for all required skills on the job. With this framework, we can decompose the urban wage premium for the high-WFH-adoption occupations into the sum of the urban wage premium of individual skills and identify *which* specific skills contribute the most to the overall decline in the urban wage premium among these jobs.

What can we learn from such a decomposition exercise? If skills that foster idea exchange, relationship building, and networking saw a disproportionate wage reduction in large cities (i.e., a decreased urban wage premium for these skills), it would suggest that productive interactive activities, where these skills are highly useful, have likely diminished in workplace in these locations. This supports the hypothesis that the rise of WFH weakened the agglomeration economies in large cities. On the other hand, if skills complementary

[29]Figures A6 show employment growth by industry in selected MSAs. Appendix A5.1 presents more discussions.

to remote work (e.g., using electronic technologies) saw a substantial drop in their urban wage premium, it would suggest that the labor supply has expanded in large cities due to remote technologies.

In addition to assessing spatial wage changes linked to skills, we also explore how the listing *intensity* of skill requirements among jobs in high-WFH-adoption occupations shifted geographically. If the agglomeration economies in large cities were indeed weakened, we should expect the listing intensity for relationship-building, communication, and networking skills to *decrease* in large cities. Conversely, if WFH led to an expanded labor pool in large cities, the listing intensity for skills complementary to remote work should *increase* in those areas.

5.1 Gelbach Decomposition

To identify which skills contribute to the decline in the urban wage premium the most, we use the Gelbach decomposition method (Gelbach, 2016). We focus on jobs in occupations with high WFH adoption (with at least a 15 percentage point rise in the share of WFH-compatible jobs).[30] To estimate the change in the urban wage premium, we use the following equation:

$$\ln(w_{ikjt}) = \gamma_0 \ln M_{kj} + \gamma_1 Post_t + \gamma_2 \ln M_{kj} \times Post_t + \mathbf{X}_{ikjt}\mathbf{\Psi} + \epsilon_{ikjt}. \tag{7}$$

The variables are defined the same as in Equation 5. The change in the urban wage premium for high-WFH-adoption occupations post-pandemic is γ_2.[31]

If we consider changes in the *skill*-specific urban wage premium as the underlying driving forces behind the overall urban wage premium, then the fully specified equation is

$$\begin{aligned}\ln(w_{ikjt}) = {} & \tilde{\gamma}_0 \ln M_{kj} + \tilde{\gamma}_1 Post_t + \tilde{\gamma}_2 \ln M_{kj} \times Post_t + \mathbf{X}_{ikjt}\tilde{\mathbf{\Psi}} \\ & + \sum_s \beta_0^s \ln M_{kj} \times Skill_{it}^s + \sum_s \beta_1^s Post_t \times Skill_{it}^s \\ & + \sum_s \beta_2^s \ln M_{kj} \times Post_t \times Skill_{it}^s + \tilde{\epsilon}_{ikjt},\end{aligned} \tag{8}$$

[30] We use a threshold of 15 percentage points instead of 20 (in the Section 4 analyses) to increase the sample size for the decomposition. This criterion includes approximately 28% of job postings. Some occupations from the upper range of moderate-WFH-adoption occupations are also included in this analysis.

[31] This is a simpler version of Equation 5, excluding occupations with low/moderate WFH adoption. The estimate of γ_2 is very similar to the estimate of $\alpha_1 + \alpha_3$ in Equation 5, which pools all jobs. The estimation results of Equation 7 are not reported due to space limitations.

where $Skill^s_{it}$ is an indicator that skill s is required in job i. β^s_2 represents the change in the skill-specific wage premium among high-WFH-adoption occupations post-pandemic. After controlling for the skill interaction terms, the change in the residual urban wage premium is likely to drop from γ_2 to $\tilde{\gamma}_2$. This reduction signifies the portion of the decline in overall urban wage premium that can be attributed to the decrease in the *skill*-specific urban wage premiums. The gap between γ_2 and $\tilde{\gamma}_2$ can also be understood as the size of the contribution of adding back the "omitted" covariates.

However, as demonstrated by Gelbach (2016), when covariates are statistically correlated, we cannot simply add or subtract each covariate to individually decompose its contribution. According to his method, to determine the contribution of each covariate, we need to estimate the effect of each covariate on the outcome variable and how each covariate correlates with the main regressors in the equation. In our context, this implies that if skill s is very frequently required in high-WFH-adoption occupations, a large estimate of β^s_2 (i.e., a substantial decline in the urban wage premium for skill s) would suggest that the decline in the urban wage premium for skill s greatly contributes to the overall decrease in the urban wage premium. In contrast, if skill s is rarely required in high-WFH-adoption occupations, even a large estimate of β^s_2 would not significantly contribute to the overall decline in the urban wage premium.

To apply the Gelbach decomposition, we estimate the following equation separately for each skill s:

$$\ln M_{kj} \times Post_t \times Skill^s_{it} = \Gamma^s_0 \ln M_{kj} + \Gamma^s_1 Post_t + \Gamma^s_2 \ln M_{kj} \times Post_t + \mathbf{X}_{ikjt}\mathbf{\Gamma}_{\boldsymbol{x}} + \eta_{ikjt}, \quad (9)$$

where Γ^s_2 represents how much each added covariate of skill s correlates with the key regressors. The contribution of the change in the urban wage premium for each skill s to the overall change in the urban wage premium in high-WFH-adoption occupations is as follows:

$$\hat{\pi}^s = \frac{\hat{\Gamma}^s_2 \cdot \hat{\beta}^s_2}{\hat{\gamma}_2}, \quad (10)$$

where $\hat{\Gamma}$, $\hat{\beta}$, and $\hat{\gamma}$ represent the estimated coefficients.

Results For computational feasibility, we define s as a skill cluster family, as defined in the Burning Glass data. There are 35 skill cluster families in total. Detailed definitions and assignments of these skill cluster families are provided in Appendix A4.3.

Table 5 presents the Gelbach decomposition results.[32] We conduct the decomposition analysis for three time periods to assess the contribution of changes in skill returns to the overall decline in the urban wage premium from 2018–2019 to 2020, from 2018–2019 to 2021, and from 2018–2019 to 2022–2023 (up until May of 2023). We separate the three time periods to account for potential changes in the returns to skills over time as work dynamics evolved to accommodate developments such as hybrid work arrangements, especially those skills linked to interpersonal interactions.

For each period, we rank the skill cluster families based on their contributions to the decline in the urban wage premium. Our findings suggest that among the skill cluster families contributing the most to the decrease in the urban wage premium are “Marketing and Public Relations,” “Business Management,” “Information Technology,” “Customer and Client Support,” “Building Relationship,” and “Communications,” although “Information Technology” drops off over the horizon to 2021.[33]

Among the skills identified, WFH likely enabled more workers with “Information Technology” skills to remotely work for firms in large cities or industry clusters. These skills are typically compatible with electronic tools, making remote work more feasible (Bloom et al., 2015; Dingel and Neiman, 2020; Barrero et al., 2021). The increased labor supply enabled by these technologies to large cities would likely drive down the wage returns to skills complementary to these technologies in large cities, which is largely consistent with the evidence.

In contrast, other prominent skills such as “Communications,” “Building Relationship,” “Marketing and Public Relations,” and “Customer and Client Support” do not inherently benefit from WFH. These skills, rather, are typically useful with productive interactive activities at the workplace. They often play a key role in facilitating knowledge spillovers, forming professional networks, and establishing client relationships (Deming, 2017; Deming and Kahn, 2018). The large decrease in the urban wage premium for skills predominantly used in interactive activities suggests that the demand for these skills declined disproportionately among employers based in large cities, which constitutes indirect evidence that in-person interactive activities at the workplace for which these skills are useful have most likely reduced. The decline in the urban wage premium due to the absence of interactive workplace activities among large-city employers supports the hypothesis that WFH weakened the agglomeration effects of cities.[34]

[32]Tables A10 and A11 in the Appendix present the Gelbach decomposition results for jobs that require a college degree and jobs without a degree requirement, respectively.

[33]Tables A8 and A9 present the most frequently listed skills that belong to these skill cluster families.

[34]In Table A13, we conduct the same decomposition exercise, but use the sample of high-WFH-adoption occupations based on the *imputed* WFH adoption levels (from the ACS and O*NET data). The results also suggest that the interactive skills and

Note that “Business Management” skills, which are ranked high on the list, might be versatile enough to facilitate both remote work and face-to-face interactions. There could be a dual effect where the rise of WFH increases the labor supply in large cities for jobs needing such skills, while the decline in interpersonal activities lowers their productivity. Thus, both factors could contribute to reduced urban wage premium associated with “Business Management” skills.

5.2 Skill Intensity

Lastly, we investigate how the listing intensity of the few key skill groups within high-WFH-adoption jobs has shifted geographically. If agglomeration economies have diminished in large cities, we would expect reduced demand for relationship-building and networking skills in these cities. Hence, in addition to a decreased urban wage premium for these skills, we should also expect decreased listings of these skills in the job ads made by firms based in large cities. Conversely, if WFH has expanded the labor pool in large cities due to remote technologies, then the supply of workers possessing IT skills should increase in large cities. Therefore, not only should the jobs that require these skills see a decreased urban wage premium due to an increased supply of workers possessing these skills, we should also expect an *increase* in the listings of these skills by employers in large cities.

We assess the spatial changes in skill demand using the following equation:

$$Skill^s_{ikjt} = \lambda^s_0 \ln M_{kj} + \lambda^s_1 Post_t + \lambda^s_2 \ln M_{kj} \times Post_t + \mathbf{X}_{ikjt}\mathbf{\Lambda}_{\boldsymbol{x}} + u_{ikjt}, \tag{11}$$

where the outcome variable is an indicator that a skill in skill cluster family s was listed in job posting i within occupation k in MSA j at time t. $\mathbf{X}_{ikjt}$ is a vector of basic job characteristics (excluding skill dummies). Other variables are defined the same as in Equation 5. We again focus on jobs in occupations with high WFH adoption (with at least a 15 percentage point rise in the share of WFH-compatible jobs).

We focus on the six skill cluster families that contribute the most to the overall decline in the urban wage premium among jobs in high-WFH-adoption occupations, as indicated by our Gelbach decomposition results. These are “Information Technology,” “Business Management,” “Building Relationship,” “Communications,” “Customer and Client Support,” and “Marketing and Public Relations.” These skills are either inherently suited to remote work, conducive to interactive activities, or both. Our prediction is that “Infor-

“Information Technology” rank prominently on the top of the list (with “Information Technology” dropping off in 2021).

mation Technology" skills may have been listed more intensively in large cities, whereas "Building Relationship," "Communications," "Customer and Client Support," and "Marketing and Public Relations" skills may have seen reduced demand due to diminished workplace interactions. As for "Business Management" skills, they could either see an increase or decrease in demand, depending on which effect is stronger: the expanded labor pool or the weakened agglomeration economies.

Results Table 6 presents the results.[35] Column 1 shows that "Information Technology" skills were listed more intensively by job postings in high-WFH-adoption occupations in large cities by 2021, but no statistical significance over other time horizons. Columns 2–6 show a general decrease in the demand for "Business Management," "Building Relationship," "Communications," and "Marketing and Public Relations" skills by 2022–2023. These findings are, for the most part, consistent with our prediction that the demand for skills enhancing interactive activities would decrease post-pandemic, lending support to the hypothesis of weakened agglomeration economies due to diminished workplace interactions.[36]

6 Conclusion

This paper studies how WFH adoption affects the agglomeration economies of large cities. Using a stylized model, we demonstrate that WFH lowers the urban wage premium through two mechanisms. On the one hand, WFH increases labor supply to high-productivity firms in large cities because workers can work remotely for these firms without incurring high housing costs. The boosted employment at high-productivity firms can raise aggregate productivity, wages, and output. On the other hand, if the number of onsite workers in large cities decreases significantly, it could lead to a decline in agglomeration economies. This may lower the productivity of large cities and thus encourage workers to shift from large cities to smaller ones, which could reduce aggregate productivity, wages, and output. We derive two testable predictions to disentangle the effects of WFH.

Using wage data from advertised job postings, we find a substantial decrease in the urban wage premium for occupations with high WFH adoption during the COVID-19 pandemic, which did not bounce back as of mid-2023. In contrast, occupations with low WFH adoption saw a much smaller decline in the urban

[35] Table A12 presents the results separately for jobs that require a college degree and jobs without a degree requirement.

[36] In Table A14 we use the same specification, but the sample of high-WFH-adoption occupations based on the *imputed* WFH adoption levels (from the ACS and O*NET data). Similar to our baseline results, these results also indicate reduced listings of interactive skills in large cities.

wage premium. Furthermore, among jobs in high-WFH-adoption industries, employment shifted from large to small cities (based on firm locations). According to our model's predictions, the decline in the urban wage premium and employment reallocation away from large cities indicate a reduction in the productivity of large cities due to WFH adoption, which is consistent with the weakening of agglomeration effects.

To provide additional empirical support that the reduced productivity in big cities has indeed been driven by weakened agglomeration economies, we perform an additional decomposition analysis. The analysis aims to identify skills that contribute the most to the decline in the urban wage premium within high-WFH-adoption occupations. We find that the overall decline in the urban wage premium can be attributed to both a decline in the urban wage premium of both skills conducive to interactive activities (e.g., relationship-building skills) and skills compatible with remote work technologies (e.g., information technology skills). Moreover, we observe a decrease in the intensity of job requirements for relationship-building skills in large cities. These findings lend support to our hypotheses: (i) the agglomeration economies of large cities were likely weakened by the adoption of WFH, and (ii) firms in large cities likely benefited from an expanded labor pool due to WFH adoption.

One limitation of our paper is that we study the adoption of WFH driven by the COVID-19 pandemic, which may not accurately reflect firms' work model in long-run equilibrium. During the pandemic, the decision to adopt WFH was largely determined by the compatibility of job tasks with existing WFH technologies, such as Zoom or Slack. However, in the long run, firms and workers are expected to make adjustments to their work tasks and WFH technologies, considering the benefits of in-person interactions and the expanded labor pool offered by remote work technologies. Hybrid work arrangements may become more prevalent as the pandemic ends. These creatively designed hybrid arrangements may mitigate the loss of productive in-person interactions while still providing the benefit of an expanded labor pool for productive firms.

It is important to note that our paper may have limited direct implications for the effect of hybrid work on agglomeration economies, and we leave this topic for future research. Despite this limitation, our paper highlights the unintended negative effect of full WFH arrangement, namely reduced productivity spillovers due to reduced workplace interaction. Our findings suggest that considering agglomeration externalities when designing future hybrid work arrangements could lead to positive effects on aggregate productivity.

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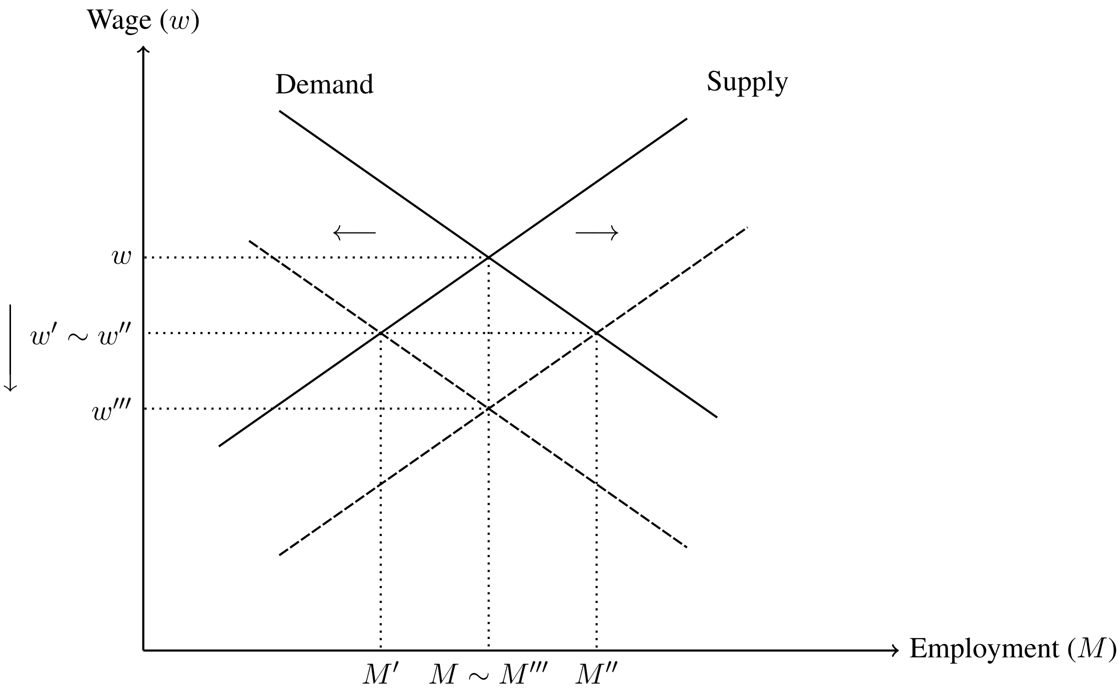
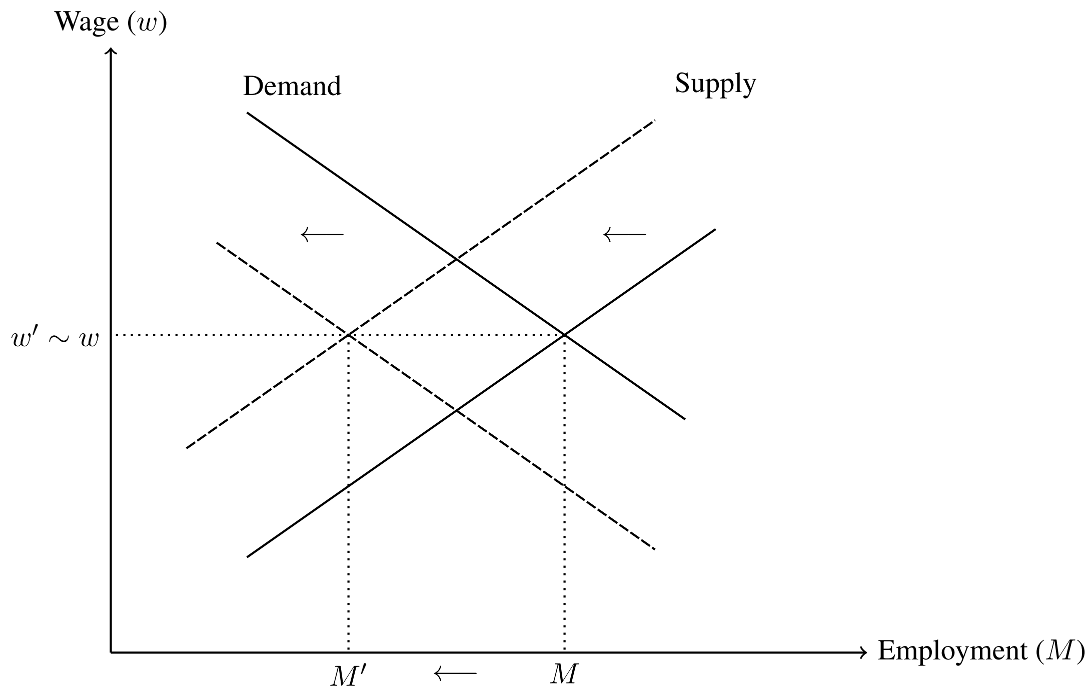
Figure 1: Changes in Labor Demand and Supply in Large Cities During COVID-19



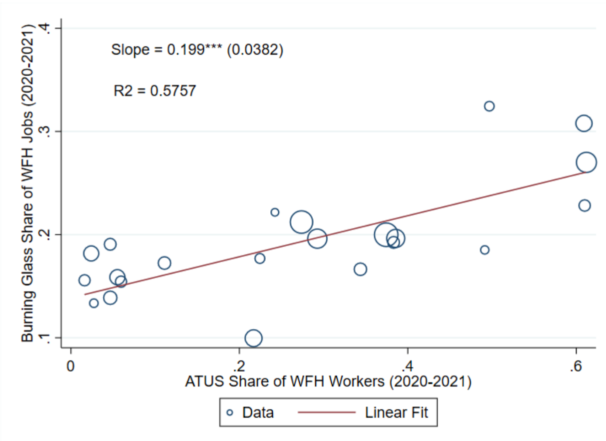
(a) Occupations with High Levels of WFH Adoption



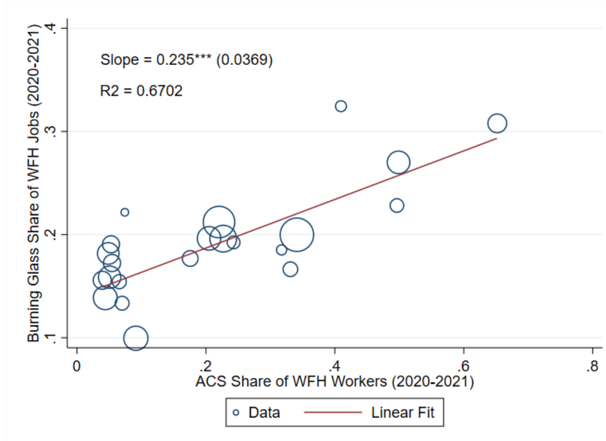
(b) Occupations with Low or Moderate Levels of WFH Adoption

Note: The figures present graphical illustrations of how the local labor markets in large cities respond to the COVID-19 pandemic. We illustrate occupations with high levels of WFH adoption in Figure 1a and occupations with low/moderate levels of WFH adoption in Figure 1b. The solid lines represent the labor demand and supply curves before the pandemic. The dashed lines represent the shifted labor demand and supply curves during the pandemic.

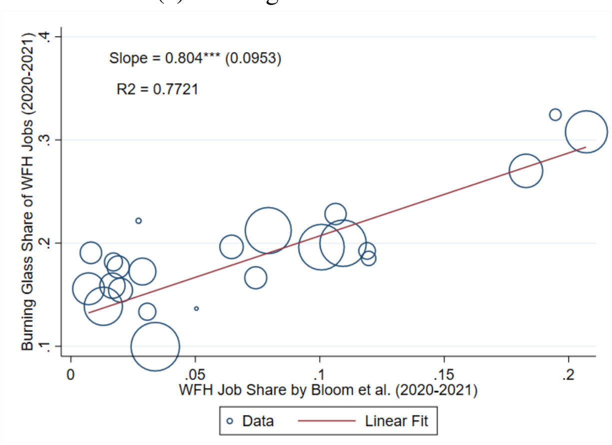
Figure 2: Comparison of WFH Shares: Data from Burning Glass, ACS, and ATUS (2020–2021)



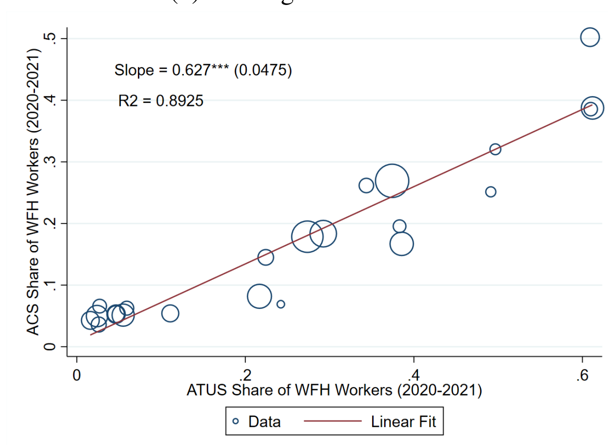
(a) Burning Glass vs. ATUS



(b) Burning Glass vs. ACS



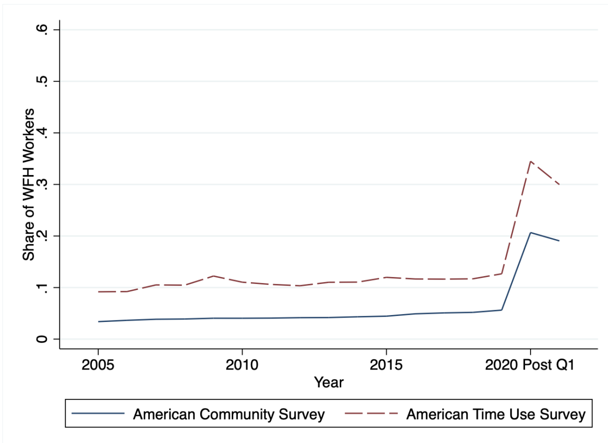
(c) Burning Glass vs. Bloom et al. (2023)



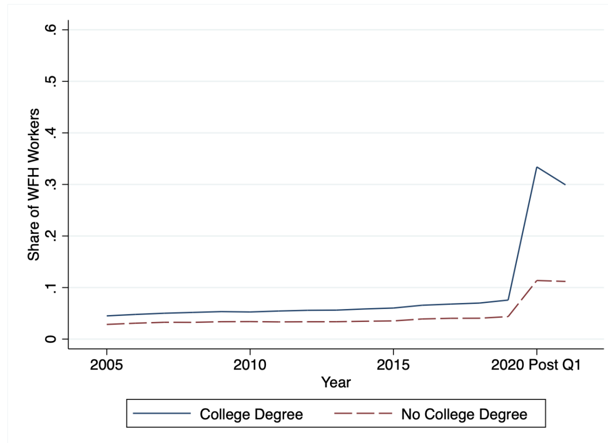
(d) ACS vs. ATUS

Note: These figures compare WFH shares computed from several datasets. Specifically, we compute the share of WFH-compatible jobs among those posted in 2020 (after the first quarter) and 2021 for each occupation or occupation group using the Burning Glass data. We also compute the share of workers who worked from home using the ACS and ATUS data for 2020 (after the first quarter) and 2021. Figure 2a presents the share of WFH-compatible jobs from the Burning Glass against the share of WFH workers from the ATUS. Figures 2b presents the share of WFH-compatible jobs from the Burning Glass against the share of WFH workers from the ACS. Figure 2c presents the share of WFH-compatible jobs from the Burning Glass (based on our dictionary approach) against the share computed by Bloom et al. (2023) based on a mechine learning approach. Figure 2d presents the share of WFH workers from the ACS against the share from the ATUS.

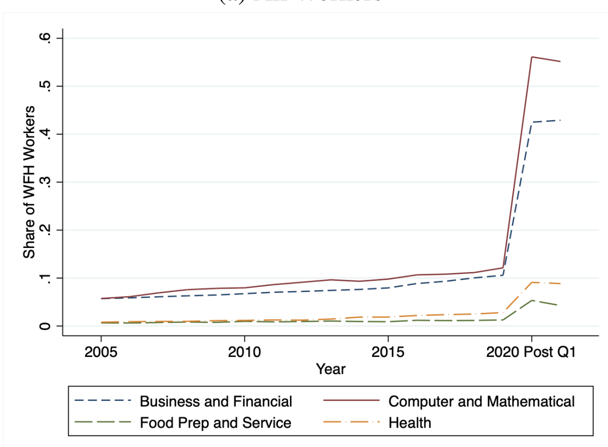
Figure 3: Share of Working-from-Home Workers



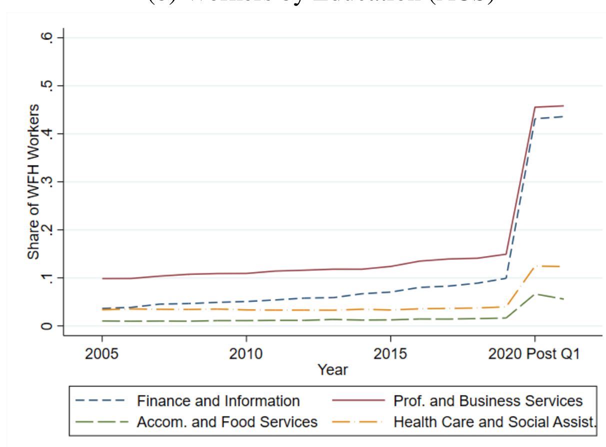
(a) All Workers



(b) Workers by Education (ACS)



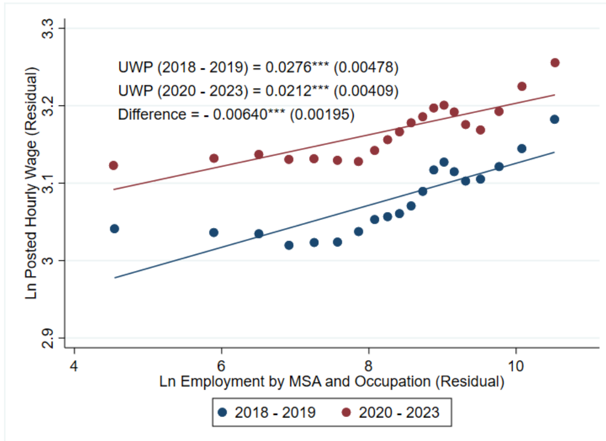
(c) Workers by Selected Occupation Groups (ACS)



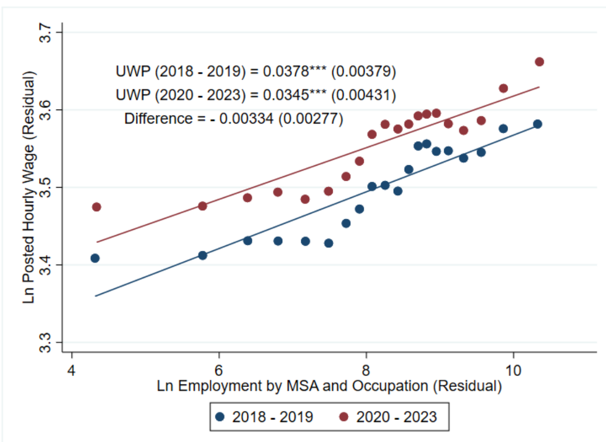
(d) Workers by Selected Industry Groups (ACS)

Note: The figures plot the share of workers who worked from home from 2005 to 2021. In Figure 3a, we use the American Community Survey (ACS) and the American Time Use Survey (ATUS) to calculate the share of all workers who worked from home in each survey year. For the year 2020, to highlight the share of workers who worked from home during the pandemic, we impute the numbers for the period after the first quarter of 2020. Specifically, we assume that both the ACS and the ATUS surveyed respondents randomly in each month of 2020 and that the share of workers who worked from home in the first quarter of 2020 is identical to the share estimated for 2019. For the ACS, we restrict the sample to workers who worked at least 35 hours a week and were aged between 25 and 65. For the ATUS, we calculate the share of workers who worked from home by dividing the number of workers whose working activities all occurred at home by the number of workers who recorded working activities during the period surveyed. Figure 3b shows the share of workers with or without college degrees who worked from home using the ACS data. Figure 3c shows the share of workers for four selected occupation groups who worked from home using the ACS data. Figure 3d shows the share of workers for four selected NAICS industry groups who worked from home using the ACS data.

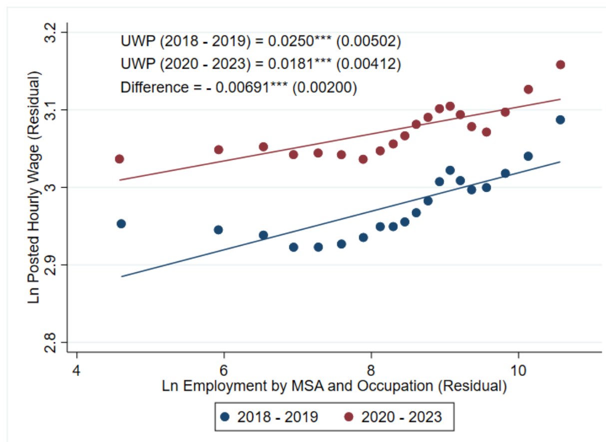
Figure 4: Urban Wage Premium: 2018–2019 vs. 2020–2023



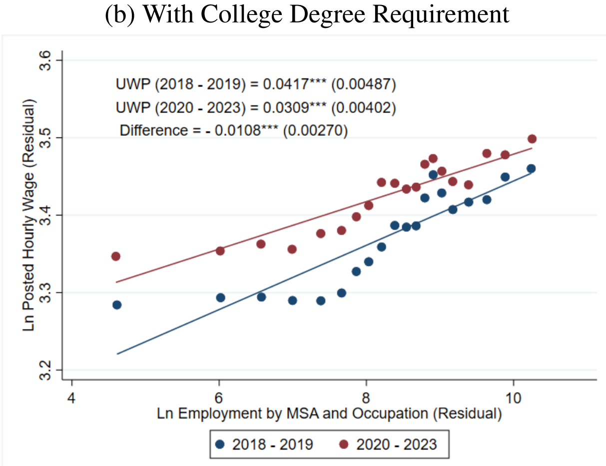
(a) All Jobs



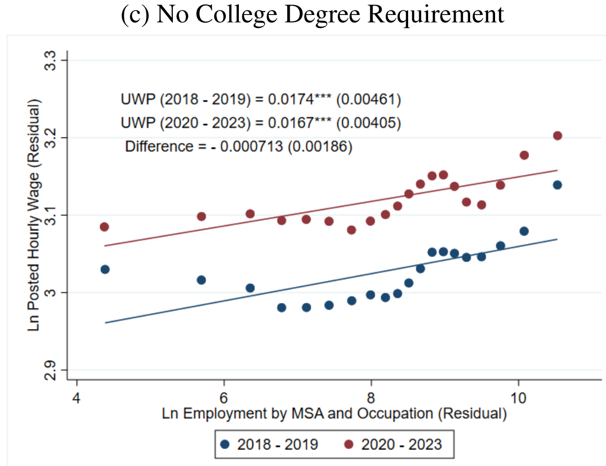
(b) With College Degree Requirement



(c) No College Degree Requirement



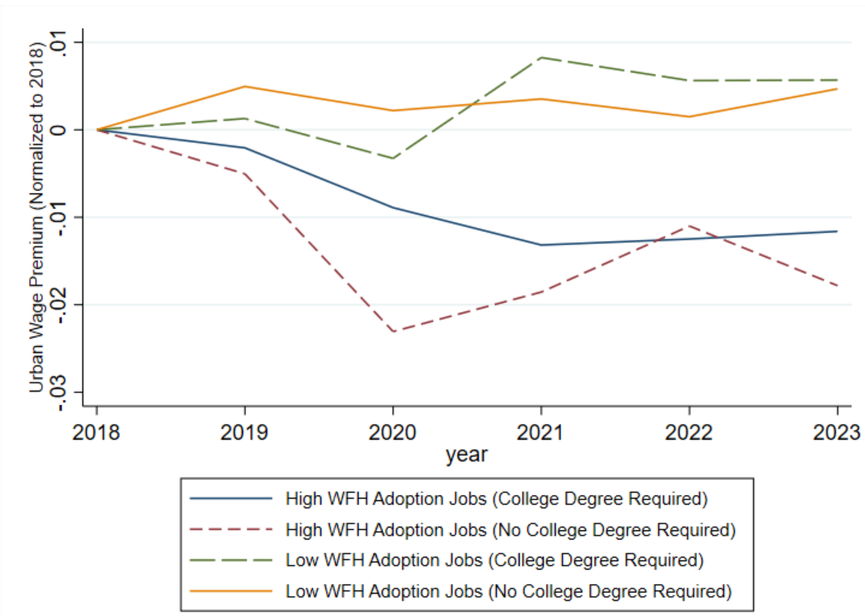
(d) High WFH Adoption



(e) Low WFH Adoption

Note: The figures present binned scatterplots of residualized log posted hourly wage against residualized log employment of the occupation and MSA of a job separately for jobs posted between 2018 and 2019 and those posted between 2020 and May 2023, using the Burning Glass data. We residualize log wage and log employment by regressing these variables on dummies for SOC occupation code, NAICS code, years of education required, salary type, full-/part-time status, tax terms, and job posting month. We then add back the means of the original variables. Figure 4a presents the plot for all posted jobs. Figures 4b and 4c present the plot for jobs that require a college degree and those without a degree requirement, respectively. Figures 4d and 4e present the plot for jobs in high-WFH-adoption occupations (more than 20 percentage points increase in the fraction of WFH-compatible jobs) and those in low-WFH-adoption occupations (fewer than 11 percentage points increase in the fraction of WFH-compatible jobs), respectively.

Figure 5: Urban Wage Premium Over Time



Note: This figure shows how the urban wage premium, normalized to the 2018 level, has changed over time by job type, based on education requirement and the level of WFH adoption during the pandemic. For each year and job type, we estimate the urban wage premium, controlling for dummies of SOC occupation code, NAICS code, years of education required, salary type, full-/part-time status, tax terms, and job posting month. We estimate the urban wage premiums using a 10% random sample of the Burning Glass data. Occupations with high WFH adoption are defined as those that have seen an increase of more than 20 percentage points in the national share of WFH-compatible jobs, as determined by comparing pooled data from 2018 to March 2020 with pooled data from April 2020 to May 2023. Occupations with low WFH adoption are defined as those that have seen an increase of less than 11 percentage points.

Table 1: Testable Predictions during the COVID-19 Pandemic

	Occupations with High WFH Adoption	
	Urban Wage Premium	Employment by City Size
Productivity Decreases in Large Cities	$\downarrow$	$\downarrow$ in H; $\uparrow$ in L
Labor Supply Increases in Large Cities	$\downarrow$	$\uparrow$ in H; $\downarrow$ in L
	Occupations with Low WFH Adoption	
	Urban Wage Premium	Employment by City Size
Labor Demand Decreases in Large Cities	$\downarrow$	$\downarrow$ in H; $\uparrow$ in L
Labor Supply Decreases in Large Cities	$\uparrow$	$\downarrow$ in H; $\uparrow$ in L

Note: This table summarizes the expected changes in the urban wage premium (column 1) and employment in large/high-density (H) and small/low-density (L) cities (column 2) in occupations with high WFH adoption (upper panel) and low/moderate WFH adoption (lower panel). Different rows indicate the effects of different underlying driving forces. Section 2.5 presents more detailed discussions.

Table 2: Changes in Urban Wage Premium by Occupation's WFH Adoption Level

	Log Posted Hourly Wages			
	(1)	(2)	(3)	(4)
Log M	0.0169***	0.0175***	0.0244***	0.0186***
	(0.00405)	(0.00400)	(0.00409)	(0.00428)
Log M × Moderate WFH	0.0193***	0.0141***		0.0209***
	(0.00165)	(0.00132)		(0.00165)
Log M × High WFH	0.0267***	0.0223***	0.0262***	0.0282***
	(0.00316)	(0.00254)	(0.00377)	(0.00323)
Log M × Post	0.00176	0.00068	-0.00261***	0.00255***
	(0.00108)	(0.0011)	(0.00087)	(0.00116)
Log M × Moderate WFH × Post	-0.00944***	-0.00628***		-0.0103***
	(0.00075)	(0.00066)		(0.000756)
Log M × High WFH × Post	-0.0123***	-0.0127***	-0.00834***	-0.0130***
	(0.00157)	(0.00136)	(0.00179)	(0.00159)
Controls: Job characteristics	X	X	X	X
Controls: Skill Requirements		X		
Specification	Baseline	Baseline	Alt. High WFH Def.	Heckman Correction
Observations	7,316,072	5,996,752	7,316,072	20,434,736

Note: This table presents the estimates of the urban wage premium pre- and post-pandemic by occupation category, based on the level of WFH adoption (i.e., α_0–α_5 in Equation 5). The sample includes job postings from a 10% random selection of the Burning Glass data, from 2018 to May 2023. The dependent variable is log posted hourly wage of a job posting. M is employment size (in 2019 Q1) of the occupation in the MSA of the posted job. Post is a post-pandemic dummy (i.e., months after March 2020). Moderate WFH is a dummy variable that is equal to 1 if the occupation of the posted job has moderate WFH adoption (i.e., occupations with an increase of 11–20 percentage points in the national share of WFH-compatible jobs, as determined by comparing pooled data from 2018 to March 2020 with pooled data from April 2020 to May 2023); High WFH is a dummy variable that is equal to 1 if the occupation of the posted job has high WFH adoption (i.e., occupations with an increase of more than 20 percentage points in the national share of WFH-compatible jobs). Column 1 controls for basic job characteristics, including dummy variables for SOC occupation code, NAICS industry code, years of education required, salary type, part-/full-time status, tax term, and posting month. Columns 2 further controls for dummy variables for 20 skill requirements. Column 3 presents results in which an occupation is defined as a high-WFH-adoption occupation if it belongs to either "Computer and Mathematical Occupations" or "Business and Financial Operations." Column 4 presents the results of the Heckman correction regression. Standard errors are clustered at the MSA level. *** $p < 0.01$, ** $p < 0.05$, *$p < 0.1$.

Table 3: Changes in Urban Wage Premium by Occupation's WFH Adoption Level
and Job's WFH Compatibility

		Log Hourly Wages		
		(1)	(2)	(3)
Panel A: Burning Glass Data 2018–2023 (All Jobs)				
Log M	WFH Jobs	0.0312***	0.0409***	0.0233***
		(0.00484)	(0.00451)	(0.00425)
	Other Jobs	0.0426***	0.0345***	0.0180***
		(0.00438)	(0.00434)	(0.00411)
Log M $\times$ Post	WFH Jobs	-0.00595**	-0.0131***	-0.00668***
		(0.00269)	(0.00262)	(0.00232)
	Other Jobs	-0.0113***	-0.00725***	-0.00002
		(0.00212)	(0.00101)	(0.00121)
Controls: Job Characteristics		X	X	X
Sample		Occupations with High WFH Adoption	Occupations with Moderate WFH Adoption	Occupations with Low WFH Adoption
Observations		563,244	2,573,786	2,893,292
Panel B: ACS Data 2018–2021 (Onsite Workers Only)				
Log M		0.0796***	0.0620***	0.0371***
		(0.00900)	(0.00763)	(0.00696)
Log M $\times$ Post		-0.0123***	-0.0116***	-0.00595***
		(0.00283)	(0.00219)	(0.00151)
Controls: Worker Characteristics		X	X	X
Sample		Occupations with High WFH Adoption	Occupations with Moderate WFH Adoption	Occupations with Low WFH Adoption
Observations		315,494	1,044,938	1,140,382

Note: This table presents the estimates of the urban wage premium pre- and post-pandemic by each job's WFH-compatibility and by occupation's overall WFH adoption level. Panel A is based on the sample of all job postings from a 10% random selection of the Burning Glass data, from 2018 to May 2023. The panel presents the estimates for WFH-compatible jobs and other jobs, separately, for occupations with high, moderate, and low levels of WFH adoption. The dependent variable is the log posted hourly wage of each job posting. M is employment size (in 2019 Q1) of the occupation in the MSA of the posted job. Post is a post-pandemic dummy (i.e., months after March 2020). All regressions control for basic job characteristics, including dummy variables for SOC occupation code, NAICS industry code, years of education required, salary type, part-/full-time status, tax term, and posting month. Panel B is based on the sample of *onsite* workers aged from 25–65 who worked at least 35 hours per week in the ACS from 2018–2021. The dependent variable is the log hourly wage of a worker. M is employment size of the occupation in the MSA of the worker's workplace. $Post$ is a post-pandemic dummy (i.e., years 2020 and 2021). All regressions control for basic worker characteristics, including dummy variables for age, gender, race, Hispanic origin, marital status, educational attainment, and occupation code. Section 3.3 describes how we define high-, moderate-, and low-WFH-adoption occupations in both datasets. Standard errors are clustered at the MSA level. *** $p < 0.01$, ** $p < 0.05$, *$p < 0.1$.

Table 4: Employment Growth by Local Employment Size: Before and After the Pandemic for Different Industry Groups

	Changes in Log Number of Jobs	
	(1)	(2)
Log M × 2017–2019 × Low WFH	-0.0265**	
	(0.0105)	
Log M × 2020–2022 × Low WFH	-0.0550***	
	(0.00696)	
Log M × 2017–2019 × Moderate WFH	-0.00741*	
	(0.00382)	
Log M × 2020–2022 × Moderate WFH	-0.0250***	
	(0.00470)	
Log M × 2017–2019 × High WFH	-0.00433	
	(0.0129)	
Log M × 2020–2022 × High WFH	-0.0373*	
	(0.0196)	
Log M × 2017–2019 × Other Ind		-0.0218***
		(0.00808)
Log M × 2020–2022 × Other Ind		-0.0457***
		(0.00571)
Log M × 2017–2019 × Fin./Info./Prof.		-0.00512
		(0.00690)
Log M × 2020–2022 × Fin./Info./Prof.		-0.0314***
		(0.00753)
Observations	97,015	97,015

Note: This table presents the estimates of how employment growth changes with respect to employment size, pre- and post-pandemic by industry category (i.e., a_1^{2019}, a_1^{2022}, a_2^{2019}, a_2^{2022}, a_3^{2019}, a_3^{2022} in Equation 6), using employment counts from the QCEW. Each observation is an industry-MSA cell (based on three-digit NAICS industry). The dependent variable is the change in log employment by industry and MSA between the 1st quarter of 2017 and the 4th quarter of 2019 or the change between the 1st quarter of 2020 and the 4th quarter of 2022. M is employment size by industry and MSA at the beginning of each period. 2017–2019 (2020–2022) is a dummy variable that is equal to 1 if the employment change in the dependent variable is between 2017 and 2019 (between 2020 and 2022). We report the coefficients on the interactions between Log M and the time period dummies and the WFH adoption dummies. Fin./Info./Prof. is a dummy variable that is equal to 1 if the three-digit NAICS industry belongs to "Information" (NAICS 51x), "Finance and Insurance" (NAICS 52x), or "Professional and Business Services" (NAICS 54x). Each estimate represents how employment growth varies with respect to the the relevant local initial employment size by time period and industry group. In both columns, we control for three-digit industry × period fixed effects. The regressions are weighted by the employment size of each MSA at the beginning of each period. Standard errors are clustered at the MSA level. *** $p < 0.01$, ** $p < 0.05$, *$p < 0.1$.

Table 5: Gelbach Decomposition: Contribution of Changes in Skill-Specific Urban Wage Premium to the Decrease in the Urban Wage Premium among High-WFH Jobs

2020		2021		2022–2023	
Skill	π	Skill	π	Skill	π
Marketing and Public Relations	13.5%	Customer and Client Support	33.3%	Communications	22.5%
Business Management	11.0%	Finance	23.5%	Information Technology	22.2%
Information Technology	10.1%	Marketing and Public Relations	23.2%	Customer and Client Support	21.4%
Physical Abilities	5.2%	Building Relationship	17.5%	Building Relationship	16.1%
Finance	4.5%	Business Management	13.7%	Administration	15.9%
Building Relationship	4.1%	Communications	11.9%	Marketing and Public Relations	14.1%
Maintenance, Repair, and Installation	3.5%	Maintenance, Repair, and Installation	9.1%	Business Management	11.6%
Engineering	1.3%	Administration	8.1%	Maintenance, Repair, and Installation	6.6%
Agriculture	1.2%	Physical Abilities	3.4%	Physical Abilities	4.6%
Creativity	1.0%	Decision Making	1.0%	Human Resources	3.1%
Environment	0.7%	Leadership	0.6%	Creativity	2.9%
Education and Training	0.5%	Education and Training	0.5%	Engineering	2.3%
Manufacturing and Production	0.4%	Environment	0.5%	Decision Making	2.2%
Design	0.4%	Design	0.4%	Personal Care and Services	2.1%
Public Safety and National Security	0.4%	Personal Care and Services	0.4%	Education and Training	1.8%
Legal	0.1%	Public Safety and National Security	0.2%	Media and Writing	0.8%
Economics, Policy, and Social Studies	0.1%	Economics, Policy, and Social Studies	0.1%	Design	0.6%
Health Care	0.0%	Legal	0.0%	Public Safety and National Security	0.5%
Decision Making	0.0%	Energy and Utilities	-0.1%	Agriculture	0.2%
Energy and Utilities	0.0%	Agriculture	-0.1%	Economics, Policy, and Social Studies	0.1%
Personal Care and Services	-0.1%	Creativity	-0.1%	Energy and Utilities	0.0%
Human Resources	-0.1%	Engineering	-0.2%	Manufacturing and Production	0.0%
Media and Writing	-0.2%	Manufacturing and Production	-0.4%	Legal	-0.2%
Planning	-0.3%	Media and Writing	-0.8%	Organizational Skills	-0.3%
Architecture and Construction	-0.8%	Architecture and Construction	-1.2%	Architecture and Construction	-0.4%
Leadership	-2.5%	Analysis	-1.2%	Environment	-0.5%
Industry Knowledge	-2.5%	Health Care	-2.1%	Finance	-0.6%
Administration	-6.4%	Industry Knowledge	-4.3%	Leadership	-1.7%
Communications	-8.5%	Planning	-4.6%	Health Care	-6.2%
Analysis	-10.6%	Human Resources	-6.2%	Planning	-7.2%
Organizational Skills	-14.7%	Organizational Skills	-19.2%	Analysis	-10.3%
Customer and Client Support	-21.5%	Information Technology	-24.7%	Industry Knowledge	-11.2%

Note: This table presents the Gelbach decomposition results, i.e., contributions of changes in the urban wage premium of various skills to the overall decline in the urban wage premium of high-WFH-adoption occupations. We conduct the analysis seperately for three periods, between 2018–2019 and 2020, between 2018–2019 and 2021, and between 2018–2019 and 2022–May 2023. The sample includes all job postings in high-WFH-adoption occupations (i.e., occupations with an increase of more than 15 percentage points in the national share of WFH-compatible jobs, as determined by comparing pooled data from 2018 to March 2020 with pooled data from April 2020 to May 2023) in the Burning Glass data. For each time period, we rank skill cluster families by their contributions to the overall decline in the urban wage premium (i.e., π in Equation 10).

Table 6: Spatial Shift in Skill Listing Intensity

	IT	Business	Building Relations	Communication	Customer Support	Marketing
	(1)	(2)	(3)	(4)	(5)	(6)
Log M	0.00717***	0.00523***	0.00574***	0.00901***	-0.00194	0.00711***
	(0.000999)	(0.00142)	(0.00141)	(0.00104)	(0.00160)	(0.000774)
Log M $\times$ 2020	-0.000173	-0.000408	0.00180***	-0.000823	0.00132***	-0.00178***
	(0.000648)	(0.000667)	(0.000578)	(0.000709)	(0.000453)	(0.000630)
Log M $\times$ 2021	0.00154*	-8.31e-05	0.000119	-0.00180**	-0.000143	-0.00205***
	(0.000806)	(0.000510)	(0.000519)	(0.000720)	(0.000654)	(0.000496)
Log M $\times$ 2022–2023	0.000136	-0.00118**	-0.00281***	-0.00143*	0.000188	-0.00221***
	(0.000773)	(0.000586)	(0.000747)	(0.000832)	(0.000580)	(0.000570)
Observations	1,792,510	1,792,510	1,792,510	1,792,510	1,792,510	1,792,510

Note: The table presents the estimates of changes in the listing intensity of various skill cluster families with respect to employment size over time, based on Equation 11. The sample includes all job postings in high-WFH-adoption occupations (i.e., occupations with an increase of more than 15 percentage points in the national share of WFH-compatible jobs, as determined by comparing pooled data from 2018 to March 2020 with pooled data from April 2020 to May 2023) in the Burning Glass data. The dependent variable is an indicator of whether a skill belonging to the skill cluster family is listed in a job posting. M is employment size (in 2019 Q1) of the occupation in the MSA of the posted job. 2020 is an indicator that is equal to 1 if the job was posted in 2020, similarly for 2021, and 2022–2023. All columns control for basic job characteristics, including dummy variables for SOC occupation code, NAICS industry code, years of education required, salary type, part-/full-time status, tax term, and the posting month. Standard errors are clustered at the MSA level. *** $p < 0.01$, ** $p < 0.05$, *$p < 0.1$.

Appendix

A1 Comparative Statics of the Model

In this section, we detail the derivation process of the comparative comparative statics for the baseline model of WFH and agglomeration presented in Section 2.

We begin with the equalized utility levels in equilibrium:

$$\bar{U} = w_H - \beta r_H$$

$$\bar{U} = w_H - \beta r_L - \phi$$

$$\bar{U} = w_L - \beta r_L.$$

We simplify the equation set by taking the difference between the first and second equations and between the third and second equations. taking the difference between the first and second equations and the difference between the third and the second equations. We then plug in the equilibrium wage and rent equations:

$$0 = -\beta(\pi_{0H} + \pi_H \ln(N_{HH})) + \beta(\pi_{0L} + \pi_L \ln(1 - N_{HH})) + \phi$$

$$0 = c + (\gamma - 1)\ln(1 - N_{HH} - N_{HL}) - \theta \ln(N_{HH}) - (\gamma - 1)\ln(N_{HH} + N_{HL}) + \phi.$$

Our primary interest lies in $\frac{\partial N_{HH}}{\partial \phi}$ and $\frac{\partial N_{HL}}{\partial \phi}$. As $N_{HH} + N_{HL} + N_{LL} = 1$, there is not need to compute compute $\frac{\partial N_{LL}}{\partial \phi}$. In these equations, N_{HH} and N_{HL} are endogenous and ϕ is exogenous. The functional forms are smooth and differentiable. Thus, we use the implicit function theorem to calculated the comparative static. We define

$$G_1 = -\beta(\pi_{0H} + \pi_H \ln(N_{HH})) + \beta(\pi_{0L} + \pi_L \ln(1 - N_{HH})) + \phi$$

$$G_2 = c + (\gamma - 1)\ln(1 - N_{HH} - N_{HL}) - \theta \ln(N_{HH}) - (\gamma - 1)\ln(N_{HH} + N_{HL}) + \phi.$$

Based on the implicit function theorem,

$$\begin{pmatrix} \frac{\partial N_{HH}}{\partial \phi} \\ \frac{\partial N_{HL}}{\partial \phi} \end{pmatrix} = - \begin{pmatrix} \frac{\partial G_1}{\partial N_{HH}} & \frac{\partial G_1}{\partial N_{HL}} \\ \frac{\partial G_2}{\partial N_{HH}} & \frac{\partial G_2}{\partial N_{HL}} \end{pmatrix}^{-1} \begin{pmatrix} \frac{\partial G_1}{\partial \phi} \\ \frac{\partial G_2}{\partial \phi} \end{pmatrix}$$

Expanding the matrices, we get:

$$\begin{pmatrix} \frac{\partial N_{HH}}{\partial \phi} \\ \\ \\ \frac{\partial N_{HL}}{\partial \phi} \end{pmatrix} = - \begin{pmatrix} \frac{\frac{\partial G_2}{\partial N_{HL}} \frac{\partial G_1}{\partial \phi} - \frac{\partial G_1}{\partial N_{HL}} \frac{\partial G_2}{\partial \phi}}{\frac{\partial G_1}{\partial N_{HH}} \frac{\partial G_2}{\partial N_{HL}} - \frac{\partial G_1}{\partial N_{HL}} \frac{\partial G_2}{\partial N_{HH}}} \\ \\ \\ \frac{\frac{\partial G_1}{\partial N_{HH}} \frac{\partial G_2}{\partial \phi} - \frac{\partial G_2}{\partial N_{HH}} \frac{\partial G_1}{\partial \phi}}{\frac{\partial G_1}{\partial N_{HH}} \frac{\partial G_2}{\partial N_{HL}} - \frac{\partial G_1}{\partial N_{HL}} \frac{\partial G_2}{\partial N_{HH}}} \end{pmatrix}$$

Plugging in G_1 and G_2, we get

$$\begin{pmatrix} \frac{\partial N_{HH}}{\partial \phi} \\ \\ \\ \frac{\partial N_{HL}}{\partial \phi} \end{pmatrix} = \begin{pmatrix} \frac{1}{\beta\left(\frac{\pi_L}{1-N_{HH}} + \frac{\pi_H}{N_{HH}}\right)} \\ \\ \\ -\frac{1}{\beta\left(\frac{\pi_L}{1-N_{HH}} + \frac{\pi_H}{N_{HH}}\right)} - \frac{\beta\left(\frac{\pi_L}{1-N_{HH}} + \frac{\pi_H}{N_{HH}}\right) - \frac{\theta}{N_{HH}}}{\beta\left(\frac{\pi_L}{1-N_{HH}} + \frac{\pi_H}{N_{HH}}\right)\left(\frac{1-\gamma}{N_{LL}} + \frac{1-\gamma}{N_{HH}+N_{HL}}\right)} \end{pmatrix}$$

Note that ϕ denotes the cost of WFH. As a result, to determine the impact of reducing the cost of WFH, a negative sign should be applied to each derivative.

A2 Alternative Model Framework: Productivity Shock on WFH

In this section, we present an alternative model of WFH and agglomeration. In this framework, the shock that propels worker to adopt WFH also stems from an increase in WFH productivity, rather than only from the disutility of WFH as outlined in the baseline model in Section 2.

This model adopts all the setups from the baseline model, with one exception in the production function for the large city or high-density location H. Here, we allow the marginal productivity of onsite and remote workers to be different—the marginal productivity of remote workers N_{HL} is δ instead of 1. It is reasonable to anticipate that on average, δ would be less than 1, but we do not explicitly impose such a restriction.

Specifically, the production function for location H is

$$F_H(B_H, N_{HH}, N_{HL}) = B_{HH}(N_{HH} + \delta N_{HL})^{\gamma}$$

In this framework, we assume that a WFH shock could either decrease the cost of WFH, ϕ, or increase the marginal productivity of remote works relative to onsite workers, δ.

Given the potentially different marginal productivity among the three types of workers, the competitive labor market implies that there would be three equilibrium wages: W_{HH}—the wage for onsite workers in H; W_{HL}—the wage for remote workers working for H but living in L; W_L—the wage for workers working and living in L.

Given that the choices available to workers remain unchanged, we continue to assume that all three options provide equal utility at equilibrium. The only difference is that wage offerings from location H are different for onsite and remote workers:

$$U_{HH} = w_{HH} - \beta r_H,$$

$$U_{HL} = w_{HL} - \beta r_L - \phi,$$

$$U_{LL} = w_L - \beta r_L,$$

Based on the specification of the production function in H, the marginal products of N_{HL} and N_{HH} maintain a constant ratio:

$$\frac{W_{HL}}{W_{HH}} = \delta.$$

This implies that log wages $w_{HL} = w_{HH} + \ln \delta$. If $\delta < 1$, then the log wage of remote workers is always lower than that of onsite workers. Plugging this relationship back into remote workers' utility function, we get

$$U_{HL} = w_{HH} - \beta r_L + \underbrace{\ln \delta - \phi}_{\substack{\text{Reduced form} \\ \text{cost of remote work: } \tilde{\phi}}}.$$

It is worth noting that this utility function resembles that in the baseline model, with one exception: the constant in U_{HL} that imposes a penalty for remote work now incorporates both the productivity discount of remote work, $\ln \delta$, and the utility cost of remote work ϕ. Therefore, in this alternative model framework, an exogenous increase in productivity δ operates much like an exogenous decrease in ϕ in the baseline model, in terms of influencing the workers' choices among the three options.

As a result, the rent premium in equilibrium is

$$r_H - r_L = \frac{\phi - \ln \delta}{\beta}.$$

Because there are two wage offerings from location H, the urban wage premiums are:

$$w_{HH} - w_L = \phi - \ln \delta,$$
$$w_{HL} - w_L = \phi.$$

The intuition behind the difference between the two wage gaps is that the wage gap between the remote workers residing in L and those employed by L should only compensate for the utility cost of remote work. Nevertheless, the wage gap between onsite workers in H and workers employed by L should reflect the additional productivity premium for working onsite at H (if $\delta < 1$).

Agglomeration and Aggregate Productivity The effect of an increase in the relative productivity of remote workers on aggregate output is

$$\frac{\partial(F_H + F_L)}{\partial \delta} = \underbrace{\theta B_{0H} N_{HH}^{\theta-1} \frac{\partial N_{HH}}{\partial \delta} (N_{HH} + \delta N_{HL})^{\gamma}}_{\substack{\text{Weakening of Agglomeration Economies} \\ < 0}} + \underbrace{(W_{HH} - W_L) \frac{\partial (N_{HH} + N_{HL})}{\partial \delta}}_{\substack{\text{Reallocation of Labor from } L \text{ to } H \\ < 0 \text{ or } > 0}}$$
$$\underbrace{-(W_{HH} - W_{HL}) \frac{\partial N_{HL}}{\partial \delta}}_{\text{Adjustment for Reallocation into WFH}} + \underbrace{W_{HH} N_{HL}}_{\text{Direct Productivity Effect of } \delta}$$

The effect of an increase in the relative productivity of remote workers on the reallocation of labor is

$$\frac{\partial N_{HH}}{\partial \delta} = -\frac{1}{\delta \beta \left(\frac{\pi_L}{1 - N_{HH}} + \frac{\pi_H}{N_{HH}} \right)}, \tag{12}$$

$$\frac{\partial N_{HL}}{\partial \delta} = \frac{1}{\delta\beta\left(\frac{\pi_L}{1-N_{HH}} + \frac{\pi_H}{N_{HH}}\right)} + \frac{\beta\left(\frac{\pi_L}{1-N_{HH}} + \frac{\pi_H}{N_{HH}}\right) - \left(N_{HL}\delta\beta\left(\frac{\pi_L}{1-N_{HH}} + \frac{\pi_H}{N_{HH}}\right) + (1-\delta)\right)\frac{1-\gamma}{N_{HH}+\delta N_{HL}} - \frac{\theta}{N_{HH}}}{\delta\beta\left(\frac{\pi_L}{1-N_{HH}} + \frac{\pi_H}{N_{HH}}\right)\left(\frac{1-\gamma}{N_{LL}} + \frac{\delta(1-\gamma)}{N_{HH}+N_{HL}}\right)}. \tag{13}$$

Similar to the baseline model results, the effect of increasing δ on the total labor supply to location H is not definitive:

$$\frac{\partial(N_{HH} + N_{HL})}{\partial \delta} = \frac{\beta\left(\frac{\pi_L}{1-N_{HH}} + \frac{\pi_H}{N_{HH}}\right) - \left(N_{HL}\delta\beta\left(\frac{\pi_L}{1-N_{HH}} + \frac{\pi_H}{N_{HH}}\right) + (1-\delta)\right)\frac{1-\gamma}{N_{HH}+\delta N_{HL}} - \frac{\theta}{N_{HH}}}{\delta\beta\left(\frac{\pi_L}{1-N_{HH}} + \frac{\pi_H}{N_{HH}}\right)\left(\frac{1-\gamma}{N_{LL}} + \frac{\delta(1-\gamma)}{N_{HH}+N_{HL}}\right)}. \tag{14}$$

A3 Alternative Model Framework: Distinguishing Between WFH and Remote Work

In our baseline model, we assume that if a worker opts to work from home for firms in H, they are required to reside in L and work remotely for H. In such a scenario, remote workers employed by H would choose *not* to live in H. This is because the baseline model does not include location-specific amenities, and therefore there are no reasons for workers to endure the high housing cost in H while opting not to work onsite. We set up the baseline model to streamline the equilibrium characterization by reducing the number of choices a workers needs to consider. However, there may be concerns as to whether the predictions and intuition of the baseline model would hold if we allowed people to work from home while residing in the same city as their employers. In this section, we present an alternative model in which workers can choose to work from home for firms in H while still residing in H. We demonstrate that all the predictions remain the same.

In this framework, we maintain the production functions in H and L, but we allow workers living in H and working for firms in H the option to work either onsite or from home. Let N^o_{HH} be the number of *onsite* workers who live and work in H, and let N^h_{HH} be the number of workers who live in H but *work from home* for firms in H. Same as the baseline model, N_{HL} denotes the number of workers who work remotely for firms in H and live in L, and N_{LL} denotes the number of workers who work for firms in L and live in L.

Rather than having three options, workers now have four: working onsite in H, working from home for H while residing in the same city (thus, not remotely), working remotely for H (thus, living and working in different cities), and working onsite in L. We define the utility associated with each choice as follows:

$$U^o_{HH} = w_H - \beta r_H - C(N^o_{HH}),$$
$$U^h_{HH} = w_H - \beta r_H - \phi,$$
$$U_{HL} = w_H - \beta r_L - \varphi\phi,$$
$$U_{LL} = w_L - \beta r_L.$$

In this alternative model, we introduce the following elements: First, we add congestion as a utility cost of onsite work, $C(N^o_{HH})$, which we assume to strictly increase in the number of onsite workers, N^o_{HH}. This term may capture the reality that if fewer people work onsite, the utility of working onsite may enhance due to lighter traffic, less workplace noise, etc. The term is introduced to ensure that N^o_{HH} and N^h_{HH} would be non-zero in equilibrium. Second, to account for the likely higher cost of living and working in different cities compared with working from home in the same city, we introduce a utility cost of cross-city remote work as $\varphi\phi$, with $\varphi > 1$. This term would ensure that $N^h_{HH} > 0$. Without $\varphi > 1$ or modeling amenities, no one would choose to work from home in H.

As workers are perfectly mobile and homogeneous, utility levels will equalize in equilibrium. Equating the first two equations implies that

$$C(N^o_{HH}) = \phi.$$

Since $C(.)$ is a strictly increasing function, the inverse function $C^{-1}(.)$ should also be increasing:

$$\frac{\partial N^o_{HH}}{\partial(-\phi)} = -C^{-1'}(\phi) < 0.$$

In other words, an exogenous decrease in the cost of WFH (ϕ) would reduce the number of onsite workers in H.

Urban Wage and Rent Premiums By equalizing the utility equations, we can get the urban wage and rent premiums:

$$w_H - w_L = \varphi\phi,$$
$$r_H - r_L = \frac{(\varphi - 1)\phi}{\beta}.$$

Same as the baseline model predictions, here too, an exogenous decrease in ϕ will unambiguously reduce both the urban wage and rent premiums.

Labor Reallocation Equalizing the second and third utility functions and then differentiating the resulting equation with respect to ϕ, we get

$$\frac{\partial N^h_{HH}}{\partial(-\phi)} = -(\varphi - 1)\frac{(N^o_{HH} + N^h_{HH})(1 - N^o_{HH} - N^h_{HH})}{\beta\pi_H\left((1 - N^o_{HH} - N^h_{HH}) + \beta\pi_L(N^o_{HH} + N^h_{HH})\right)} - \frac{\partial N^o_{HH}}{\partial(-\phi)}.$$

Equalizing the third and fourth utility functions and then differentiating the resulting equation with respect to ϕ, we can determine the effect of ϕ on total employment in H:

$$\frac{\partial(N^o_{HH} + N^h_{HH} + N_{HL})}{\partial(-\phi)} = -\left(\frac{(N^o_{HH} + N^h_{HH} + N_{HL})N_{LL}}{\gamma - 1}\right)\left(\varphi - \frac{\theta}{N^o_{HH}}\frac{\partial N^o_{HH}}{\partial\phi}\right).$$

We can see that the effect of the WFH shock on total employment (either onsite, WFH in the same city, or working remotely) is theoretically uncertain. If $\theta = 0$, i.e., there are no agglomeration spillovers, the effect would be positive. In that case, a lower cost of WFH/remote work would bring a larger labor supply to location H. In contrast, if $\theta > 0$ and is sufficiently large, the decrease in the number of onsite workers may significantly reduce productivity in H, leading to a possbile shift of total employment from H to L. The model's prediction and the underlying intuition regarding the impact of ϕ on employment remains exactly the same as in the baseline model.

A4 Data Appendix

A4.1 Determining WFH-Compatible Jobs Using Original Texts from Job Postings

We evaluate the content of job descriptions in the Burning Glas data to determine whether the job is likely to accommodate remote work. We start with scanning the text of each job posting for keywords that indicate a remote work setup. These keywords include "remote," "telework," "work from home," "work at home," "wfh," "home office," "virtual," "work anywhere," and "mobile office." If any of these keywords appear, the job is initially classified as being compatible with remote work.

However, a serious concern is the potential misclassification because these keywords may appear in a negated context. For instance, a job description stating "You cannot work from home" would be incorrectly be labeled as remote-compatible. To mitigate the issue, we conduct a search for negation words such as "cannot," "couldn't," or "don't" within 20 characters preceding each keyword. Similarly, we look for "no" or "not" immediately following any keywords. If any of these negation words are found, we exclude the job posting from the remote-compatible classification.

Lastly, we search for a separate list of keywords that indicate onsite work. These keywords include "fully onsite," "fully on-site," "attendance," "physical appearance," "physically," "show up on time," "in office," "in person," "requires onsite," "requires on-site," "require onsite," "require on-site," "onsite required," "on-site required," "onsite only," and "on-site only." If any of these keywords appear, the job is classified as being not WFH-compatible.

We acknowledge that our classification method may result in measurement errors. Specifically, there is the possibility of false positives and false negatives. For instance, a false positive might occur in situations when the remote work keywords appear without any negation but may be construed in contexts other than work arrangements. For example, if a job ad mentions that "our team also serves geographically remote areas of the state", where the word "remote" does not indicate remote work. Conversely, a false negative might occur in cases where remote work is implied in the ads but none of the keywords appear. For example, if a job ad says that "locations of work are flexible" or "our team members are located across the nation."

Despite the potential presence of measurement errors, it is important to note that the goal of our empirical exercise is not to quantify the prevalence of WFH per se, in which these false-positive and false-negative errors would skew the summary statistics of WFH-compatibility. Instead, our aim is to capture variations in WFH adoption across occupations, based on their relative changes in the levels of WFH adoption after the pandemic started. We use these variations to analyze whether the adoption of WFH disproportionately affects the wages and productivity of firms in large cities. In other words, it is the *ranking* of WFH adoption across occupations that is relevant for our analysis, not the exact the level. Figure 2c compares our estimated shares of WFH-compatible jobs by occupation group with those estimated by Bloom et al. (2023), who address these measurement errors through a combination of manual classification and machine-learning approach, suggesting a high correlation between the two measures with an R-squared value exceeding 0.75.

Potential Threat to Identification from Measurement Errors There exists a potential threat to identification if occupations with an increase in false-positives also saw a disproportionate reduction in the urban wage premium for reasons unrelated to local productivity changes. This may incorrectly attribute such a disproportionate decrease in the urban wage premium among incorrectly measured "high-WFH-adoption" occupations to the adoption of WFH. As previously mentioned, certain occupations might have seen an increase in jobs that require interaction with customers in remote areas post-pandemic. This may result in a surge of false positives in WFH-compatible jobs due to the use of the term "remote." If the demand for these "false-positive" jobs in large cities declined relative to smaller cities since the start of the pandemic, then the disproportionate decrease in the urban wage premium among the "high-WFH-adoption" occupations may not entirely be a result of WFH adoption.

Our empirical strategy assumes that the occupations with a rise in false positive or drop in false negative classifications do not see a disproportionate drop in labor demand or disproportionate increase in labor supply in large cities for reasons unrelated to remote work. Under this assumption, the measurement errors present in our classification should dilute the estimated change in the urban wage premium among the high-WFH occupations. This means that the more severe the measurement error is, the more likely the true effect of WFH on urban wage premium is actually larger than the number implied by our estimate.

In our analysis, we also include a number of robustness checks where we use alternative definitions of WFH adoption that do not rely on the above-mentioned classification procedure. Results are all consistent with our baseline findings.

A4.2 Imputing WFH Adoption Levels with ACS and O*NET Data

For robustness checks, we also measure the levels of WFH adoption using the change in the fraction of workers who report that they work from home before and after the start of the pandemic. Since the ACS data categorize occupations by the Census Occupation Code, there are many SOC occupation codes in the Burning Glass data that cannot be matched to the occupations categorized in the ACS. To enable all of the SOC occupations in the Burning Glass data to be matched to a level of WFH adoption measured by the information provided by the ACS data, we combine the ACS data with the Occupational Information Network (O*NET) work context characteristics.

The O*NET is developed by the U.S. Department of Labor and the Employment and Training Administration. The data report the levels and importance of skills required for each occupation, the activities involved in performing the jobs, and the work context in terms of the nature of human interaction, physical work conditions, and structural job characteristics. Each occupation is scored across 57 work context characteristics. Because of the universal coverage of occupations in the O*NET, we use the occupational characteristics to impute changes in WFH prevalence based on the similarity of occupational characteristics in the Burning Glass occupations to the occupations observed in the ACS data.

The imputation procedure works as follows:

1. We use the Lasso regression to select the O*NET occupational characteristics that can best predict changes in WFH adoption based on occupations that *can* be matched between the ACS and O*NET. We then estimate an OLS regression model using the selected characteristics. Table A6 shows the Lasso coefficients and the OLS coefficients post-estimation. Figure A7 plots the predicted changes in the fraction of workers who WFH against the observed changes in the fraction workers who WFH in the ACS among occupations that can be matched between SOC and Census Occupation Code. It shows that the predicted changes in the share of WFH workers line up well with the observed changes from the ACS.

2. We then match the SOC occupations in the Burning Glass data to the same set of work context occupational characteristics. We use the estimated OLS regression coefficients from step 1 to impute the predicted change in the fraction of workers who WFH for each SOC occupation occupation.

A4.3 Definition and Assignment of Skill Cluster Families

The Burning Glass data provide over 13,000 distinct skills associated with the job postings, extracted directly from the job descriptions. These skills serve a dual purpose in our paper. First, they allow us to include detailed job-level controls when estimating changes in the urban wage premium. Second, they facilitate our analysis of changes in the urban wage premium by skill and the shift of skill listing intensity, as detailed in Section 5.

The data structure poses a challenge for estimation due to the varying lengths of skill vectors across job postings; some list only one or two skills, while others feature nearly 20. To tackle this, we include controls for the top 20 skills associated with each job, ranked by each skill's overall frequency of appearance in the dataset. About 90% of jobs in the sample mention fewer than 20 skills. In job postings with fewer than 20 skills, the remaining slots are filled as "na."

To decompose the overall decrease in the urban wage premium into changes in the urban wage premium by skill, we need to interact $\ln M$ with skill dummies. However, using the detailed skill dummies is not feasible due to the large number. The Burning Glass data organize skills into broader categories known as skill clusters and skill cluster families. There are over 650 skill clusters and 29 skill cluster families. We use these skill cluster families for our decomposition analysis. Notably, not all skills are assigned to a skill cluster family, so we manually allocate some commonly listed unassigned skills. Table A7 presents our manual assignment of these unassigned skills.

Lastly, we note that the skill cluster family "Business" in the Burning Glass data includes a broad range of skills, mostly related to management. To improve the interpretability of this category, we reclassify skills typically related to team and people management under "Human Resources." These reassignments are shown in Table A7.

A5 Robustness Tests

A5.1 Changes in Wages and Employment in Selected MSAs

Figure A5 presents changes in residualized log posted hourly wage for four occupation groups across various selected MSAs, between the pre-pandemic and pandemic periods. Notably, the most pronounced relative wage declines in computer and mathematical occupations are evident in cities traditionally considered hubs for the computer industry. Similarly, cities renowned as significant business and financial centers suffered the greatest wage reductions in business and financial occupations. However, such patterns are not discernible in food preparation, service, and health occupations. Correspondingly, Figure A6 shows a substantial departure of employment from cities traditionally associated with the finance and information industries for the associated industry groups.

While the patterns generally hold true, there are exceptions. For example, despite a significant wage decline in high-WFH-adoption occupations in San Jose and San Francisco, the employment decrease in the relevant finance and information industry was comparatively mild in San Jose, and San Francisco actually saw some employment growth in that industry. This suggests that San Jose and San Francisco's wage decline might have been in part due to a labor supply increase from remote workers residing elsewhere. Austin, TX serves as another exception. Although it saw a wage drop in high-adoption occupations, it also experienced an exceptionally high employment growth in these fields. This could be attributed to an increased labor supply through remote working or possibly due to the inflow of high-tech firms into Austin during the pandemic.

Figures A5 and A6 also highlight a notable case in the food preparation and service occupations and the food and accommodation industries. While the wage decline does not show a strong correlation with city size, the employment drop is more pronounced in larger cities and business hubs. This is likely a result of both declining labor demand and supply in service sectors in large cities, leading to a steep decrease in employment but ambiguous wage changes, as illustrated in Figure 1b.

A5.2 Reduced Compensating Differentials: An Alternative Source of Decreasing Urban Wage Premium

Another reason for the observed decline in the urban wage premium for jobs in high-WFH-adoption occupations could be a reduction in compensating wage differentials. Firms might have reduced wages following WFH adoption because workers could now avoid lengthy commutes. Since commute time was likely longer in larger cities or dense areas pre-pandemic, the drop in the urban wage premium might be driven by the disproportionate decrease in compensating differentials in large cities, in addition to (or instead of) the reduced agglomeration economies. We cannot directly disentangle this possibility from our hypothesis with our main analysis because the Burning Glass data do not include workers' residential locations.

However, we can examine this alternate explanation indirectly using the ACS data from 2015–2021. We exploit the idea that the reduction in commuting due to WFH adoption should be larger for workers who previously had longer commutes. Therefore, if reduced commute time led to wage reductions, we would expect the largest drops in wages among workers who likely had the greatest reductions in commuting—those working in high-WFH-adoption occupations living in neighborhoods with traditionally long commutes for their occupations. Specifically, we estimate the following triple-difference regression:

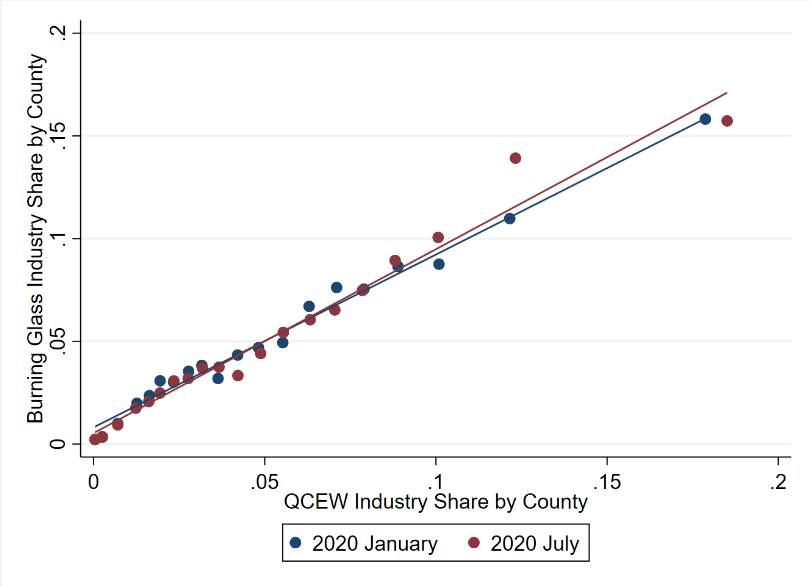
$$\begin{aligned} y_{ikjmt} = {} & \lambda_0 High_k + \lambda_1 High_k \times Post_t + \lambda_2 C_{kjm} + \lambda_3 C_{kjm} \times Post_t + \lambda_4 High_k \times C_{kjm} \\ & + \lambda_5 High_k \times C_{kjm} \times Post_t + \xi_m \times \zeta_t + \Lambda_t X_i + \epsilon_{ikjmt}, \end{aligned} \tag{15}$$

where y_{ikjmt} is log hourly wage or commute time of individual i in occupation k in PUMA j of MSA m in year t; $High_k$ is an indicator that occupation k has high WFH adoption during the pandemic; $Post_t$ is an indicator for post-pandemic period (i.e., $t = 2020$ or 2021); C_{kjm} is the average commute time faced by workers in occupation k living in PUMA j in MSA m between 2015 and 2019. We approximate C_{kjm} by calculating the average commute time experienced by two broad occupation groups: high-WFH-adoption occupations and low/moderate-WFH-adoption occupations.[37] X_i is a vector of workers' characteristics, including indicators of sex, age, race, Hispanic status, marital status, and education. We allow the coefficients Λ_t to vary over time to account for changes in sorting of workers over time. The coefficient of interest in λ_5.

Table A5 presents the estimates of λ_0–λ_5. The sample comprises workers aged from 25–65 who worked at least 35 hours per week. In Columns 1–2, the dependent variable is the log hourly wage. In Columns 3–4, the dependent variable is the commute time. All columns control for the interaction between year fixed effects and MSA fixed effects. Columns 2 and 4 further control for workers' demographic characteristics. The estimates of λ_5 in Columns 1 and 2 suggest that during the pandemic, workers in high-WFH-adoption occupations who lived in neighborhoods with high commute time pre-pandemic saw a wage increase relative to others, although the magnitude is small. Adding workers' characteristics does not significantly affect the result. This finding is contradict the hypothesis of changing compensating differentials. In contrast, as Columns 3 and 4 show, these workers experienced a more substantial decrease in commute time, translating to increased amenities of reduced commuting, as expected. If the change in compensating differentials was driving the observed reduction in the urban wage premium, the increased amenities should have led to a wage decrease. Therefore, the results Table A5 offer some indirect evidence that our finding of reduced urban wage premium is unlikely solely driven by reduced compensating wage differentials.

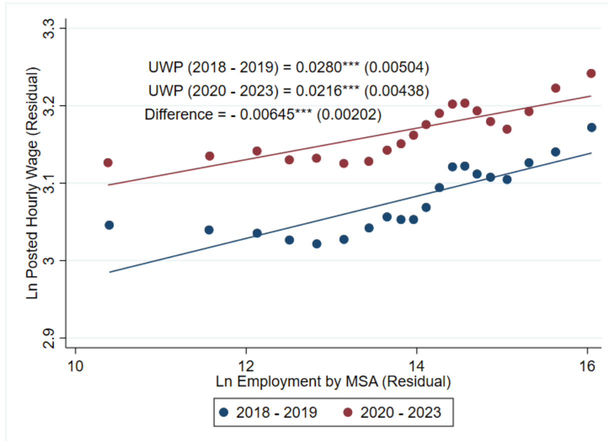
[37] We calculate commuting time at a higher occupation group level because commute time at a detailed occupational and geographical level tends to have many sparsely populated cells.

Figure A1: Industry Share within MSAs in the Burning Glass Data vs. QCEW

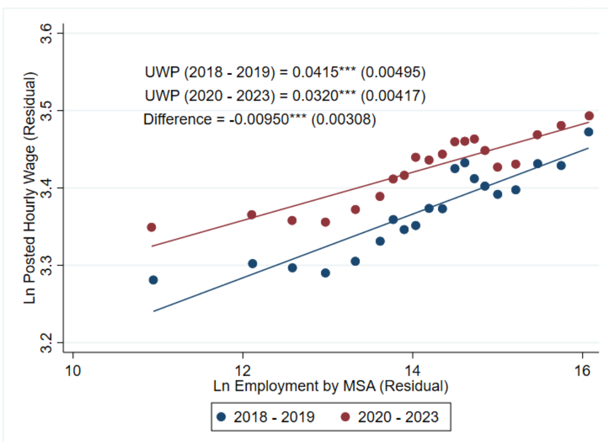


Note: This figure aims to validate that the geographical distribution of job postings in the Burning Glass data is likely to represent the locations of employers. The y-axis represents the 3-digit NAICS industry share in each MSA from the Burning Glass data, and the x-axis represents the 3-digit NAICS industry share in each MSA from the Quarterly Census of Employment and Wages (QCEW), which is based on employer locations. We present the binned scatterplot of the shares, separately for January 2020 (pre-pandemic) and July 2020 (during the pandemic).

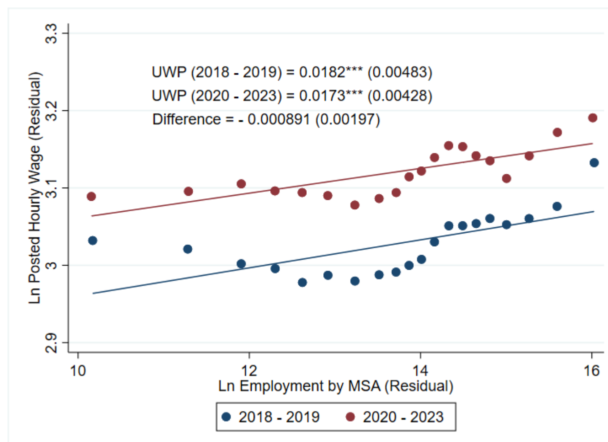
Figure A2: Urban Wage Premium: Estimation based on Total Employment by MSA



(a) All Jobs



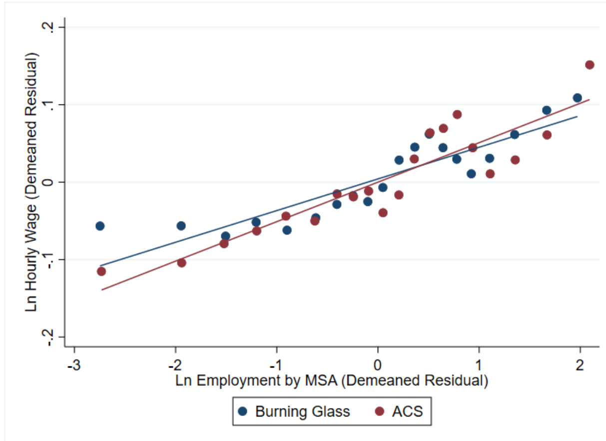
(b) High WFH Adoption



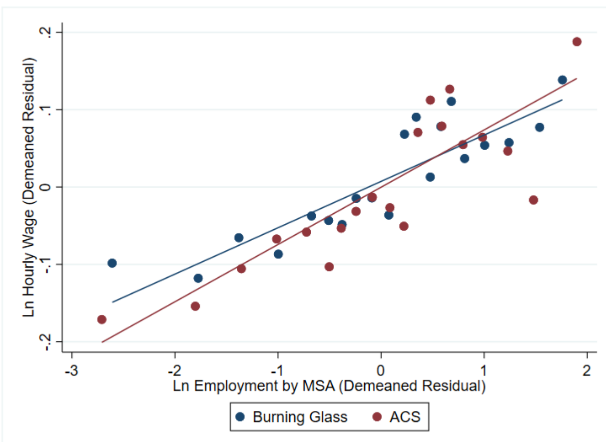
(c) Low or Moderate WFH Adoption

Note: The figures present binned scatterplots of residualized log posted hourly wage against residualized log employment of the MSA of a job, separately for jobs posted between 2018 and 2019 and those posted between 2020 and May 2023, using the Burning Glass data. We residualize log wage and log employment by regressing these variables on dummies for SOC occupation code, NAICS code, years of education required, salary type, full-/part-time status, tax terms, and job posting month. We then add back the means of the original variables. Figure A2a presents the plot for all posted jobs. Figures A2b and A2c present the plot for jobs in high-WFH-adoption occupations and those in low-WFH-adoption occupations, respectively.

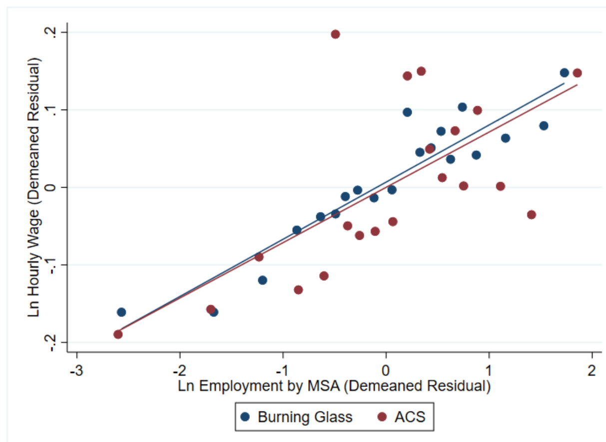
Figure A3: Urban Wage Premium: Estimation from the Burning Glass Data vs. ACS (2019)



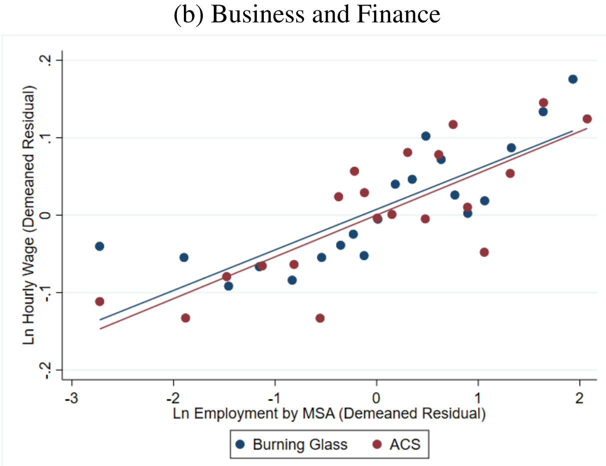
(a) All Jobs



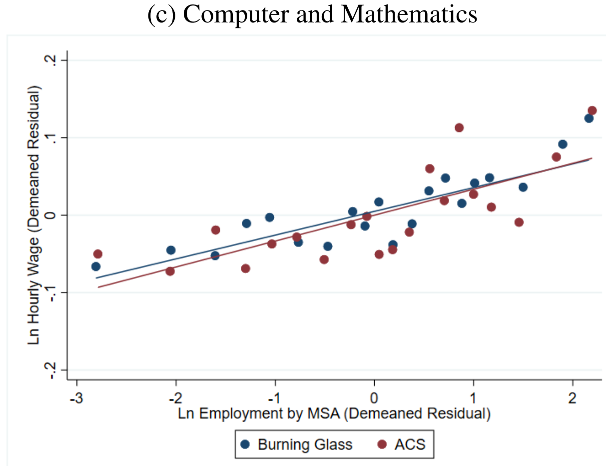
(b) Business and Finance



(c) Computer and Mathematics



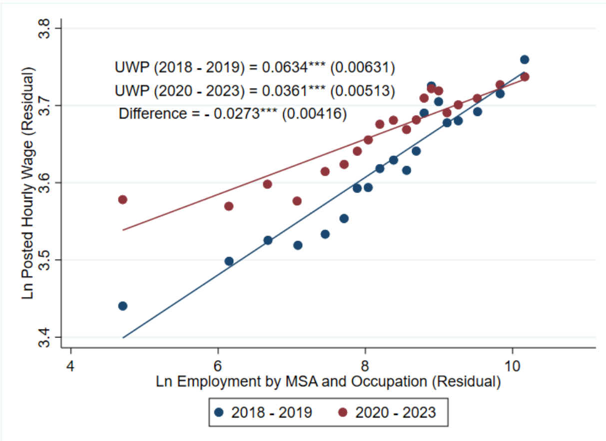
(d) Food Services



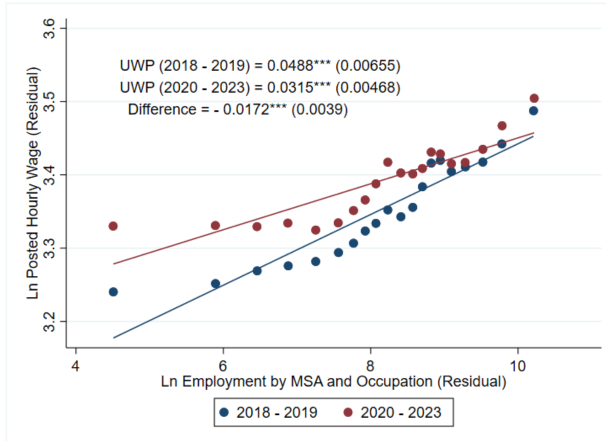
(e) Health Care

Note: These figures validate the urban wage premium estimates from the Burning Glass data with the ACS estimates. We estimate the urban wage premium using the 2019 Burning Glass data by regressing log posted hourly wage on log employment of the MSA of the corresponding job, controlling for dummy variables for SOC occupation code. We estimate the urban wage premium using the 2019 ACS data by regressing log hourly wage on log employment of the MSA, controlling for dummy variables for occ2010 occupation code. Figure A3a presents the demeaned binned scatterplots based on all jobs/workers. Figure A3b, A3c, A3d, and A3e present the demeaned binned scatterplots for four selected occupation groups.

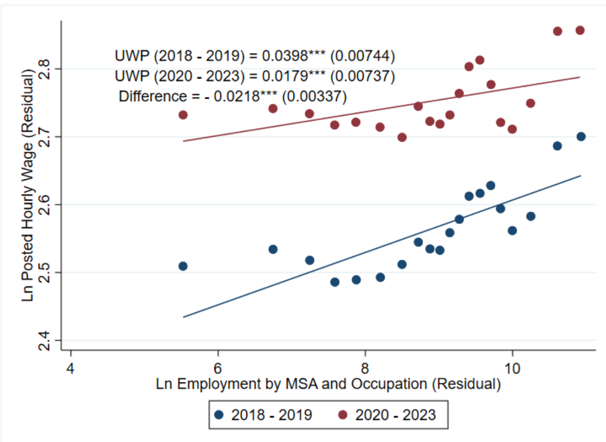
Figure A4: Urban Wage Premium: Selected Occupation Groups



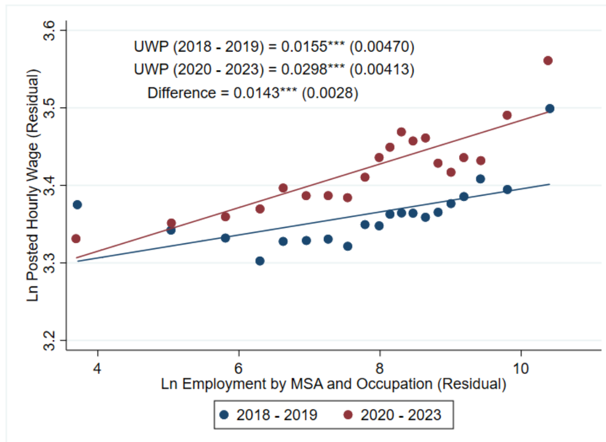
(a) Computer and Mathematics



(b) Business and Finance



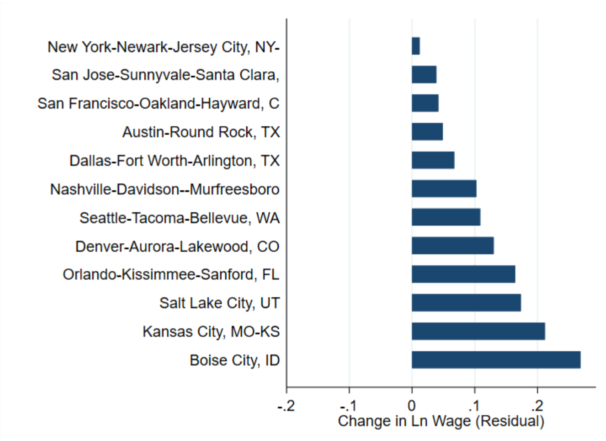
(c) Food Prep and Service



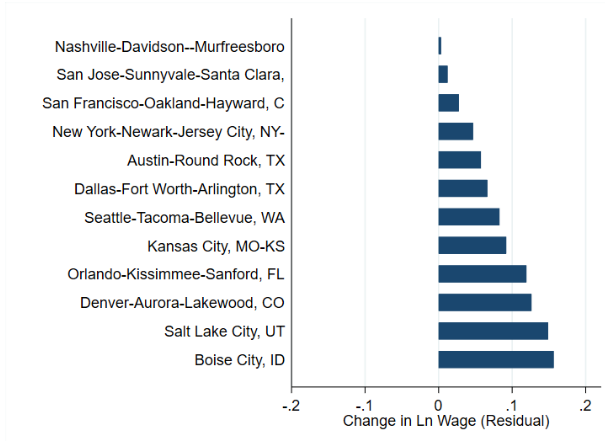
(d) Health

Note: The figures present binned scatterplots of residualized log posted hourly wage against residualized log employment of the occupation and MSA of a job, separately for jobs posted between 2018 and 2019 and those posted between 2020 and May 2023, using the Burning Glass data. We residualize log wage and log employment by regressing these variables on dummies for SOC occupation code, NAICS code, years of education required, salary type, full-/part-time status, tax terms, and job posting month. We then add back the means of the original variables. Figure A4a presents the plot for jobs categorized in the occupation group of "Computer and Mathematical Occupations." Figure A4b presents the plot for jobs in "Business and Financial Operations Occupations." Figure A4c presents the plot for jobs in "Food Preparation and Serving Related Occupations." Figure A4d presents the plot for jobs in "Healthcare Practitioners and Technical Occupations."

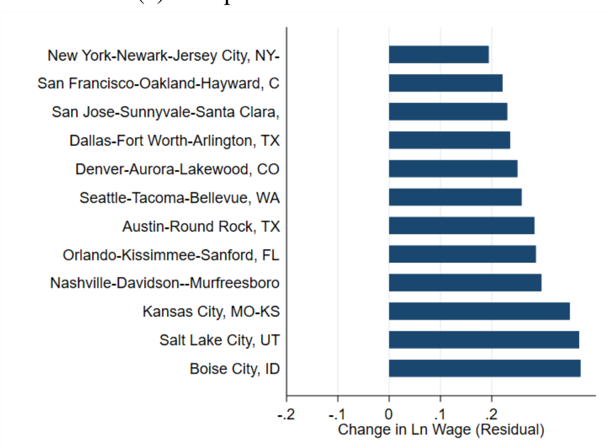
Figure A5: Residual Wage Growth of Selected Occupation Groups



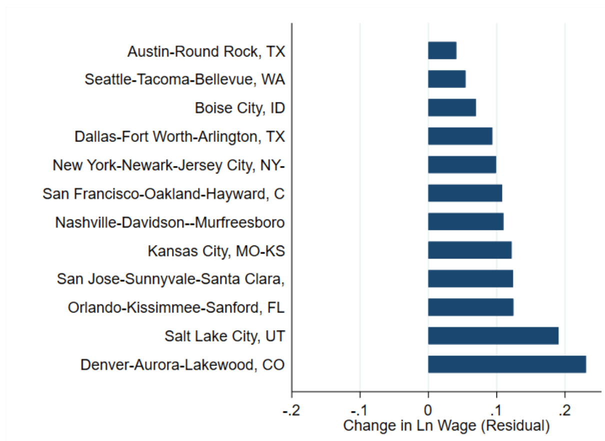
(a) Computer and Mathematical



(b) Business and Finance



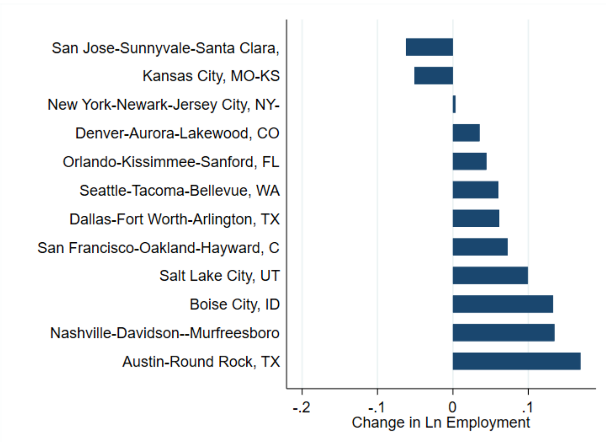
(c) Food Prep and Service



(d) Health

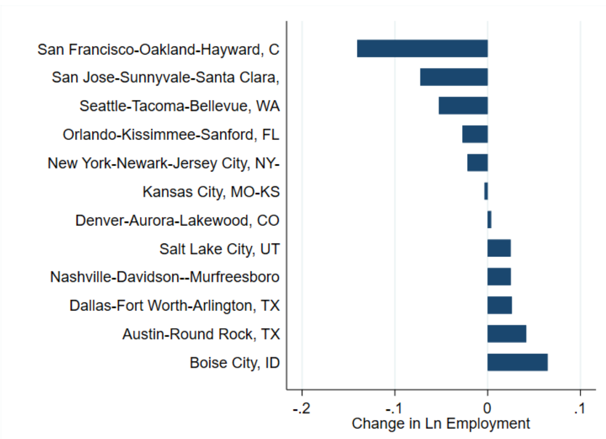
Note: The figures present changes in residualized log posted hourly wage between the pre-pandemic period (2018–2019) and the post-pandemic period (2022–May 2023) for four occupation groups across selected MSAs, using the Burning Glass data. We residualize log wage by regressing these variables on dummies for SOC occupation code, NAICS code, years of education required, salary type, full-/part-time status, tax terms, and job posting month. We then add back the means of the original variables. Figure A5a presents the residualized wage growth across selected MSAs for jobs in the occupation family of "Computer and Mathematical Occupations." Figure A5b is for jobs in "Business and Financial Operations Occupations." Figure A5c is for jobs in "Food Preparation and Serving Related Occupations." Figure A5d is for jobs in "Healthcare Practitioners and Technical Occupations."

Figure A6: Employment Growth of Selected Industry Groups

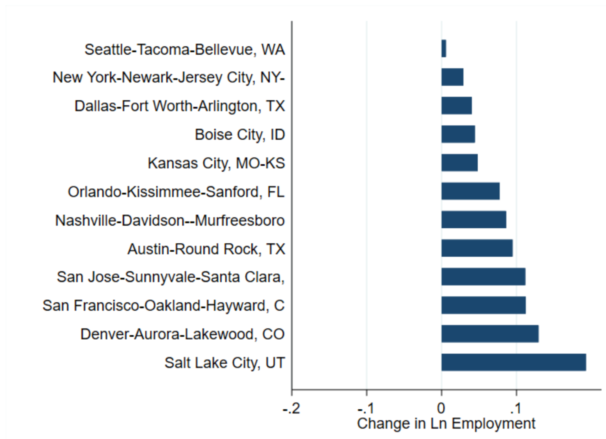


(a) Finance and Information

(b) Prof. and Business Services



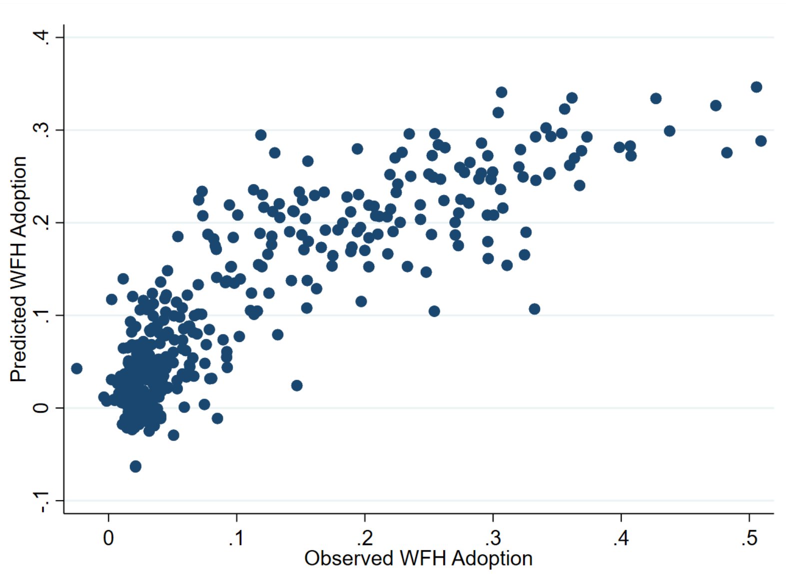
(c) Accom. and Food Services



(d) Health Care and Social Assist.

Note: The figures present changes in log employment between the pre-pandemic period (2018–2019) and the post-pandemic period (2022–May 2023) for four industry groups across selected MSAs, using the QCEW. Figure A6a presents employment growth across selected MSAs for jobs in the industry group of "Finance and Information", which include NAICS 51x and 52x. Figure A6b is for jobs in "Professional and Business Services." (NAICS 54x) Figure A6c is for jobs in "Accommodation and Food Services." (NAICS 72x) Figure A6d is for jobs in "Health Care and Social Assistance." (NAICS 62x)

Figure A7: Observed WFH Adoption vs. Predicted WFH Adoption



Note: This figure validates the predicted adoption of WFH with the observed adoption of WFH. We use the subset of occupations that the vectors of O*NET occupational characteristics can be matched to the ACS occupation code. Please see section A4.2 for imputation details.

Table A1: Changes in Urban Wage Premium by Occupation's WFH Adoption Level: Robustness Checks

	Log Posted Hourly Wages			
	(1)	(2)	(3)	(4)
Log M	0.0275***	0.0204***	0.0169***	0.0175***
	(0.00842)	(0.00658)	(0.00405)	(0.00340)
Log M × Moderate WFH	0.0122***	0.00844***	0.0193***	0.0141***
	(0.00129)	(0.00114)	(0.00165)	(0.00132)
Log M × High WFH	0.0130***	0.0108***	0.0267***	0.0223***
	(0.00234)	(0.00210)	(0.00316)	(0.00254)
Log M × Post	0.00238	0.00277	0.00176	0.000676
	(0.00480)	(0.00379)	(0.00108)	(0.00108)
Log M × Moderate WFH × Post	-0.00538***	-0.00363***	-0.00944***	-0.00629***
	(0.000818)	(0.000678)	(0.000753)	(0.000658)
Log M × High WFH × Post	-0.00267*	-0.00513***	-0.0123***	-0.0127***
	(0.00160)	(0.00124)	(0.00157)	(0.00136)
Controls: Job Characteristics	X	X	X	X
Controls: MSA FE × Post, Occ × Post	X	X		
Controls: Skill Requirements		X		X
WFH Def Based on	SOC Occ.	SOC Occ.	NAICS Ind.	NAICS Ind.
Observations	7,316,061	5,996,739	7,316,072	5,996,752

Note: This table presents the estimates of the urban wage premium pre- and post-pandemic by occupation and industry category, based on the level of WFH adoption, as robustness checks. The sample includes job postings from a 10% random selection of the Burning Glass data, from 2018 to May 2023. The dependent variable is log posted hourly wage of a job posting. M is employment size (in 2019 Q1) of the occupation or industry in the MSA of the posted job. Post is a post-pandemic dummy (i.e., months after March 2020). Moderate WFH is a dummy variable that is equal to 1 if the occupation or industry of the posted job has moderate WFH adoption (i.e., occupations or industries with an increase of 11–20 percentage points in the national share of WFH-compatible jobs, as determined by comparing pooled data from 2018 to March 2020 with pooled data from April 2020 to May 2023); High WFH is a dummy variable that is equal to 1 if the occupation or industry of the posted job has high WFH adoption (i.e., occupations or industries with an increase of more than 20 percentage points in the national share of WFH-compatible jobs). All columns control for basic job characteristics (including dummy variables for SOC occupation code, NAICS industry code, years of education required, salary type, part-/full-time status, tax term, and posting month). Columns 1 and 2 define WFH adoption based on occupation categories and include the interaction between occupation fixed effects and the post-pandemic dummy, and the interaction between MSA fixed effects and the post-pandemic dummy. Columns 3 and 4 define WFH adoption based on industry categories (three-digit NAICS). Columns 2 and 4 include controls of the indicators of skill requirements. Standard errors are clustered at the MSA level. *** $p < 0.01$, ** $p < 0.05$, *$p < 0.1$.

Table A2: Changes in Urban Wage Premium by Occupation's WFH Adoption Level: Cross-County and Within-MSA Comparisons

	Log Posted Hourly Wages	
	(1)	(2)
Log M	0.0117***	0.00794***
	(0.00278)	(0.00174)
Log M $\times$ Moderate WFH	0.0192***	0.0170***
	(0.00196)	(0.00129)
Log M $\times$ High WFH	0.0268***	0.0290***
	(0.00353)	(0.00259)
Log M $\times$ Post	0.00454***	0.00156**
	(0.000672)	(0.000608)
Log M $\times$ Moderate WFH $\times$ Post	-0.0103***	-0.00654***
	(0.000775)	(0.000664)
Log M $\times$ High WFH $\times$ Post	-0.0118***	-0.0127***
	(0.00155)	(0.00122)
Controls: Job Characteristics	X	X
Controls: MSA $\times$ M / H WFH $\times$ Post		X
Measurement of M	Emp Size by Occ and County	Emp Size by Occ and County
Observations	7,429,678	7,315,951

Note: This table presents the estimates of the urban wage premium pre- and post-pandemic by occupation category, based on the level of WFH adoption. The sample includes job postings from a 10% random selection of the Burning Glass data, from 2018 to May 2023. The dependent variable is log posted hourly wage of a job posting. M is employment size of the occupation in the county of the posted job. Post is a post-pandemic dummy (i.e., months after March 2020). Moderate WFH is a dummy variable that is equal to 1 if the occupation of the posted job has moderate WFH adoption (i.e., occupations with an increase of 11–20 percentage points in the national share of WFH-compatible jobs, as determined by comparing pooled data from 2018 to March 2020 with pooled data from April 2020 to May 2023); High WFH is a dummy variable that is equal to 1 if the occupation of the posted job has high WFH adoption (i.e., occupations with an increase of more than 20 percentage points in the national share of WFH-compatible jobs). Both columns control for basic job characteristics (including dummy variables for SOC occupation code, NAICS industry code, years of education required, salary type, part-/full-time status, tax term, and posting month). Columns 2 further include the interaction of the MSA fixed effects, dummy for high- or moderate WFH adoption, and the post-pandemic dummy. Standard errors are clustered at the MSA level. *** $p < 0.01$, ** $p < 0.05$, *$p < 0.1$.

Table A3: Changes in Urban Wage Premium by Occupation's WFH Adoption Level: Imputed WFH Adoption Levels by O*NET Characteristics

	Log Posted Hourly Wages	
	(1)	(2)
Log M	0.0178***	0.0183***
	(0.00390)	(0.00402)
Log M $\times$ Moderate WFH	0.0120***	0.00901***
	(0.00163)	(0.00139)
Log M $\times$ High WFH	0.0305***	0.0234***
	(0.00393)	(0.00339)
Log M $\times$ Post	0.000248	0.000117
	(0.00106)	(0.00103)
Log M $\times$ Moderate WFH $\times$ Post	-0.00451***	-0.00341***
	(0.000744)	(0.000655)
Log M $\times$ High WFH $\times$ Post	-0.00777***	-0.00893***
	(0.00149)	(0.00133)
Controls: Job Characteristics	X	X
Controls: Skill Requirements		X
Specification	Baseline	Baseline
Observations	6,913,047	5,661,761

Note: This table presents the estimates of the urban wage premium and its change over time for occupations with different levels of WFH adoption. We present the results from the baseline specification using the Burning Glass job posting data, similar to columns 1 and 2 in Table 2. The difference is that we define occupations' WFH adoption levels using the imputed WFH share based on O*NET occupation characteristics. Please see Appendix A4.2 for the imputation procedure. We define the level of WFH adoption for an occupation based on changes in the imputed share of remote workers within the occupation between 2019 and 2021. We classify occupations as high-WFH-adoption occupations if they experienced an over 25 percentage point increase in the national share of WFH workers, comparing data from 2019 and 2021 (corresponding to the 90th percentile of the distribution in change of WFH worker share). Moderate-WFH-adoption occupations experienced an 10 to 25 percentage point increase in the share of WFH workers (representing the 50th and 90th percentiles), while low-WFH-adoption occupations experienced less than a 10 percentage point increase. *** $p < 0.01$, ** $p < 0.05$, *$p < 0.1$.

Table A4: Changes in Urban Wage Premium by Occupation's WFH Adoption Level: Average Weekly Earnings from QCEW

	Log Average Weekly Earnings	
	(1)	(2)
Log M × Post	0.00277***	
	(0.000798)	
Log M × 2020		0.00242**
		(0.000958)
Log M × 2021		0.00200***
		(0.000728)
Log M × 2022		0.00528***
		(0.00130)
Log M × Moderate WFH × Post	-0.00399***	
	(0.000783)	
Log M × High WFH × Post	-0.0185***	
	(0.00273)	
Log M × Moderate WFH × 2020		0.00194
		(0.00163)
Log M × Moderate WFH × 2021		-0.00127
		(0.000878)
Log M × Moderate WFH × 2022		-0.00936***
		(0.00130)
Log M × High WFH × 2020		-0.00861***
		(0.00258)
Log M × High WFH × 2021		-0.00732
		(0.00585)
Log M × High WFH × 2022		-0.0290***
		(0.00303)
Observations	1,921,245	1,921,245

Note: This table presents the estimates of the urban wage premium pre- and post-pandemic by industry's WFH adoption level. The sample comprises quarterly average weekly earnings by MSA and industry (3-digit NAICS) from the QCEW for Q1 2018 to Q4 2022. The dependent variable is log average weekly earning by MSA and industry. Observations are weighted by employment size (2019 Q1) of the MSA and industry. Moderate WFH is dummy for industries with an increase of 11–20 percentage points in the national share of WFH-compatible jobs, as determined by comparing pooled data from 2018 to Q1 2020 with pooled data from Q2 2020 to 2022). High WFH is dummy for industries with an increase of more than 20 percentage points in the national share of WFH-compatible jobs. Standard errors are clustered at the MSA level. *** $p < 0.01$, ** $p < 0.05$, *$p < 0.1$

Table A5: Compensating Differentials: Alternative Explanation of Changes in the Urban Wage Premium

	Log Hourly Wage		Commute Time	
	(1)	(2)	(3)	(4)
High WFH	0.355***	0.196***	0.249**	0.119
	(0.0170)	(0.0099)	(0.0987)	(0.1000)
High WFH × Post	-0.0135	0.0023	2.838***	3.671***
	(0.00948)	(0.00895)	(0.335)	(0.324)
Pre-Pandemic Commute	-0.00746***	-0.00344***	0.989***	0.985***
	(0.00114)	(0.00066)	(0.00438)	(0.00441)
Pre-Pandemic Commute × Post	-0.00052	-0.00036	-0.060***	-0.101***
	(0.00035)	(0.00030)	(0.0138)	(0.0124)
High WFH × Pre-Pandemic Commute	0.00693***	0.00348***	-0.00398	-0.00554
	(0.00064)	(0.00036)	(0.00366)	(0.00366)
Hig -WFH × Pre-Pandemic Commute × Post	0.00059*	0.00064**	-0.370***	-0.351***
	(0.00033)	(0.00031)	(0.0124)	(0.0120)
Controls: Year FE × MSA FE	Yes	Yes	Yes	Yes
Controls: Year FE × Worker Characteristics	No	Yes	No	Yes
Observations	7,471,296	7,471,296	7,313,590	7,313,590

Note: This table presents the estimates of changes in log hourly wage and commute time pre- and post-pandemic by occupation's WFH adoption level and the average pre-pandemic commute time of the worker's residential location and occupation group. The sample comprises workers aged from 25–65 who worked at least 35 hours per week in the ACS from 2015–2021. $Post$ indicates the pandemic period (i.e., 2020 or 2021). $High\ WFH$ is an indicator that is equal to 1 if the occupation of the posted job has a high level of WFH adoption. $Pre\text{-}Pandemic\ Commute$ is the average commute time between 2015 and 2019 by workers' residential PUMA and high-WFH indicator. All columns include year fixed effects, MSA fixed effects, and their interaction. Columns 2 and 4 further include the interactions between year fixed effects and various demographic characteristics, including indicators of sex, age, race, Hispanic status, marital status, and education. Standard errors are clustered at the PUMA level. *** $p < 0.01$, ** $p < 0.05$, *$p < 0.1$.

Table A6: Lasso Selection Results:
Work Context Characteristics as Predictors for WFH Adoption During the Pandemic

	Lasso	OLS
Deal With External Customers	-0.0086	-0.0184***
		(0.00459)
Deal With Physically Aggressive People	-0.0126	-0.0155*
		(0.00840)
Electronic Mail	0.0073	0.0089**
		(0.00397)
Exposed to Contaminants	-0.0121	-0.0123**
		(0.00527)
Exposed to Disease or Infections	-0.0035	-0.0042
		(0.00443)
Exposed to Minor Burns, Cuts, Bites, or Stings	-0.0031	-0.0032
		(0.00594)
Level of Competition	0.0110	0.0262***
		(0.00622)
Physical Proximity	-0.0103	-0.0137**
		(0.00692)
Public Speaking	0.0023	0.0085
		(0.00646)
Responsible for Others' Health and Safety	-0.0277	-0.0380***
		(0.00656)
Spend Time Sitting	0.0168	0.0120
		(0.0115)
Spend Time Standing	-0.0113	-0.0144
		(0.0124)
Spend Time Using Your Hands to Handle, Control, or Feel Objects, Tools, or Controls	-0.0215	-0.0195***
		(0.00576)
Work With Work Group or Team	0.0077	0.0278***
		(0.00865)
Constant	0.2695	0.2520***
		(0.0773)

Note: This table presents the results of the Lasso regression and the OLS regression after selecting variables. We use the O*NET work context characteristics as predictors for the change in the share of WFH workers during the pandemic. There are 57 work context characteristics. We show the regression coefficients for the variables retained by Lasso. The shrinkage parameter λ is searched for based on Extended Bayesian information criterion (EBIC) (Chen and Chen, 2008). *** $p < 0.01$, ** $p < 0.05$, *$p < 0.1$.

Table A7: Manual Assignment of Unassigned Skills

Skill	Skill Cluster Family
Building Effective Relationship	Building Relationship
Teamwork / Collaboration	Building Relationship
Mentoring	Building Relationship
Verbal / Oral Communication	Communication
Telephone Skills	Communication
Written Communication	Communication
Writing	Communication
Communication Skills	Communication
Presentation Skills	Communication
Oral Communication	Communication
Microsoft Excel	Information Technology
Microsoft Word	Information Technology
Computer Literacy	Information Technology
Problem Solving	Analysis
Critical Thinking	Analysis
Creativity	Analysis
Decision Making	Analysis
Research	Science and Research
Repair	Maintenance, Repair, and Installation
Cleaning	Maintenance, Repair, and Installation
Preventive Maintenance	Maintenance, Repair, and Installation
Work Area Maintenance	Maintenance, Repair, and Installation
Planning	Planning
Leadership	Leadership
Organizational Skills	Organizational Skills
People Management	Human Resources
Staff Management	Human Resources
Supervisory Skills	Human Resources
Conflict Management	Human Resources
Team Management	Human Resources
Personnel Management	Human Resources
Escalation Management	Human Resources
Employee Training	Human Resources
Employee Relations	Human Resources
Employee Engagement	Human Resources
People Development	Human Resources
Employee Coaching	Human Resources
Staff Development	Human Resources
Typing	Administration
Troubleshooting	Administration
Time Management	Administration

Notes: We manually assign some of the unassigned skills to skill cluster families. We select the skills that appear in the skill vectors very frequently but are unassigned to any skill cluster families. Some skill cluster families shown above are created by us because the existing categories do not fit. "Building Relationship", "Communication", "Organizational Skills" are created by us.

Table A8: Most Frequently Listed Skills Under Key Skill Cluster Families (Part 1)

Rank	Custumer and Client Support	Business Management	Marketing and Public Relations
1	Customer Service	Project Management	Social Media
2	Customer Contact	Quality Assurance and Control	Packaging
3	Customer Checkout	Process Improvement	Salesforce
4	Cash Handling	Business Process	Client Base Retention
5	Basic Mathematics	Key Performance Indicators (KPIs)	Marketing
6	Guest Services	Business Administration	Facebook
7	Cash Register Operation	Project Planning and Development Skills	Market Strategy
8	Point of Sale System	Product Management	Customer Relationship Management (CRM)
9	Claims Knowledge	Performance Appraisals	Market Research
10	Customer Accounts	Cost Control	Digital Marketing
11	Refunds Exchanges and Adjustments	Change Management	Newsletters
12	Customer Complaint Resolution	Performance Management	Instagram
13	Processing Item Returns	Stakeholder Management	Market Trend
14	Needs Assessment	Operations Management	Marketing Materials
15	Client Needs Assessment	Strategic Planning	LinkedIn
16	Customer Experience Improvement	Business Acumen	Fundraising
17	Claims Adjustments	Performance Analysis	Social Media Platforms
18	Service Improvement	Business Planning	Customer Retention
19	Payment Collection	Business Analysis	Market Analysis
20	Payment Processing	Thought Leadership	Product Marketing
21	Bagging Items	Business Operations	Brand Experience
22	Checking Out Customers	Contract Review	Market Planning
23	Satisfaction Failure Correction	Business Strategy	Competitive Analysis
24	Processing Customer Requests	Property Management	Brand Awareness Generation
25	Issuing Receipts	Root Cause Analysis	Community Relations
26	Presenting Solutions	Business Management	Google Analytics
27	Customer Service Enhancement	Contract Preparation	Customer Acquisition
28	Responding to Patient Phone Calls	Lifecycle Management	Marketing Management
29	Product Availability	Technical Assistance	Business-to-Business Sales
30	End-user training	Service Level Agreement	Youtube
31	Product Assortment	Event Planning	Promotional Materials
32	Account Information Maintenance	Contract Management	Marketing Strategy Development
33	Customer Referrals	Process Design	Copywriting
34	Claims Processing	Business Solutions	Crisis Management
35	Wellness Services	Restaurant Management	Effective Communications
36	Deposit Collection	Due Diligence	Email Marketing
37	Inventory Checking	Real Estate Experience	CRM software
38	Pizza Delivery	Professional Services Marketing	Consumer Behavior
39	Customer Relationship Marketing	Progress Reports	Marketing Communications
40	Settlement Negotiation	Business Systems Analysis	Ad Campaigns
41	Credit Card Transaction Processing	Resource Management	Marketing Programs
42	Providing Warranties	Business Communications	Focus groups
43	Product Features Assistance	Profit Targets	Social Media Marketing
44	Price Checks	Policy Implementation	Direct Mail
45	Store Communications	5S Methodology	Consumer Segmentation
46	Charge and Disbursement Determination	Business Case Analysis	Branding Strategy
47	Credit Card Applications	Benchmarking	Email Campaigns
48	Deposit Preparation	Contract Negotiation	Account Development
49	Client Care	Order Entry	Consumer Research
50	Customer Account Review	Strategic Development	Social Content

Table A9: Most Frequently Listed Skills Under Key Skill Cluster Families (Part 2)

rank	Information Technology
1	Microsoft Office
2	Computer Literacy
3	Microsoft Word
4	Microsoft Powerpoint
5	SQL
6	Software Development
7	Python
8	Spreadsheets
9	Software Engineering
10	Java
11	Technical Support
12	Microsoft Outlook
13	Software as a Service (SaaS)
14	Information Systems
15	SAP
16	Enterprise Resource Planning (ERP)
17	Oracle
18	JavaScript
19	Microsoft Azure
20	Scrum
21	Word Processing
22	Linux
23	DevOps
24	Data Management
25	Atlassian JIRA
26	Git
27	Telecommunications
28	Information Security
29	Microsoft Windows
30	Microsoft Sharepoint
31	Microsoft C#
32	Microsoft Access
33	Microsoft Project
34	ServiceNow
35	Agile Development
36	Systems Engineering
37	Amazon Web Services (AWS)
38	C++
39	Kubernetes
40	Troubleshooting Technical Issues
41	Systems Development Life Cycle (SDLC)
42	Network Hardware/Software Maintenance
43	System Design
44	Debugging
45	Relational Databases
46	Unit Testing
47	System Administration
48	UNIX
49	SQL Server
50	OpenStack

Table A10: Gelbach Decomposition: Contribution of Changes in Skill-Specific Urban Wage Premium to the Decrease in the Urban Wage Premium within High-WFH-Adoption Occupations—Jobs Requiring College Education

2020		2021		2022–2023	
Skill	π	Skill	π	Skill	π
Communications	35.7%	Finance	58.4%	Information Technology	58.1%
Business Management	24.7%	Communications	49.5%	Marketing and Public Relations	43.6%
Leadership	8.9%	Marketing and Public Relations	36.9%	Business Management	34.0%
Creativity	5.7%	Business Management	30.3%	Building Relationship	21.9%
Planning	4.4%	Building Relationship	27.5%	Communications	19.7%
Education and Training	3.2%	Customer and Client Support	8.3%	Finance	15.9%
Human Resources	2.5%	Leadership	4.8%	Creativity	9.0%
Marketing and Public Relations	2.5%	Maintenance, Repair, and Installation	4.7%	Analysis	4.5%
Media and Writing	1.8%	Education and Training	2.9%	Education and Training	2.6%
Physical Abilities	1.0%	Planning	2.6%	Leadership	1.7%
Decision Making	0.9%	Analysis	1.1%	Decision Making	1.4%
Public Safety and National Security	0.8%	Manufacturing and Production	1.1%	Public Safety and National Security	1.3%
Analysis	0.7%	Economics, Policy, and Social Studies	0.2%	Agriculture	0.6%
Agriculture	0.7%	Agriculture	0.2%	Physical Abilities	0.3%
Maintenance, Repair, and Installation	0.7%	Administration	0.2%	Maintenance, Repair, and Installation	0.2%
Legal	0.5%	Energy and Utilities	0.1%	Energy and Utilities	0.1%
Health Care	0.4%	Media and Writing	0.1%	Media and Writing	0.0%
Energy and Utilities	0.2%	Public Safety and National Security	0.1%	Engineering	-0.1%
Environment	0.0%	Environment	0.0%	Legal	-0.1%
Design	-0.3%	Legal	0.0%	Architecture and Construction	-0.5%
Economics, Policy, and Social Studies	-0.4%	Health Care	-0.1%	Economics, Policy, and Social Studies	-0.6%
Engineering	-0.9%	Architecture and Construction	-0.2%	Design	-1.4%
Finance	-1.3%	Physical Abilities	-0.2%	Planning	-1.5%
Architecture and Construction	-1.9%	Decision Making	-0.3%	Manufacturing and Production	-1.7%
Manufacturing and Production	-2.7%	Design	-0.4%	Personal Care and Services	-1.9%
Information Technology	-4.0%	Creativity	-0.5%	Environment	-3.6%
Building Relationship	-5.4%	Engineering	-1.2%	Health Care	-4.2%
Personal Care and Services	-7.0%	Personal Care and Services	-3.4%	Administration	-4.7%
Industry Knowledge	-14.4%	Industry Knowledge	-4.2%	Organizational Skills	-7.3%
Administration	-22.4%	Information Technology	-10.7%	Industry Knowledge	-7.6%
Organizational Skills	-26.4%	Organizational Skills	-14.8%	Customer and Client Support	-7.9%
Customer and Client Support	-54.2%	Human Resources	-15.6%	Human Resources	-14.2%

Note: This table presents the Gelbach decomposition results for jobs that require a college degree. We conduct the analysis separately for three periods: between 2018–2019 and 2020, between 2018–2019 and 2021, and between 2018–2019 and 2022–May 2023. The sample includes jobs postings that require a college degree in high-WFH-adoption occupations (i.e., occupations with an increase of more than 15 percentage points in the national share of WFH-compatible jobs, as determined by comparing the pooled data from 2018 to March 2020 with pooled data from April 2020 to May 2023) in the Burning Glass data. For each time period, we rank the skill cluster families by their contributions to the overall decline in the urban wage premium (i.e., π in Equation 10).

Table A11: Gelbach Decomposition: Contribution of Changes in Skill-Specific Urban Wage Premium to the Decrease in the Urban Wage Premium within High-WFH-Adoption Occupations—Jobs Not Requiring College Education

2020		2021		2022–2023	
Skill	π	Skill	π	Skill	π
Marketing and Public Relations	10.9%	Customer and Client Support	55.1%	Customer and Client Support	42.1%
Information Technology	8.7%	Marketing and Public Relations	24.2%	Communications	29.5%
Building Relationship	8.0%	Administration	23.2%	Administration	26.5%
Business Management	7.7%	Building Relationship	17.5%	Building Relationship	14.1%
Physical Abilities	6.4%	Finance	12.6%	Information Technology	8.1%
Finance	4.8%	Maintenance, Repair, and Installation	10.9%	Maintenance, Repair, and Installation	7.7%
Maintenance, Repair, and Installation	4.0%	Business Management	8.5%	Human Resources	7.4%
Customer and Client Support	3.1%	Physical Abilities	5.2%	Business Management	6.5%
Industry Knowledge	2.9%	Communications	4.3%	Physical Abilities	6.1%
Engineering	1.9%	Decision Making	2.5%	Marketing and Public Relations	4.2%
Agriculture	1.6%	Personal Care and Services	0.5%	Engineering	3.1%
Manufacturing and Production	1.3%	Engineering	0.4%	Decision Making	2.9%
Administration	1.0%	Environment	0.4%	Media and Writing	1.8%
Personal Care and Services	0.8%	Design	0.4%	Personal Care and Services	1.4%
Human Resources	0.3%	Economics, Policy, and Social Studies	0.2%	Agriculture	0.8%
Economics, Policy, and Social Studies	0.2%	Education and Training	0.0%	Education and Training	0.7%
Design	0.2%	Legal	0.0%	Creativity	0.6%
Education and Training	0.1%	Agriculture	-0.1%	Design	0.3%
Energy and Utilities	0.1%	Energy and Utilities	-0.2%	Organizational Skills	0.3%
Legal	0.0%	Public Safety and National Security	-0.3%	Environment	0.2%
Creativity	-0.1%	Creativity	-0.8%	Economics, Policy, and Social Studies	0.1%
Environment	-0.2%	Analysis	-1.0%	Public Safety and National Security	0.0%
Public Safety and National Security	-0.3%	Media and Writing	-1.2%	Energy and Utilities	-0.1%
Decision Making	-0.4%	Manufacturing and Production	-1.3%	Manufacturing and Production	-0.1%
Health Care	-0.4%	Human Resources	-1.4%	Legal	-0.1%
Architecture and Construction	-0.6%	Architecture and Construction	-1.7%	Architecture and Construction	-0.2%
Planning	-0.8%	Leadership	-3.0%	Finance	-2.0%
Media and Writing	-1.1%	Health Care	-4.7%	Leadership	-3.3%
Leadership	-6.2%	Industry Knowledge	-6.8%	Health Care	-6.9%
Organizational Skills	-10.5%	Planning	-9.5%	Planning	-12.4%
Analysis	-13.0%	Organizational Skills	-21.1%	Industry Knowledge	-13.8%
Communications	-13.9%	Information Technology	-31.7%	Analysis	-14.2%

Note: This table presents the Gelbach decomposition results for jobs that do not require a college degree. We conduct the analysis separately for three periods: between 2018–2019 and 2020, between 2018–2019 and 2021, and between 2018–2019 and 2022–May 2023. The sample includes jobs postings that do not require college education in high-WFH-adoption occupations (i.e., occupations with an increase of more than 15 percentage points in the national share of WFH-compatible jobs, as determined by comparing the pooled data from 2018 to March 2020 with pooled data from April 2020 to May 2023) in the Burning Glass data. For each time period, we rank the skill cluster families by their contributions to the overall decline in the urban wage premium (i.e., π in Equation 10).

Table A12: Spatial Shift in Skill Listing Intensity: By College Education Requirement

	IT	Business	Building Relations	Communication	Customer Support	Marketing
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Jobs Requiring College Education						
Log M	0.00808***	0.000456	0.00537***	0.00841***	-0.00278*	0.00662***
	(0.00126)	(0.00238)	(0.00208)	(0.00138)	(0.00166)	(0.00104)
Log M $\times$ 2020	0.00154	0.00510***	0.00124	0.000467	0.00196**	0.00238***
	(0.00111)	(0.00133)	(0.00118)	(0.00127)	(0.000928)	(0.000881)
Log M $\times$ 2021	0.000508	0.00266**	-0.00345***	-0.00283**	0.000375	3.51e-05
	(0.00117)	(0.00107)	(0.00119)	(0.00112)	(0.000760)	(0.000836)
Log M $\times$ 2022-2023	-0.000795	0.00352***	-0.00352***	-0.000789	0.000900	-0.00151*
	(0.00118)	(0.00103)	(0.00132)	(0.00147)	(0.000838)	(0.000781)
Observations	549,972	549,972	549,972	549,972	549,972	549,972
Panel B: Jobs Not Requiring College Education						
Log M	0.00602***	0.00658***	0.00531***	0.00919***	-0.00145	0.00653***
	(0.00103)	(0.00113)	(0.00115)	(0.00116)	(0.00163)	(0.000785)
Log M $\times$ 2020	-0.000203	-0.00192***	0.00222***	-0.00112	0.00115**	-0.00264***
	(0.000687)	(0.000548)	(0.000568)	(0.000755)	(0.000542)	(0.000738)
Log M $\times$ 2021	0.00191**	-0.00101**	0.00166***	-0.00181**	-0.000364	-0.00254***
	(0.000808)	(0.000476)	(0.000535)	(0.000739)	(0.000806)	(0.000570)
Log M $\times$ 2022-2023	0.000828	-0.00270***	-0.00182***	-0.00194***	-0.000152	-0.00219***
	(0.000767)	(0.000597)	(0.000618)	(0.000748)	(0.000665)	(0.000629)
Observations	1,242,522	1,242,522	1,242,522	1,242,522	1,242,522	1,242,522

Note: The table presents the estimates of changes in the listing intensity of various skill cluster families with respect to employment size over time, based on Equation 11. Panel A uses the sample of job postings that require a college degree in high-WFH-adoption occupations (i.e., occupations with an increase of more than 15 percentage points in the national share of WFH-compatible jobs, as determined by comparing pooled data from 2018 to March 2020 with pooled data from April 2020 to May 2023) in the Burning Glass data. Panel B uses the sample of job postings without a degree requirement in high-WFH-adoption occupations. The dependent variable is an indicator of whether a skill belonging to the skill cluster family is listed in a job posting. M is employment size of the occupation in the MSA of the posted job. 2020 is an indicator that is equal to 1 if the job was posted in 2020, similarly for 2021, and 2022–2023. All columns control for basic job characteristics, including dummy variables for SOC occupation code, NAICS industry code, years of education required, salary type, part-/full-time status, tax term, and the posting month. Standard errors are clustered at the MSA level. *** $p < 0.01$, ** $p < 0.05$, *$p < 0.1$.

Table A13: Gelbach Decomposition: Contribution of Changes in Skill-Specific Urban Wage Premium to the Decrease in the Urban Wage Premium within High-WFH-Adoption Occupations (Based on Imputation from O*NET Characteristics)

2020		2021		2022–2023	
Skill	π	Skill	π	Skill	π
Information Technology	25.4%	Marketing and Public Relations	53.6%	Information Technology	86.6%
Business Management	11.1%	Finance	45.4%	Marketing and Public Relations	50.5%
Marketing and Public Relations	8.6%	Business Management	37.0%	Business Management	31.0%
Physical Abilities	4.4%	Building Relationship	22.6%	Communications	28.4%
Industry Knowledge	3.7%	Communications	16.8%	Organizational Skills	19.9%
Building Relationship	2.7%	Customer and Client Support	16.7%	Building Relationship	19.6%
Engineering	2.7%	Leadership	8.8%	Customer and Client Support	15.7%
Creativity	2.2%	Creativity	4.6%	Administration	10.8%
Education and Training	1.8%	Maintenance, Repair, and Installation	3.2%	Personal Care and Services	10.2%
Environment	1.3%	Physical Abilities	2.9%	Maintenance, Repair, and Installation	7.6%
Human Resources	0.7%	Personal Care and Services	2.6%	Decision Making	5.1%
Public Safety and National Security	0.7%	Environment	2.0%	Physical Abilities	4.8%
Maintenance, Repair, and Installation	0.5%	Decision Making	1.6%	Finance	4.7%
Agriculture	0.3%	Analysis	1.5%	Engineering	4.6%
Economics, Policy, and Social Studies	0.1%	Industry Knowledge	0.8%	Creativity	3.5%
Decision Making	0.0%	Education and Training	0.7%	Human Resources	2.4%
Legal	0.0%	Manufacturing and Production	0.3%	Education and Training	1.2%
Media and Writing	-0.1%	Economics, Policy, and Social Studies	0.3%	Public Safety and National Security	1.1%
Manufacturing and Production	-0.2%	Energy and Utilities	0.3%	Leadership	1.0%
Energy and Utilities	-0.3%	Public Safety and National Security	0.1%	Agriculture	0.4%
Health Care	-0.4%	Agriculture	0.0%	Legal	0.4%
Design	-0.6%	Media and Writing	-0.1%	Energy and Utilities	0.2%
Architecture and Construction	-0.8%	Legal	-0.1%	Economics, Policy, and Social Studies	0.1%
Finance	-0.8%	Engineering	-0.2%	Environment	-0.3%
Planning	-0.9%	Design	-0.5%	Media and Writing	-0.3%
Leadership	-3.3%	Architecture and Construction	-2.0%	Manufacturing and Production	-0.7%
Personal Care and Services	-3.9%	Health Care	-2.5%	Architecture and Construction	-1.0%
Analysis	-4.1%	Information Technology	-2.7%	Design	-1.3%
Organizational Skills	-8.3%	Planning	-7.3%	Planning	-7.9%
Communications	-17.6%	Organizational Skills	-13.2%	Health Care	-9.9%
Customer and Client Support	-26.2%	Human Resources	-18.8%	Industry Knowledge	-11.3%
Administration	-44.0%	Administration	-42.0%	Analysis	-16.6%

Note: This table presents the Gelbach decomposition results for jobs with or without college degree requirements. We conduct the analysis between 2018–2019 and 2020–May 2023. The sample includes jobs postings in high-WFH-adoption occupations as defined by the levels of WFH adoption predicted by O*NET work context characteristics (occupations with at least 20 percentage points increase in the imputed fraction of workers WFH). For the detailed imputation procedures, please see section A4.2. For each time period, we rank the skill cluster families by their contributions to the overall decline in the urban wage premium (i.e., π in Equation 10).

Table A14: Spatial Shift in Skill Listing Intensity among High-WFH-Adoption Occupations (Based on Imputation from O*NET Characteristics)

	IT	Business	Building Relations	Communication	Customer Support	Marketing
	(1)	(2)	(3)	(4)	(5)	(6)
Ln M	0.00964***	0.00643***	0.00695***	0.0105***	-0.000939	0.00694***
	(0.000954)	(0.00168)	(0.00141)	(0.00106)	(0.00154)	(0.000790)
Ln M $\times$ 2020	0.000523	0.000767	0.000702	0.000546	0.000968**	-0.000157
	(0.000610)	(0.000570)	(0.000611)	(0.000621)	(0.000491)	(0.000491)
Ln M $\times$ 2021	0.000190	0.000191	-0.00156***	-0.00182***	-3.72e-05	-0.00142***
	(0.000764)	(0.000556)	(0.000506)	(0.000697)	(0.000544)	(0.000430)
Ln M $\times$ 2022-2023	-0.000466	-0.00102*	-0.00270***	-0.000931	3.56e-05	-0.00162***
	(0.000755)	(0.000555)	(0.000752)	(0.000831)	(0.000513)	(0.000462)
Observations	2,249,696	2,249,696	2,249,696	2,249,696	2,249,696	2,249,696

Note: The table presents the estimates of changes in the listing intensity of various skill cluster families with respect to employment size over time, based on Equation 11. The sample includes jobs postings in high-WFH-adoption occupations as defined by the levels of WFH adoption predicted by O*NET work context characteristics (occupations with at least 20 percentage points increase in the imputed fraction of workers WFH). For the detailed imputation procedures, please see section A4.2. The dependent variable is an indicator of whether a skill belonging to the skill cluster family is listed in a job posting. M is employment size of the occupation in the MSA of the posted job. 2020 is an indicator that is equal to 1 if the job was posted in 2020, similarly for 2021, and 2022–2023. All columns control for basic job characteristics, including dummy variables for SOC occupation code, NAICS industry code, years of education required, salary type, part-/full-time status, tax term, and the posting month. Standard errors are clustered at the MSA level. *** $p < 0.01$, ** $p < 0.05$, *$p < 0.1$.