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Liu, Sitian and Su, Yichen

Queen's University, Federal Reserve Bank of Dallas

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Sitian Liu*   Yichen Su†

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Abstract

We analyze the effect of working from home on the agglomeration economies of large cities and the aggregate productivity implications of such an effect. Using advertised wages from job ads, we show that occupations with the highest work-from-home adoption during the COVID-19 pandemic saw a strong decrease in the urban wage premium. The decline in the urban wage premium is accompanied by an exodus of employment (based on firms' locations) from large cities to small cities. In contrast, occupations with low or moderate levels of work-from-home adoption saw much smaller overall reduction in the urban wage premium. The empirical evidence in our paper points to weakened agglomeration economies in large cities among professions with the highest prevalence of working from home. A decomposition exercise reveals that a sizable portion of the decline in the urban wage premium is driven by the decline in the urban wage premium of relationship-building skills, suggesting that the decreased agglomeration effect in large cities is at least partially a result of reduced occurrence of 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

*Queen's University. Email: sitian.liu@queensu.ca.

†Federal Reserve Bank of Dallas. Email: yichensu@outlook.com. The views expressed in this article are those of the authors and do not necessarily represent the views of the Federal Reserve Bank of Dallas or the Federal Reserve System. We thank Nathaniel Baum-Snow, Andra Ghent, Edward Glaeser, and Emma Harrington for their helpful comments.

1 Introduction

Much evidence has shown that productivity and wages tend to be higher in large cities than in small cities and rural areas (Ciccone and Hall, 1996; Glaeser and Mare, 2001; Baum-Snow and Pavan, 2012; Moretti, 2013; Diamond, 2016). A key driver of the higher productivity and wages in large cities is the agglomeration effect stemming from the geographic clustering of workers and firms. The increased interaction and physical proximity between workers in large cities facilitate the interchange of knowledge and the learning of new skills from each other, which boosts the productivity of local workers (Jaffe et al., 2003; Glaeser, 1999; Wheaton and Lewis, 2002; Charlot and Duranton, 2004; Akcigit et al., 2018; Davis and Dingel, 2019; Jarosch et al., 2021; Baum-Snow et al., 2021). The co-agglomeration between firms and industries in large cities also reduces the cost of professional networking and the friction of building new business relationships, both of which create positive externalities on the productivity in large cities and industry clusters (Ellison et al., 2010).

This paper studies the effect of working from home (WFH) on the agglomeration economies of cities and the aggregate productivity implications of such an effect. On the one hand, WFH increases job flexibility, which has been shown to have positive productivity impact on some workers (Bloom et al., 2015; Barrero et al., 2021; Emanuel and Harrington, 2022). Workers could also access the high-productivity firms in large cities without having to bear the cost of housing there by supplying their labor input to large and expensive cities remotely while living in smaller and cheaper cities. In such a case, the adoption of WFH could have increased the labor supply to the high-productivity firms in large cities, which could enhance the aggregate productivity, wages, and output.

On the other hand, a possible negative effect of WFH is that the positive productivity spillovers stemming from the spontaneous interactions between workers facilitated by their physical proximity at workplace could be eliminated. The interactive "coffee talks" that went missing due to WFH may have reduced the amount of knowledge and idea exchanges between workers within firms and between workers across firms within industry clusters in large cities. In addition, the reduction in physical presence due to WFH may have also diluted large cities' role of facilitating the formation of strong professional networks and the fostering of complex business relationships. If the agglomeration effect of large cities is indeed weakened, productivity and wages of firms in large cities could be negatively affected and this could lead to workers switching to lower-productivity firms in smaller cities, resulting in not only a decline in the urban wage premium but also a decline in the aggregate productivity, wages, and output.

We present a highly stylized spatial equilibrium model to crystallize the competing forces of how WFH affects the strength of agglomeration economies, the urban wage premium, and the aggregate economic output. In the model, there is a large city and a small city. Workers choose either to work onsite—i.e., working and living in the same city, or to work remotely; remote work is only an option for jobs in the large city. The model shows that reducing the cost of WFH lowers both the wage and the rent premiums of the large city (where teleworkable jobs are more available), regardless of whether the agglomeration effect is weakened in the large city.[1] If the strength of the agglomeration economies does not weaken with the reduction of onsite workers, reducing the cost of WFH would increase labor supply to firms in the large city, resulting in a greater number of workers working for firms located in the large city while living in the small city. This would lead to more workers accessing the high productivity of firms in the large city, resulting in both a higher aggregate wage and higher output levels. In contrast, if the strength of the agglomeration economies decreases greatly with the reduction of onsite workers, then workers switching from onsite to remote working encouraged by the rise of WFH may strongly lower the strength of the agglomeration economies and productivity of the large city. If the strength of the agglomeration economies in the large city weakens enough, the lowered productivity in the large city may encourage workers to switch to low-productivity firms in the small city. The decreased productivity in the large city and the equilibrium reallocation of workers would lower aggregate wages and output levels.

Based on the model, we derive two sets of testable predictions to test the validity of the model and whether the agglomeration economies have been weakened by the rise of WFH. First, the increased adoption of WFH implies that the urban wage premium would necessarily decrease, *regardless of* whether the agglomeration economies are reduced in large cities. Second, if the weakening of the agglomeration effects is the primary driver of the decreased urban wage premium, then employment (based on firms' locations) in occupations with high WFH adoption should see a disproportionate decrease in large cities compared to in smaller cities. In contrast, if the increased labor supply is the primary driver of the decreased urban wage premium, then employment in occupations with high WFH adoption should see a disproportionate increase in large cities.[2]

[1] The model assumes that the agglomeration effect only comes from productivity externalities created by *onsite* workers.

[2] One note of caution is that if we see a disproportionate increase in employment in high-WFH occupations in large cities, the observation may still be consistent with decreased agglomeration effects. The decrease just may not be enough to offset the increased labor supply. In contrast, if we see a disproportionate decrease in employment and decrease in wages in high-WFH occupations in large cities, the observation would be strong evidence for declined agglomeration effects in large cities.

To empirically analyze whether the adoption of WFH has an impact on local productivity and whether the effect on productivity is owing to the reduction in the agglomeration economies, we use the COVID-19 pandemic as an empirical setting since the pandemic has forced firms in many occupations to massively adopt WFH (Bick et al., 2022; Bartik et al., 2020; Brynjolfsson et al., 2020). It is noteworthy that this paper does not intend to analyze the short- or long-run effect of the pandemic per se, predicting the extent to which on-site working will return over 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 of the study.

We use several data sources to test the model predictions. First, we use data on advertised wages from Emsi Burning Glass (now Lightcast) to study changes in the urban wage premium across occupations year by year around the pandemic. We show that the urban wage premium decreased considerably for jobs in which WFH adoption during the COVID-19 pandemic was very prevalent. In contrast, the urban wage premium decreased with a much smaller magnitude for jobs in which the level of WFH adoption was low or moderate. We also find that for jobs with a high level of WFH adoption in the wake of the pandemic, the urban wage premium decreased sharply regardless of whether the jobs require college degrees.

One potential concern for our finding is that the results may be spuriously driven by spatial sorting of skill supply or demand during the pandemic. In particular, the demand for high-reward skills, which are associated disproportionately with white-collar teleworkable jobs, may have sorted out of large cities during the pandemic (Dingel and Neiman, 2020). Therefore, our results may have captured the spatial sorting of skills rather than a genuine decrease in the urban wage premium. Fortunately, the Burning Glass data provide detailed skill requirements associated with each job posting. We find that while a portion of the decline in the estimated urban wage premium can be attributed to skill sorting, holding each job's observable skills constant, the urban wage premium still declined significantly among jobs with high WFH adoption.

We next proceed to test whether the decreased urban wage premium among the high-WFH jobs was primarily driven by reduced agglomeration effects in large cities or increased labor supply (of remote workers) in large cities. To do so, we use the Quarterly Census of Employment and Wages (QCEW) to examine whether the count of employment of occupations with high WFH adoption grew faster or slower during the pandemic in large cities than in small cities. We find that compared with the year prior to the pandemic, employment (based on firms' locations) of occupations with high WFH adoption declined disproportionately in large cities during the pandemic. In other words, not only did the relative wage of the high-WFH jobs decrease in large cities, there was also an accelerated exodus of high-WFH jobs from large cities. This empirical observation implies that the declined relative wage in large cities is not likely due to an increase in the remote labor supply but likely due to the weakening of agglomeration economies in large cities.[3]

Lastly, in addition to directly testing the model predictions, we provide further evidence supporting the hypothesis that the decreased urban wage premium among the jobs with high WFH adoption has been driven by a decrease in agglomeration economies in large cities. Since the Burning Glass data provide skill requirements of each job posted online, we conduct a Gelbach decomposition exercise in which we dissect the change in the urban wage premium of high-WFH jobs into the urban wage premiums of *skills* required in those jobs (Gelbach, 2016). We hypothesize that if increased labor supply to large cities enabled by the possibility of WFH drove down the urban wage premium, we should see the urban wage premium of skills that complement particularly well with remote work decrease and contribute significantly to the overall decrease in the urban wage premium among the high-WFH jobs. Alternatively, if the weakening of agglomeration economies in large cities was the primary driving force behind the decreased urban wage premium, we should see a decrease in the urban wage premium of skills commonly associated with or conducive to knowledge spillovers, building networks, and nurturing business relationships.

The Gelbach decomposition exercise shows that skill families such as “Building Relationship” and “Marketing and Public Relations” experienced a sizable decrease in the urban wage premium and contributed significantly to the decrease in the urban wage premium of high-WFH jobs. The decline in the urban wage premium of the relationship-building skills suggests a loss of marginal value of these skills in large cities, indicating that activities which complement the skills such as exchanging ideas and building new business partners in large cities are likely to have diminished.

Our paper contributes to several strands of literature. First, our findings add to the actively ongoing studies of how the rise of WFH during the COVID-19 pandemic affected cities and productivity. Many studies have documented the shift of housing demand from city centers to the suburbs and from large cities to small cities as a result of the increasing prevalence of WFH (Liu and Su, 2021; Gupta et al., 2021; Althoff et al., 2022; Ramani and Bloom, 2021; Delventhal et al., 2022; Li and Su, 2022). Other papers analyze the role of the endogenous change in productivity due to the WFH shock and how such a change in

[3]Some studies have shown that workers’ productivity became higher or higher-than-expected when working remotely compared with working onsite (Bloom et al., 2015; Barrero et al., 2021; Emanuel and Harrington, 2022). Our findings do not contradict these results. Specifically, we do not compare the productivity of WFH workers and onsite workers, holding all else equal. Instead, our result suggests that the adoption of WFH may have disproportionately affected the relative productivity of the jobs based in larger cities. This reduction in the relative productivity could have happened to onsite workers and remote workers *alike*, because fewer workers working onsite as a result of WFH affects the degree of spillovers benefited by both onsite and remote workers.

productivity affects the well-being and inequality of the U.S. population (Behrens et al., 2021; Delventhal and Parkhomenko, 2022; Davis et al., 2021). Our paper shows that jobs for which WFH became very prevalent saw a decline in the strength of agglomeration economies in large cities. We also present evidence of declined productivity due to the missing physical presence of onsite workers, and highlight the weakening physical interaction and its productivity consequence as a negative side effect of the adoption of WFH.

Moreover, our paper contributes to the vast literature that investigates the agglomeration economies of cities and urban productivity premium. This literature seeks to understand why workers and firms are more productive in larger cities. Previous studies find evidence that the productivity premium of large cities is driven both by more productive firms and workers sorting into large cities and large cities raising the productivity of firms and workers (Combes et al., 2008; D'Costa and Overman, 2014; Gaubert, 2018; Martellini, 2022). Additionally, Glaeser and Mare (2001), De La Roca and Puga (2017), and Eckert et al. (2022) show that the experience in large cities not only raises the productivity and wages of workers but also raises workers' wage growth even after they leave large cities.

Our paper sheds light particularly on the mechanisms of cities' agglomeration effects. Earlier papers have provided micro-foundations of and evidence for various mechanisms that give rise to agglomeration economies, three of which are the most prominently discussed: knowledge spillovers, input-output linkages, and labor pooling (Duranton and Puga, 2004; Rosenthal and Strange, 2003; Bleakley and Lin, 2012). Our paper provides one more piece of evidence that in-person interaction afforded by physical proximity with a large group of workers likely enhances productivity of local workers. This finding is manifested in the relative productivity decline in large cities due to the sudden increase in the prevalence of WFH. We further validate this conclusion by showing that declined relative wage returns to relationship-building skills in large cities drove down the urban wage premium of high-WFH jobs. The declined marginal value of social skills in large cities indirectly suggests that the occurrence of events rewarding these skills decreased.

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 and tests the model predictions. Section 5 presents the Gelbach decomposition exercise to further shed light on the mechanism of the changing agglomeration economies. Section 6 concludes.

2 Stylized Model of Working from Home and Agglomeration

To illustrate how the increased adoption of WFH could affect agglomeration economies, the urban wage premium, and productivity, we present a highly stylized model to capture the mechanisms at play and to summarize the key implications of WFH in the presence of local agglomeration externalities.

Assume there are two locations: H and L. H represents a large and high-density city, and L represents a small and low-density city. We assume that people who work in location H can either be physically present (onsite) by also living in location H, or can live in location L and work remotely.[4] However, if they live and work in two different locations, they incur a long-distance cost ϕ. We assume those who work in location L must also live in L.

Let N_{HH} be the number of people working for firms located in location H and living in H and let N_{HL} be the number of workers working in H but living in L. Likewise, N_{LL} denotes the number of people working for firms located in L and living in L. We normalize the total number of workers in the economy to be 1.

Workers make the location choice: (i) working and living in H: HH, (ii) working in H and living in L: HL, or (iii) working and living in L: LL. For simplicity, we assume all workers are identical.

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 location H take as given. Given the level of B_H, firms use labor, supplied either onsite N_{HH} or long-distance N_{HL}, as the input for production. Outside each firm's determination, the presence of onsite workers carries productivity externalities such that $B_H = B_H(N_{HH})$ is a function of the number of onsite workers present in location H:

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

[4]For simplicity, we assume that workers living in location H never work remotely.

where $\theta > 0$, which captures the intensity of the productivity externalities driven by the agglomeration economies of workers in location H. We can consider this as externalities created by spontaneous physical interaction and the ease of relationship-building in large and densely packed locations.

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 with a higher level of labor supply due to the diminishing marginal return of labor. However, thanks to the production externality term, a higher presence of onsite workers can drive up the wage due to the agglomeration effect.

Small/Low-Density City L: The production function in the small and low-density location L is simpler since only onsite workers can be 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 not a function of the number of onsite workers. This is equivalent to assuming that the intensity of production externality $\theta = 0$. We believe this is a sensible assumption because the production externality has been shown to be a phenomenon facilitated by high-intensity of communication and knowledge exchange more frequently occurring in large cities and industry clusters.

Firms' profit-maximizing problem yields that the local wage is

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

2.2 Housing Market

We assume that housing cost responds to local housing demand, though with different responsiveness depending on the local housing supply elasticity. Local housing demand in location j, $j \in \{H, L\}$, is the sum of 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 can be written as

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

The total housing demand in location H is simply the number of workers who work and live in H. The rent in location L can be written as

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

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

2.3 Workers' Location Choice

Workers potentially have three choices: they can work and live in location H, work in location H but live in location L, or work and live in location L. We include an exogenous cost ϕ associated with working and living in different locations. Before the pandemic, ϕ was likely to be high. As a result, most people tended to work and live in the same city. The cost exogenously declined when the remote work option became prevalent. We then examine the impact of WFH on the equilibrium outcome by evaluating the comparative static of a decline in ϕ.[5]

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

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

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

[5]Our way of modeling the adoption of WFH is more stylized than some of other recent papers that study the cause and effect of WFH on productivity such as Davis et al. (2021) and Delventhal and Parkhomenko (2022). Instead of investigating the origin of the adoption of WFH like the other two papers do, we focus on how WFH affects the agglomeration spillovers. In our model, we keep the marginal productivity of remote and onsite workers the same and conveniently use ϕ to force the change in the fraction of workers working remotely. We do so for the purpose of simplifying the analysis in the stylized model. One can think of the reduction of ϕ during the pandemic as a reduced-form way of capturing both the relative productivity increase of WFH as described by Davis et al. (2021) and the change in social norm by Delventhal and Parkhomenko (2022). The purpose of our analysis does not require making explicit assumptions on that front. In addition, our stylized model abstracts away from commuting and hybrid arrangement combining WFH and working onsite. We only have two locations, and workers who work and live in the same location are assumed to be working onsite. Otherwise, they are working remotely. This is clearly a highly stylized abstraction. Nevertheless, our model is designed to crystallize the intuition of how WFH can affect agglomeration, and thus we purposefully simplify other driving forces to present a focused picture.

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

where w_H and w_L are the log wages in locations H and L; r_H and r_H are log rents in locations H and L; 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 the case of a corner solution where U_{HL} is too low such that no one lives in L and works in H):

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

The equalization property of the homogeneity assumption allows us to easily solve for the comparative static results and study the insights from the model.

2.4 Effect of WFH in Equilibrium

Urban Wage Premium Based on the equalized utility levels, it is clear that the reduction of ϕ as a result of the rise of WFH technologies would force the spatial gap in both rents and wages to narrow. If we take the difference between the first and the second equations, we can see that the rent premium between H and L is a function of ϕ:

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

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

$$w_H - w_L = \phi.$$

Therefore, when the cost of remote working ϕ decreases, the urban wage premium would decrease. However, these conditions cannot reveal how much the equilibrium wages and output levels in H and L are affected by the decrease of ϕ and how much the aggregate wages and output levels are affected, which are analyzed below.

Agglomeration and Aggregate Productivity To analyze the impact of lowering ϕ on the equilibrium productivity, wages, and output, we totally differentiate the sum of production in both locations with respect to ϕ. This allows us to see the channels 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 is the same as the direction of change for wages and productivity.

Here is how output is affected by a decrease in ϕ:

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

The effect of reducing ϕ can be decomposed into two components:

1. A decrease in output due to decreasing agglomeration economies in production in location H: The output loss will be large if the rise of WFH lead to a large reduction in the number of onsite workers *and* if the strength of the agglomeration economies is very sensitive to the number of onsite workers (i.e., θ is large).

2. A change in output due to the reallocation of labor from location L to location H: Under the assumption that $W_H > W_L$, if the rise of WFH leads to more workers switching to working for firms located in H (i.e., $N_{HH} + N_{HL}$), the aggregate output would increase by the difference in the marginal product of labor (i.e., wages) between the two locations due to the reallocation. If the rise of WFH leads to more workers switching to working for firms located in L, the reverse would happen, and aggregate output would decrease due to the reallocation.

Based on the model assumptions, the first component is definitively negative, if $\theta > 0$. However, the sign of the second component depends on the direction of the reallocation of labor between H and L. The intuition of this equation is the following: The rise of WFH will reduce the number of onsite workers, which lowers the strength of agglomeration effect of H location, negatively impacting output. However, if WFH enables enough workers to remotely supply their labor to the higher-productivity location H while living in L, the gains from such reallocation may offset the productivity loss due to the weakening agglomeration. However, if the strength of agglomeration economies in H is reduced so much that workers reallocate from H to L, then the aggregate output will definitively decrease. One note of caution is that there exists a middle case where more workers on net switch to working for firms in the higher-productivity location H, but the weakening of agglomeration economies still leads to a net loss of output.

To analyze the sign of the second component, we need to know the direction of the reallocation of labor due to the rise of WFH (whether $\frac{\partial N_{HH}}{\partial(-\phi)}$ and $\frac{\partial(N_{HH}+N_{HL})}{\partial(-\phi)}$ are positive or negative). To do so, we present the comparative static exercises for the equilibrium reallocation of population and labor in response to the change in ϕ. Since the log wages and rents w_H, w_L, r_H, and r_L are all functions of N_{HH}, N_{HL}, and N_{LL}, we can calculate how these population numbers are affected by the size of ϕ in the spatial equilibrium by applying the implicit function theorem. Appendix A1 shows the precise derivation procedure. Here, we present the effect of reducing ϕ on the numbers of onsite and remote workers working for firms in H:

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

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

Consistent with intuition, we can see lowering the cost of WFH reduces the number of onsite workers (N_{HH}). However, the effect of reducing ϕ on the overall labor supply to production in location H is not definitive:

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

Interestingly, whether the effect is positive or negative depends on the intensity of the agglomeration externality θ. If $\theta = 0$ (without considering any externality spillovers), lowering ϕ would unambiguously increase the total labor supply to location H. The intuition is that a high remote work cost forces everyone who receives wage from firms in H to bear the cost of housing in location H. This lowers the number of workers who are able to realize the productivity offered in location H. The drop in the cost of remote work allows more workers to switch their residential to location L while working for firms in H. In other words, reducing ϕ alleviates the congestion problem facing those choosing to work in H.

Alternatively, if $\theta > 0$ (the agglomeration productivity externality is activated), the effect is lowered and could turn negative if θ is sufficiently large. The reason for the counteracting effect of agglomeration externality is that as workers switch from onsite work to remote work, the productivity spillover from onsite workers is reduced, which lowers the marginal product of *both* onsite workers and remote workers. Moreover, since such externalities are not internalized in firms' profit maximization problem and thus not priced in wages, the number of onsite workers will be lower than the optimum.

Model Predictions In summary, the model implies that the rise of WFH (reduction in ϕ) will lead to a reduction in the urban wage premium, regardless of whether the agglomeration economies in large cities are weakened or not. An increase in the labor pool for firms in large cities enabled by WFH could also drive down the urban wage premium.

To further test whether the agglomeration economies decreased in large cities, we need to test whether $\frac{\partial(N_{HH}+N_{HL})}{\partial(-\phi)} < 0$. If in addition to a declined urban wage premium, we also find that total employment *decreased* in large cities as a result of WFH, that would imply that θ is not only positive but also large enough to lead to people switching out of working for firms in large cities, which means the agglomeration economies in large cities must have decreased due to WFH. In such case, the model implies that the declining agglomeration economies in large cities would lead to aggregate output loss, as well as aggregate productivity and wage losses.

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

We use the sudden increase in the prevalence of WFH during the COVID-19 pandemic as the empirical setting to test the above predictions and disentangle the effects of WFH. The adoption of WFH during the pandemic varied widely across different industries and occupations. We test the model predictions by examining observed changes in spatial patterns in wages and employment of occupations with high levels of WFH adoption and occupations with low/moderate levels of WFH adoption, separately.

Occupations with Low/Moderate Levels of WFH We first discuss what to expect in the local labor markets for occupations with low/moderate levels of WFH adoption. It is important to keep in mind that, in addition to the rise in the adoption of WFH, the COVID-19 pandemic has also led to a surge in net migration from large cities to smaller cities. The migration has been not only fueled by the shifting location demand away from locations of employers due to the prevalence of WFH but also driven by the reduced value of urban amenities and activities in large cities during the pandemic. The shifted residential demand from large to small cities is likely to have reduced the local labor *supply* in large cities for occupations that require onsite presence (low adoption of WFH) but is unlikely to have impacted the local labor supply for occupations with high adoption of WFH.

In addition, as people move to smaller cities, the demand for local services (e.g., restaurants) is also likely to be shifted from large to small cities. The spatial shift in the demand for local services during the pandemic is likely to have reduced local labor *demand* in large cities in local service sectors, which tend to require onsite presence of their workers (low adoption of WFH). In contrast, occupations with high adoption of WFH during the pandemic tend to be in professional services, which do not respond to local service demand nearly as much (Eckert et al., 2022). Hence, the local labor demand in high-WFH occupations should not have been impacted much by the shifted demand for local services.

Figure 1a illustrates how such shifts in the labor demand and supply curves may affect the equilibrium wage and employment in large cities for occupations with low/moderate levels of WFH adoption. The double shifts downward could lead to a decrease in employment in large cities in occupations with low/moderate WFH adoption ($M \to M'$). However, equilibrium wages in these occupations in large cities may not move in a particular direction. Thus, the urban wage premium for jobs with low/moderate WFH adoption may not move much if the local labor demand and supply offset each other. Nevertheless, we should expect employment in occupations with low/moderate WFH adoption based in large cities to decrease and many of them should shift to smaller cities.

Occupations with High Levels of WFH For occupations with high WFH adoption during the pandemic, the predictions are very different. First, for high-WFH occupations, as mentioned previously, neither the labor demand nor supply should have been affected by changes in demand for residential locations or local services. Hence, the migration forces that profoundly affected the labor market of low-WFH occupations should not apply here.

In contrast, the forces described in the model should play the first-order roles in what to expect in the labor market of high-WFH occupations during the pandemic. On the one hand, there may be an increase in the labor supply of (remote) workers for firms in large cities due to the increased prevalence of WFH. On the other hand, the reduction in onsite workers in large cities may reduce the productivity in large cities due to the weakening of agglomeration economies, which may reduce the labor demand in large cities.

Figure 1b illustrates how such shifts in the labor demand and supply curves may affect the equilibrium wage and employment in large cities for occupations with high WFH adoption. The reduced labor demand and expanded labor supply in large cities will reduce the wages ($w \to w'''$) and thus reduce the urban wage premium for the jobs with high WFH adoption. Crucially, if we observe that such occupations saw an increase in employment in large cities, it implies that there is a relatively strong increase in labor supply due to firms' adoption of WFH in large cities. Note that such an observation does not necessarily imply that the demand curve has shifted down. In contrast, if we observe that employment of these occupations decreased in large cities, it implies that labor demand in large cities must have shifted down (because labor supply curve shifted up due to WFH). Because labor demand in these sectors is likely to be detached from local demand for services, a downward shift in labor demand is likely to imply a decrease in local productivity, which presents evidence that WFH leads to declining agglomeration economies in large cities.

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

3 Data

3.1 Advertised Wages by Occupation and Geography: Burning Glass

The wage data come from Lightcast, which is the new name of Burning Glass Technologies. We refer to the data as Burning Glass data from here on. Burning Glass Technologies (merged with Emsi) is a company that scrapes and cleans job postings off online platforms such as online job boards, company websites, and large online listings. The data come from roughly 40,000 company websites and online job boards. The company aims to collect the universe of job postings in the U.S. They use a de-duplication algorithm to avoid multiple showings of the same job posting. The Burning Glass data cover around 70% of the vacancies in the U.S. (Carnevale et al., 2014).[6] Moreover, since we rely on the wage information of the job postings and only around 20% of the postings in the data contain wage information, the wage sample in the Burning Glass data represents about 14% of the U.S. job vacancies. The wage information contains both total salary and hourly salary and is shown in the form of a range: a maximum and a minimum value. We take the mid-point of the maximum and the minimum hourly salary of each job as the wage of the job.

Crucially, the job postings contain extremely detailed occupation codes (SOC), which Burning Glass Technologies produces using the written texts in each job posting. We use the occupational categories to assign the degree of WFH adoption for the job posting using separate datasets (Hazell et al., 2022). The data also provide the counties of the locations associated with the job postings. We assume that the locations

[6]Carnevale et al. (2014) show that online job ads tend to be over-represented by vacancies of higher-skilled and white-collar positions, which implies that the Burning Glass data are susceptible to this bias. However, we do not use the Burning Glass data to study the total number or the local composition of jobs, or their changes. Instead, we mainly use the wage information of the posted jobs to analyze how local wages changed differentially across occupations.

embedded in the job postings are the locations of the firms' office.[7] This county variable is used for the location of the job.

The job postings also provide various job-level characteristics such as the minimum degree requirement, full-/part-time status, salary types, tax terms, and highly detailed arrays of skill requirements.[8] The provision of job-level characteristics allows us to study changes in the urban wage premium controlling for job characteristics. By observing detailed skill requirements, we are able to disentangle changes in the composition of workers or local skill demand from changes in the local wage premium holding skill demand constant. Because such information is absent in most datasets, including administrative data, Burning Glass data provide unique resources to conduct our analysis. For computational convenience, we take a 10% random sample from the raw Burning Glass data for our statistical analysis including binned scatterplots and regression analyses.

3.2 Geography of Jobs by Occupation

We calculate the number of jobs in each occupation by county using data from the Quarterly Census of Employment and Wages (QCEW). The data provide a quarterly count of employment covering more than 95% of all U.S. jobs across industries as defined by the NAICS code. We use the Burning Glass data to create a highly detailed crosswalk between NAICS and ONET occupational codes. Using the crosswalk, we calculate the employment number by occupation and county. Importantly, because the QCEW is based on employment information from business establishments covered by the Unemployment Insurance programs, the employment counts reported by QCEW are based on the location of the employers not workers. This is crucial for us when we try to test how the rise of WFH affected the labor supply to firms in large cities vs. in small cities.

[7] Some may be concerned that the location associated with each job posting may not be the location of the primary job location or the location of the firm but instead the location of the workers targeted by the job ads. Since Burning Glass scrapes the Internet job boards for the data, there are no direct ways to verify whether the job location truly represents the location of the job/firm. To verify that the location associated with each job posting is largely based on the location of the job, we validate the local industry shares in the job postings with the local industry shares observed in the QCEW data, which are based on employers' locations. We calculate each of the 3-digit NAICS industry share in each MSA for both datasets. In Figure A2, we plot those shares in a binned scatterplot, separately for the samples in January 2020 (before the start of the pandemic) and in July 2020 (after the start of the pandemic). The industry compositions largely line up with the compositions based on employers' locations before and after the start of the pandemic.

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

3.3 Measuring the Adoption of Working from Home (WFH)

American Community Survey The American Community Survey (ACS) asks respondents how they usually get to work in the last week (Ruggles et al., 2022). Besides the means of transportation, the respondents are allowed to choose having worked from home. The information on whether a respondent works from home, combined with the occupation code (OCC2010), allows us to compute the fraction of workers reporting to have worked from home for each occupation in 2019 and 2020, respectively. We then can compute the prevalence of WFH for each occupation before and after the start of the pandemic.

Current Population Survey We validate the measurement from the ACS with data from the Current Population Survey (CPS) (Flood et al., 2022). Beginning in May 2020, the Bureau of Labor Statistics started to release supplemental information on the effect of the COVID-19 pandemic on the labor force. In particular, the survey started to report monthly whether a respondent worked remotely for pay due to the pandemic. Since the CPS also reports the occupation code (OCC2010), we are able to do a similar exercise as with the ACS.

However, we only use the CPS as a supplement data source to validate the measurement from the ACS, because the CPS data on remote work only started in May 2020. Thus, it is not possible to measure differential *increases* in the prevalence of WFH across occupations. Another drawback of the CPS is that it only asks whether one worked remotely *due to* the COVID-19 pandemic. In the beginning of the pandemic, most workers turned remote due to the pandemic. However, as the pandemic progressed, the reasons for continuing to work remotely may become less directly attributed to the pandemic per se. The adoption of WFH technologies may have compelled some workers and employers to stick with WFH arrangement even when the pandemic danger subsided. Hence, the CPS reporting on remote work may have become increasingly inaccurate as the pandemic progressed.

American Time Use Survey The American Time Use Survey (ATUS) provided by the Bureau of Labor Statistics is another source from which we get information on the increase in the adoption of WFH by occupation (Hofferth et al., 2020). The ATUS measures the amount of time people spend doing various activities through a 24-hour period. Each activity is accompanied by a reported location. Hence, the data enable us to record the fraction of working hours that occurred at home by occupation over time. The ATUS releases data annually, which allows us to compare the prevalence of WFH before and after the pandemic.

However, the drawback of the ATUS is that the number of respondents tends to be vastly smaller than the ACS. Hence, we use the ATUS to validate the measurement from the ACS.

O*NET We analyze changes in the adoption of WFH by occupation by examining which occupational characteristics best predict a more pronounced increase in WFH. We use the Occupational Information Network (O*NET) data as the source of occupational characteristics. The O*NET is developed by the U.S. Department of Labor/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.

In addition, because of the universal coverage of all occupations, we are able to use the multitude of occupational characteristics to impute changes in WFH prevalence for some occupations not identified in the ACS data, based on their similarity of job characteristics to jobs observed in the ACS data.

4 Empirical Evidence

4.1 The Adoption of WFH Arrangement

We begin the empirical analysis by documenting changes in the adoption of WFH arrangement since the start of the pandemic. First, we present the aggregate share of workers who work remotely based on the ACS and the ATUS from 2005–2020. Both datasets have long reported information on locations where people work. To highlight differences in WFH during the pandemic, we present the number for 2020 as the imputed share of workers working remotely in 2020 after the first quarter (Q1). We impute the share of WFH assuming that the share of workers who worked remotely in Q1 of 2020 is the same as the share observed in 2019.[9] Figure 2a shows that the overall prevalence of WFH skyrocketed after the pandemic started in 2020. Such patterns are reflected in both the ACS and ATUS data.

Consistent with the prediction of Dingel and Neiman (2020) and the documentations of other papers, we show that the level of WFH adoption differed widely across different types of workers and occupations (Barrero et al., 2021; Bick et al., 2022; Brynjolfsson et al., 2020).[10] Figure 2b shows the evolution of the

[9]Assume that the share of WFH in 2019 is $share_{2019}$ and the observed share of WFH in 2020 whole year is $share_{2020}$. Then the share of WFH in post-Q1 2020 is just $share_{Q2-Q42020} = \frac{share_{2020}-0.25share_{2019}}{0.75}$.

[10]A few recent papers use customized surveys to document differential changes in the prevalence of WFH during the pandemic—

share of WFH workers for those with and without college degrees. We find that college-educated workers were more likely to have started WFH in 2020. Across occupations, Figure 2c shows a very high level of WFH adoption by computer and mathematical occupations, followed by business and finance occupations. In contrast, occupations related to food services and health care saw a much lower level of WFH adoption.[11]

Imputation of WFH Adoption for All SOC-ONET Occupations To determine which jobs saw a high level of WFH adoption and which jobs saw a low or moderate level of WFH adoption, we measure the level of WFH adoption using both the directly observed share of WFH workers from the ACS and the work context variable from the O*NET occupational characteristics. Despite the large sample size, ACS has a relatively coarse occupation code (OCC2010). As a result, matching the observed changes in WFH shares by occupation obtained from the ACS with the SOC-ONET occupation code in the Burning Glass data would create a relatively small successfully matched sample. To improve the matching, we use the Lasso regression to select the O*NET occupation characteristics that can best predict WFH adoption, and then we project the observed level of WFH adoption by occupation onto the selected O*NET occupation characteristics, all of which contain SOC-ONET code and provide a much wider coverage of occupations than the occupation code provided by the ACS.

Table A1 in the Appendix shows the Lasso coefficients and the OLS coefficients post-estimation. Figure A4 in the Appendix shows a scatterplot between the predicted change in the share of WFH workers and the observed change in the share of WFH workers by occupation within the sample of the regression. We show that based on the work context characteristics retained by Lasso, the predicted adoption of WFH lines up well with the observed adoption of WFH.

Definition of High WFH Adoption In the rest of the paper, we conduct analysis for jobs in occupations with high levels of WFH adoption and jobs in occupations with low/moderate levels of WFH adoption separately. In our main analysis, we define occupations with high levels of WFH adoption as occupations in which the national share of WFH workers increased by more than 25 percentage points in 2020 after the first quarter. We define occupations with low/moderate levels of WFH adoption as the rest of the occupations.

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 highly detailed occupation code, which is not available in these surveys.

[11]Changes in the adoption of WFH are computed with the ACS. To test the validity of the measurement, we use the ATUS and the CPS data for comparison. For each dataset, we calculate the share of WFH workers in the time period in 2020 under the pandemic for each occupation group as defined in the IPUMS USA. We then plot the ACS-computed shares against the ATUS- and CPS-computed shares. See Figure A1 in the Appendix.

Around 9% of job postings in our Burning Glass sample belong to occupations of high levels of WFH adoption.

4.2 The Effect of WFH Adoption on the Urban Wage Premium

In this section, we analyze the effect of the adoption of WFH during the COVID-19 pandemic on the urban wage premium. Based on the empirical tests described in Section 2.5, we expect that occupations with high levels of WFH adoption would experience a drop in the urban wage premium during the pandemic, while occupations with low or moderate levels of WFH adoption would experience little changes.

First, we plot the residualized log posted hourly wages on the residualized log employment number of each job's occupation and MSA. The log employment size measures the size of the local labor market relevant for each job. Hourly wages are from the Burning Glass data and the employment size is from the QCEW. To residualize the variables, we control for the SOC-ONET occupation code, three-digit NAICS code, years of education required by the job, salary type, full-/part-time status, tax terms, and the job posting month.

Figure 3a shows the plot using the sample of all jobs from two separate periods: the pre-pandemic period (2018 and 2019) and the pandemic period (2020, 2021, and the first five months of 2022). Cross-sectionally, residual wages tend to be higher in larger labor markets, consistent with the prior empirical evidence. The urban wage premium, which is the *slope* of the plotted curve, decreased from 0.0289 to 0.0223 during the pandemic, which is a 0.668 percentage point decrease with statistical significance.

Figures 3b and 3c break the sample into jobs that require a college degree and jobs without the requirement, respectively. We find that the urban wage premium for both sets of jobs saw a decline. The decline for jobs that require a college degree is from 0.0379 to 0.0333. The decline for jobs that do not require a college degree is from 0.0267 to 0.0201. Both declines are statistically significant.

Finally, if we focus on the jobs that belong to occupations with high levels of WFH adoption, the results are much more striking. Figure 3d shows that the decline in the urban wage premium is very large and statistically significant for the high WFH-adoption jobs: from 0.0623 to 0.0356, which is a 2.67 percentage point drop from a starting number of 6.23 percentage point, which is approximately a 43% drop. In contrast, for jobs with low or moderate levels of WFH adoption (shown in Figure 3e), the drop in the urban wage premium is much smaller, from 0.0259 to 0.0210, which is about 19% from a much lower base number. The finding that the urban wage premium has dropped drastically for the jobs with very high levels of WFH adoption but declined markedly smaller for jobs with low or moderate levels of WFH adoption is consistent with the empirical prediction outlined in Section 2.5.[12]

To further analyze how the urban wage premium progressed before and after the pandemic, we examine four groups of jobs separately (based on the level of WFH adoption and whether the job requires a college degree) year by year from 2018 to the first five months of 2022. We normalize the annual urban wage premium by the estimates in 2018. Figure 5 presents the evolution of the urban wage premiums. The results suggest that the urban wage premium for jobs with high levels of WFH adoption declined sharply in 2020 and stayed at low levels in 2021. In particular, the high-WFH jobs without a college degree requirement saw a big drop in their urban wage premium in 2020, but such dip was reversed in 2021 and recovered back to the pre-pandemic level by early 2022. In contrast, the high-WFH jobs that require a college degree saw a persistently lower urban wage premium after 2020 and only saw a very weak recovery. The discrepancy between the high-WFH jobs with and without a college degree requirement may be a result of a more permanent adoption of WFH for higher-skilled jobs, while WFH arrangements could be more of a temporary contingency for lowered-skilled jobs. In addition, our measurement of the WFH adoption comes only from the 2020 data, which may not accurately reflect the status of each occupation's prevalence of WFH in 2021 and 2022. This may be another reason for the discrepancy.

In contrast to the sudden drop of the urban wage premium among the high-WFH jobs, the low- or moderate-WFH jobs, regardless of the college degree requirement, did not see a decrease in the urban wage premium during the entire course of the pandemic.[13]

Spatial Sorting of Skill Demand It could be a concern that the pandemic may have led to increased exits of higher-wage firms from large cities for various reasons, e.g., declining local productivity of large cities, which will lead to spatial sorting of skill demand. As a result, the reduction in the relative wage in large cities may not necessarily imply that the urban wage premium declined for a given set of jobs but may instead reflect the exits of higher-skill jobs from large cities. Thus, we need to further analyze how much

[12] We also conduct similar exercises in which we plot the residualized log posted wage against the residualized log employment size by *MSA as a whole* (rather than by MSA and occupation). The results are shown in Figure A5 in the Appendix. The results are largely comparable.

[13] In Figure A7 in the appendix, we plot the residual changes in log posted wages for the four occupation groups in a few selected MSAs between the pandemic period and the pre-pandemic period. We can clearly see that the cities that experienced the largest decline in the residual wages in the computer and mathematical occupations are the ones traditionally associated with being clusters of the computer industries. Similarly, the cities that experienced the largest decline in the residual wages in the business and finance occupations are ones traditionally considered large centers of business and finance. In contrast, these patterns do not appear obvious across MSAs in food preparation, service and health occupations.

our estimates of the decline in the urban wage premium is driven by spatial sorting of skill demand, and how much is driven by a decline in the urban wage premium for a given set of worker skills.

Fortunately, the Burning Glass data provide a very rich vector of skill requirements associated with each job posting. The added complexity of the data is that some jobs specify one or two skill requirements while other jobs may specify more than ten distinct skills in their postings. Thus, the length of the skill vector varies across jobs. For computational convenience, we specify the first 20 skills specified by each job, ranked by each skill's overall frequency of mentions across all job postings.[14] If a job contains fewer than 20 skills, then the extra skill slots are all categorized as "na."

To study changes in the urban wage premium for jobs in high-WFH occupations after the pandemic for a given set of worker skills, we estimate the following equation:

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

where w_{ikjt} is the posted hourly wage of job i in occupation k at location j in year t; M_{kj} is the employment size of occupation j in MSA j (or the employment density—i.e., employment/area of each occupation at the county level);[15] $Post_t$ is an indicator of post-pandemic period (i.e., 1 if $t = 2020, 2021, 2022$, and 0 if $t = 2018, 2019$); $High_k$ is an indicator that k is an occupation with high levels of WFH adoption; $\mathbf{X}_{ikjt}$ is a vector of job-level characteristics, including the dummies for SOC-ONET occupation code, three-digit NAICS code, years of education required by the job, salary type, full-/part-time status, tax terms, job posting month, and required skills. The parameter α_1 represents the change in the urban wage premium after the start of the pandemic for occupations with low/moderate levels of WFH adoption; $\alpha_1 + \alpha_3$ represents the change in the urban wage premium after the pandemic for occupations with high levels of WFH adoption. We estimate the regression using the Burning glass data from 2018 to the first five months of 2022.

Table 2 presents the estimates of α_0, α_1, α_2, and α_3 in Equation 5. Columns 1–3 present the results with M defined as employment size. Column 1 does not control for any job-specific characteristics. Column

[14] Around 90% of the jobs in the sample specify fewer than 20 skills in their postings.

[15] An essential ingredient of agglomeration economies is frequently argued to be the compact proximity between similar workers, which facilitates communications and idea exchanges. Since employment *density* is better at capturing the compactness of workers, we use employment density at the occupation and county level as an alternative measurement of agglomeration. We calculate employment density at the county level rather than the MSA level because employment density often varies widely below the level of MSA. Since county is the lowest level of geography for the wage data, to best capture the geographic variation in employment density, we compute density at the county level.

2 includes basic controls (i.e., indicators of occupation, industry, education requirement, salary type, full-/part-time status, tax terms, and job posting month). Column 3 further controls for the skill fixed effects using the 20 skills assigned to the jobs. Column 4 presents the results with M defined as employment density, with the full set of control variables.

Throughout Columns 1–4, estimated changes in the urban wage premium for jobs with low/moderate WFH adoption are either positive or negative, and the magnitudes are small. In contrast, changes in the urban wage premium for jobs with high WFH adoption are strongly negative across all specifications. Specifically, the urban wage premium for jobs with high WFH adoption decreased by 0.0221 without any controls, and 0.02276 with basic controls. The estimated decline is reduced to 0.01773 with the full set of controls of skill fixed effects. This implies that a small part of the decline in the urban wage premium for the high-WFH jobs can be directly attributed to the spatial sorting of skill demand. Still, much of the decline appears to be a genuine reflection of the decreased price of labor in large cities holding skills constant.

Alternative Measurements of WFH Adoption It could be a concern that the results are specific to the way in which we define occupations as high WFH-adoption occupations. Next, we relax the assumption by defining 5 different indicators for occupations based on the imputed change in the prevalence of WFH (referred to as Δ): $\Delta < 0.1$, $0.1 \leq \Delta < 0.15$, $0.15 \leq \Delta < 0.2$, $0.2 \leq \Delta < 0.25$, and $\Delta \geq 0.25$.[16] The results are reported in Column 1 of Table 3. The results suggest that the urban wage premium for occupations with very low adoption of WFH saw no change. In addition, while the decrease in the urban wage premium did show up among occupations with moderate levels of WFH adoption, the largest decrease in the urban wage premium is concentrated among occupations with the highest level of WFH adoption.

In Column 2 of Table 3, we define an indicator based on whether an occupation belongs to the occupation groups of business/finance and computer/mathematics. As is shown in Figure 2c, these twp occupation groups demonstrate spectacular adoption of WFH in 2020. This regression result indeed suggests that these two occupation groups saw a disproportionate decrease in the urban wage premium compared to other occupations.

Lastly, we replace the indicator of high WFH adoption with the teleworkability indicator developed by Dingel and Neiman (2020). The result is reported in Column 3, which suggests that the teleworkable occupations saw a weakly larger decrease in the urban wage premium than other occupations. This is

[16] The fractions of job postings in the sample that fall in the five categories are the following: $\Delta < 0.1$: 51%; $0.1 \leq \Delta < 0.15$: 11%; $0.15 \leq \Delta < 0.2$: 18%; $0.2 \leq \Delta < 0.25$: 12%; $\Delta \geq 0.25$: 9%.

likely because the Dingel and Neiman indicator is a highly inclusive measurement of WFH possibility, but the result in Column 1 suggests that the decrease in the urban wage premium tends to be concentrated in occupations with the highest level of WFH adoption.

4.3 The Effect of WFH on Local Employment

The model in Section 2 suggests that the rise of WFH would lower the urban wage premium, either driven by reduced agglomeration economies in large cities or by an increased labor supply to firms in large cities due to the availability of WFH.

One way to distinguish whether the decline in the urban wage premium is primarily a result of weakening agglomeration economies is to test whether employment (based on firms' locations) decreased in large cities in response to the rise of WFH. If firms in large cities employed fewer workers in occupations with high WFH adoption *and* relative wages in large cities declined, this provides strong evidence that the agglomeration economies in large cities have been weakened.

We use the following simple regressions to study whether employment increased or decreased in MSAs with large employment sizes or employment density for jobs with different levels of WFH adoption:

$$\Delta \ln(Emp_{kjt}) = \sum_{t=2020,2021} a_1^t \ln M_{kj} \times Low_k + \sum_{t=2020,2021} a_2^t \ln M_{kj} \times High_k + \eta_{kt} + \theta_j + e_{kjt}, \tag{6}$$

and

$$\Delta \ln(Emp_{kjt}) = \sum_{t=2020,2021} a_1^t \ln M_{kj} \times Other_k + \sum_{t=2020,2021} a_2^t \ln M_{kj} \times CF_k + \eta_{kt} + \theta_j + e_{kjt}, \tag{7}$$

where $\Delta \ln(Emp_{kjt})$ is the change in log employment in occupation k and MSA j between January 2019 and January 2020, or between January 2020 and August 2021; M_{kj} is the employment size or employment density; Low_k is an indicator that occupation k has low/moderate levels of WFH adoption; $High_k$ is an indicator that occupation k has high levels of WFH adoption; $Other_k$ is an indicator that occupation k does not belong to the occupation groups "Computer and Mathematical" and "Business and Finance," CF_k is an indicator that occupation k belongs to the occupation groups "Computer and Mathematical" or "Business and Finance"—these occupations have been shown to be more prone to WFH adoption. Parameters a_1^{2020} and a_2^{2020} represent how employment changed between 2019 and 2020 with respect to the employment size of an MSA or employment density for low-/moderate-WFH occupations and high-WFH occupations, respectively. Similarly, parameters a_1^{2021} and a_2^{2021} represent how employment changed between 2020 and 2021 with respect to the employment size or density for low-/moderate-WFH occupations and high-WFH occupations, respectively. We also control for occupation $\times$ time period fixed effects and MSA fixed effects. We estimate the equations using the QCEW data.[17]

Table 4 we presents the results. Results in Columns 1 and 3 suggest that employment growth of both high- and low-/moderate-WFH occupations was relatively slower in MSAs with larger employment size and density even before the pandemic—estimates of both a_1^{2020} and a_2^{2020} are negative. However, after the pandemic started, employment declined much more in MSAs with larger employment size and density for both types of occupations—the estimate of both a_1^{2021} and a_2^{2021} are negative, and their magnitudes are much larger than a_1^{2020} and a_2^{2020}. Results in Column 2 also suggest that employment declined much more in MSAs with larger employment sizes after the pandemic compared with the pre-pandemic period.

It is noteworthy that the finding that occupations with low/moderate WFH adoption also saw a disproportionate drop in employment in large cities after the pandemic is consistent with the predictions outlined in Section 2.5. However, the driving forces behind the disproportionate drop in employment in large cities after the pandemic for the low-/moderate-WFH occupations and for the high-WFH occupations are different (the upper vs. lower panel of Table 1).

In summary, the findings on (i) the strong decline in the urban wage premium for jobs with high WFH adoption, and (ii) the disproportionate negative growth of employment in larger cities and industry clusters suggest that large cities' productivity premium stemming from their agglomeration economies has weakened among occupations in which WFH has been widely adopted.[18]

[17] All employment numbers are obtained from the QCEW data at the three-digit NAICS code and county level. We use the Burning Glass data to generate a crosswalk between the three-digit NAICS code and the SOC-ONET occupation code. Each job posting in the Burning Glass data is assigned with a three-digit NAICS code and SOC-ONET occupation code. We calculate the empirical distribution of three-digit NAICS conditional on each SOC-ONET. Using the probabilistic crosswalk, we impute the number of jobs for each SOC-ONET occupation in each county. We then use the county to MSA crosswalk to compute the numbers at the MSA level.

[18] Case-by-case analysis reveals the same story but with some added idiosyncratic complexity. In Figure A7, we plot the change in residual log posted wage for the high-adoption occupations and the low-adoption occupations in a few selected MSAs, and in Figure A9, we plot the employment growth of high-adoption occupations and low-adoption occupation in the same selected MSAs. We can see that among the high-adoption occupations, the decline in wages occurred disproportionately in cities commonly associated with high-tech and business clusters with a large concentration with white-collar jobs, and the dispersion of wage growth

5 Changes in the Urban Wage Premium by Skill

Lastly, we zoom out from the empirical tests of the model and indirectly assess the role of the changing agglomeration economies in the decreasing urban wage premium by analyzing how the urban wage premium of specific skills changed due to the rise of WFH. We seek to assess *which* skill types can explain the decline in the urban wage premium among high-WFH jobs most. If skills that are most complementary with or conducive to ideas exchange, relationship building, and networking saw a large drop in the urban wage premium and contribute strongly to the decline in urban wage premium of the high-WFH jobs, this would further validate the hypothesis that the rise of WFH weakened agglomeration economies in large cities.

We decompose the residual urban wage premium by applying the Gelbach decomposition method (Gelbach, 2016). Here is the intuition of the decomposition: Part of the reasons why the high-WFH jobs have a high urban wage premium is that the skills that are required for these jobs tend to carry very high urban wage premium. In other words, the skills such as relationship-building ability exhibit larger returns at firms in larger cities than at firms in smaller cities. The decrease in the urban wage premium carried by these skills would necessarily drive down the urban wage premium of jobs in which these skills used. We use the Gelbach decomposition method to empirically quantify which skill types saw the largest decline in the urban wage premium and were statistically the largest drivers of the decline in urban wage premium of the jobs with high WFH adoption.

5.1 Gelbach Decomposition

We use a simpler version of Equation 5 to estimate the change in the urban wage premium for high-WFH occupations during the pandemic by restricting the sample to jobs in high-WFH occupations only, since the results in Table 2 suggest that the decline in the urban wage premium is mainly relevant for high-WFH

is very large. In contrast, among the low-adoption occupations, wage growths are much more similar across these MSAs. The contrasting case-by-case observations are consistent with our statistical results. If we look at employment growth among both the high-adoption and low-adoption, the decline is generally more pronounced in large cities and industry clusters, consistent with our statistical results. However, there are exceptions. While San Jose, CA's wage decline in the high-adoption occupations was much more pronounced than New York or San Francisco, the employment decline was much more muted. This suggests that for San Jose, the decline in wages may have been significantly driven by a rise in labor supply from workers living elsewhere enabled by remote working. Another exception is Austin, TX. Even though Austin experienced a decline in wage among high-adoption occupations, the employment growth in these occupations in Austin was exceedingly high. This could certainly reflect a rise in labor supply due to remote working. But it may also be the result of the inflow of high-tech firms into Austin during the pandemic. Furthermore, we also plot the similar numbers for wage growth and employment growth by the selected occupation group, shown in Figure A7 and Figure A9. These figures reveal another notable case in the food prep and service occupations. Even though the decline in wages does not appear strongly correlated with the sizes of the city, the employment decline is strikingly stronger in large cities and business clusters. This is likely due to the mechanisms depicted in Figure 1a, where both labor demand for service sectors and labor supply declined in large cities, leading to a vast decline in employment but indeterminate changes in wages.

occupations:

$$\ln(w_{ikjt}) = \gamma_0 \ln M_{kj} + \gamma_1 Post_t + \gamma_2 \ln M_{kj} \times Post_t + \mathbf{X}_{ikjt}\mathbf{\Psi} + \epsilon_{ikjt}. \tag{8}$$

The change in the urban wage premium for high-WFH occupations during the pandemic is simply γ_2.[19]

If we consider changes in the skill-specific urban wage premiums are the variables omitted in this baseline estimating equation, then the fully specified estimating equation should be the following:

$$\begin{aligned}\ln(w_{ikjt}) = {} & \tilde{\gamma}_0 \ln M_{kj} + \tilde{\gamma}_1 Post_t + \tilde{\gamma}_2 \ln M_{kj} \times Post_t + \mathbf{X}_{ikjt}\tilde{\mathbf{\Psi}} \\ & + \sum_s \beta_0^s \ln M_{kj} \times Skill_i^s + \sum_s \beta_1^s Post_t \times Skill_i^s \\ & + \sum_s \beta_2^s \ln M_{kj} \times Post_t \times Skill_i^s + \tilde{\epsilon}_{ikjt},\end{aligned} \tag{9}$$

where $Skill_i^s$ is an indicator that skill s is required in job i. β_2^s represents the change in the skill-specific wage premium for high-WFH jobs after the pandemic. The change in the residual urban wage premium is likely to drop from γ_2 to $\tilde{\gamma}_2$. The reduced portion is the decline in the urban wage premium that can be attributed to the decline in all of the skill-specific urban wage premiums.

However, Gelbach (2016) demonstrates that to decompose the contribution of each covariate, we cannot simply add and subtract each covariate if the covariates are statistically correlated. Based on his method, to decompose the contribution of each covariate, we need to estimate the effect of each covariate on the outcome variable and how each covariate covaries with the key coefficient in the equation. The intuition in our context is that if a skill is very frequently required in high-WFH jobs, then a large estimate of β_2^s (i.e., a large decline in the urban wage premium for skill s) would imply that the decline in s's urban wage premium contribute greatly to the overall decline in the urban wage premium in high-WFH jobs. Conversely, if a skill is rarely required in high-WFH jobs, even a large decline in urban wage premium in such a skill would not have contributed much to the overall decline in the urban wage premium in high-WFH jobs.

Hence, we must also estimate the following equation separately for each skill s:

$$\ln M_{kj} \times Post_t \times Skill_i^s = \Gamma_0^s \ln M_{kj} + \Gamma_1^s Post_t + \Gamma_2^s \ln M_{kj} \times Post_t + \mathbf{X}_{ikjt}\mathbf{\Gamma}_{\boldsymbol{x}} + \eta_{ikjt}, \tag{10}$$

[19]The estimate of $\alpha_1 + \alpha_3$ using Equation 5 by pooling all jobs is very similar to the estimate of γ_2. We do not report the estimation results of Equation 8 because of space constraint.

where Γ_2^s represents how much each added covariate of skill s covaries with the key regressors. The contribution of the change in the urban wage premium of each skill s to the overall change in the urban wage premium in high-WFH jobs is the following:

$$\hat{\pi}^s = \frac{\hat{\Gamma}_2^s \cdot \hat{\beta}_2^s}{\hat{\gamma}_2}, \tag{11}$$

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

Results For computational feasibility, we define s as a skill cluster family defined in the Burning Glass data. There are 32 skill cluster families. Their definitions are described in Appendix A2.2.

Table 5 presents the Gelbach decomposition results, i.e., the contribution of the change in the urban wage premium of each skill cluster family to the overall decline of the urban wage premium for jobs with high levels of WFH adoption. Column 1 presents the estimates of β_2^s in Equation 9. Column 2 presents the estimates of Γ_2^s in Equation 10. Column 3 presents the estimates of π^s according to Equation 11. Column 4 presents the contribution shares.

We rank the skill cluster families by their contribution to the overall decline in the urban wage premium for the high WFH-adoption jobs. The skills that contributed most to the overall decline in the urban wage premium are "Building Relationship", "Information Technology", "Marketing and Public Relations", "Sales", and "Customer and Client Support." The decline in the urban wage premium of these skills could theoretically be driven by either a relative decline of productivity of these skills in large cities or an increased supply of these skills to large cities.

By intuition, among these skill cluster families, the rise of WFH is likely to have enabled more workers with skills in the family of "Information Technology" (e.g., IT support staff) to remotely supply labor to large cities or industry clusters because skills related to "Information Technology" tend to complement electronic tools both for analytical tasks and for support services.[20] However, the other skill cluster families picked up in the decomposition exercise do not immediately appear likely to enjoy more inherent advantages from the

[20]Tables A6 and A7 show the Gelbach decompositions for job postings that require college education and do not require college education, respectively. It is notable that skills belonging to "Business", "Building Relationship", and "Customer and Client Support" are the largest contributors to the decrease in the urban wage premium among the high-WFH jobs that require college education, while skills belonging to "Information Technology" are the largest contributors among the high-WFH jobs that do not require college education. This suggests that the diminishing marginal value of relationship-cultivating and network-building skills in large cities matters more for high-skill jobs than for low-skill jobs. In contrast, for low-skill high-WFH jobs, the increased supply of remote workers well-versed in information technologies may have been driving down the urban wage premium of those jobs.

rise of WFH. Instead, these other skills mostly involve relationship-building ability and the ability to manage public relations, which seem to be particularly compatible with activities interacting with customers, clients, supply-chain partners, and coworkers. These skills are naturally associated with facilitating knowledge spillovers, connecting with customers and clients, and forming professional networks.

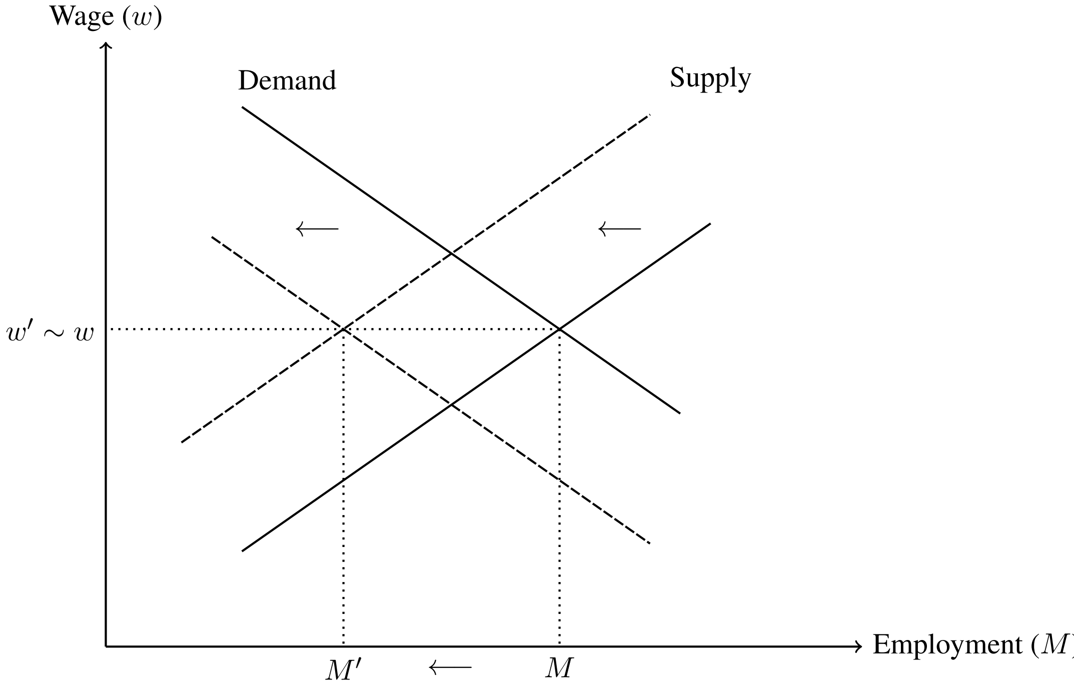
Assuming the decline in the urban wage premium of the relationship-building skills in large cities is not driven by a rise in supply of these skills to large cities, the decline in the urban wage premium of these skills would imply that the marginal product of these skills decreased more in large cities. Since intuition suggests that these skills are highly complementary to interactive activities, the declined marginal product of these skills implies a reduced expected occurrence of these interactive activities at work. However, if these interactive activities generate productivity externalities as suggested in numerous prior papers, the reduction in these activities in the large cities would further suggest that the agglomeration economies may have indeed weakened.

6 Conclusion

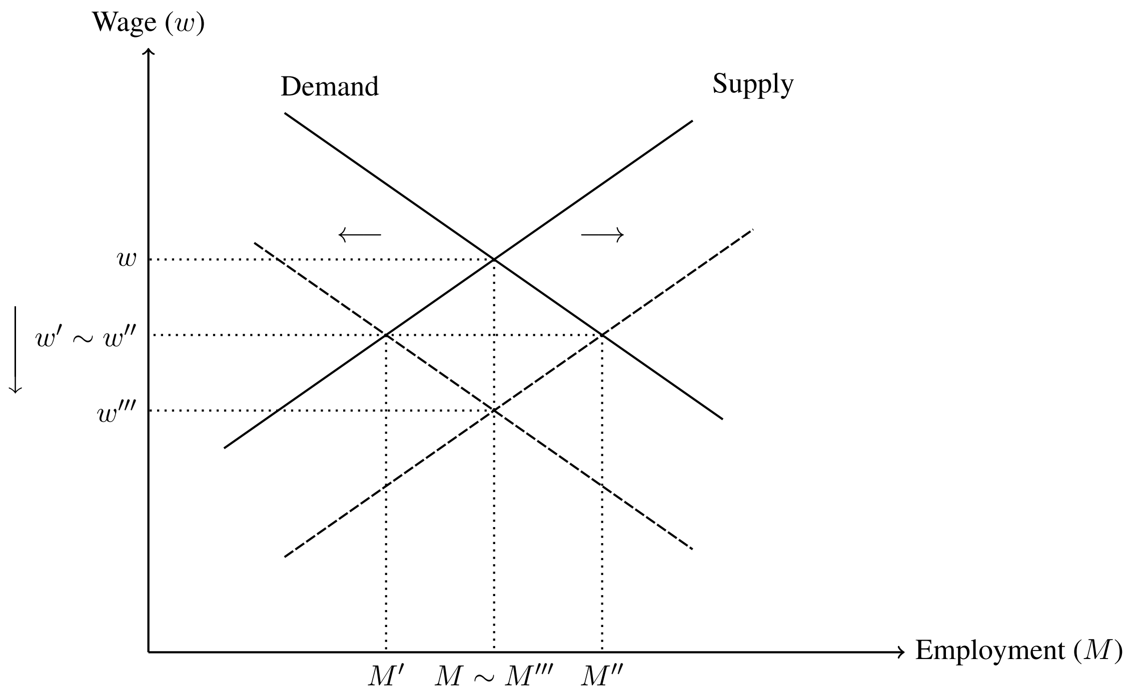
This paper studies the effect of WFH on the agglomeration economies of large cities. Using a stylized model, we show that the reduction in the cost of WFH would lower the urban wage premium through two potential mechanisms. On the one hand, the lower cost of WFH may increase the labor supply to high-productivity firms in large cities because of the increase in the number workers who live in small cities but work remotely for firms in large cities. The increased employment at high-productivity firms in large cities may raise the aggregate productivity, wages, and output. On the other hand, if large cities' agglomeration economies decreased severely due to the reduction in the number of onsite workers, workers may switch from working for high-productivity firms in large cities to lower-productivity firms in smaller cities, leading to a decrease of aggregate productivity, wages, and output. To test the model and distinguish the effect of WFH on aggregate productivity, we derive two testable predictions and take them to data.

Using wage data from advertised job postings, we show that the urban wage premium of occupations with high levels of WFH adoption decreased significantly during the COVID-19 pandemic. In contrast, the urban wage premium of occupations with low or moderate levels of WFH adoption saw a much more moderate decline. In addition, we demonstrate that among the occupations with high levels of WFH adoption, employment declined (based on firms' locations) more in larger cities than in smaller cities. Based on our model implications, we argue that the decline in the urban wage premium and the exiting of employment from large cities imply that the agglomeration economies of large cities decreased as a result of the rise in WFH adoption. Lastly, we conduct a decomposition exercise in which we dissect the decline in the urban wage premium into the changes in skill-specific urban wage premiums. We find that the decline in the urban wage premium for jobs with high WFH adoption is led by the decline in the urban wage premiums of relationship-building skills and other skills that are compatible with interactive activities with co-workers, customers, clients, and other professionals, based on intuition. This further suggests that the agglomeration economies of large cities were weakened by the adoption of WFH.

Figure 1: The Labor Demand And Supply in Large Cities After COVID-19 Outbreak



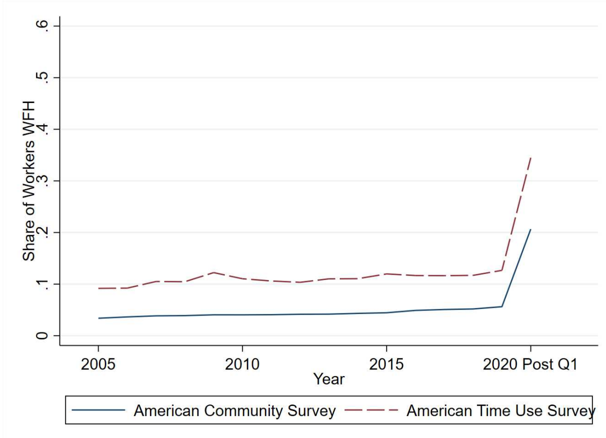
(a) Occupations with Low or Moderate Levels of WFH Adoption



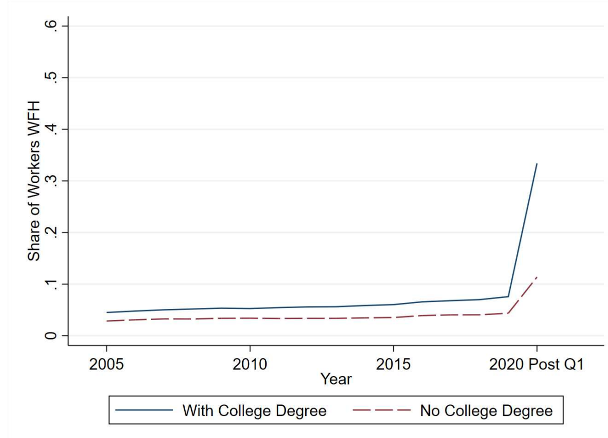
(b) Occupations with High Levels of WFH Adoption

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

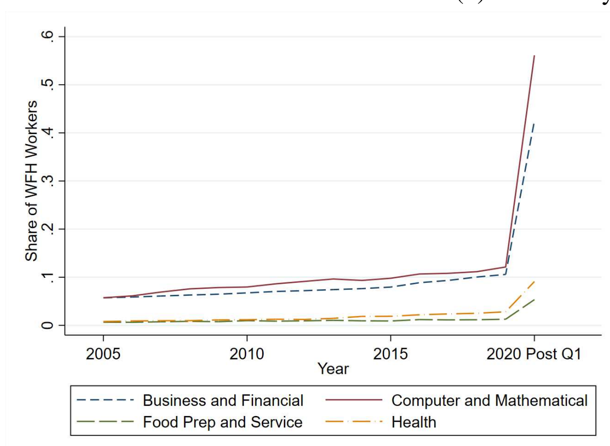
Figure 2: The Share of Workers Working from Home



(a) All Workers



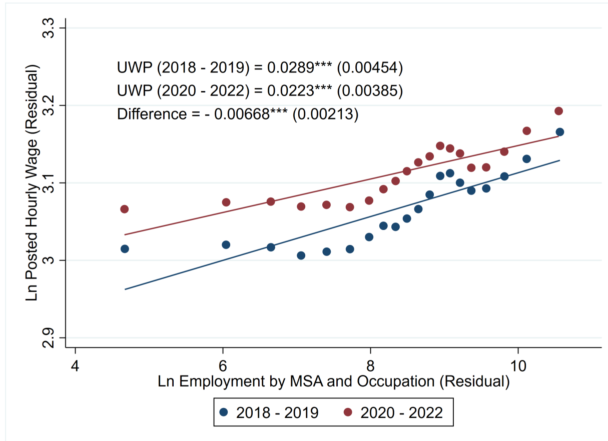
(b) Workers by Education (ACS)



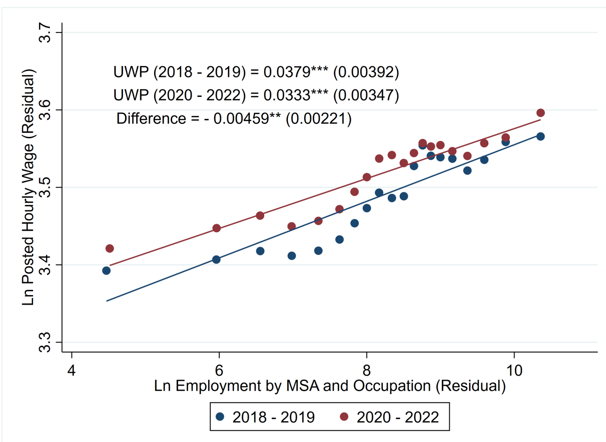
(c) Workers by Selected Occupation Groups (ACS)

Note: The figures plot the share of workers who work from home from 2005 to 2020. In Figure 2a, we use the American Community Survey (ACS) and the American Time Use Survey (ATUS) to calculate the share of all workers who work from home in each survey year. For the year 2020, to highlight the share of workers working from home under the pandemic, we impute the numbers for the period after the first quarter of 2020. We assume that both the ACS and the ATUS data surveyed respondents randomly in each month of 2020 and that the shares of working from home in the Q1 of 2020 are identical to the shares estimated for 2019. For the ACS, we study the sample working at least 35 hours a week and aged between 25 and 65. For the ATUS, we calculate the share of workers working from home by dividing the number of workers whose working activities all occur at home by the number of workers who recorded working activities during the period surveyed. Figure 2b shows the shares of workers with or without college degree working from home, based on the ACS data. Figure 2c shows the shares of workers from four selected occupation groups working from home, based on the ACS data.

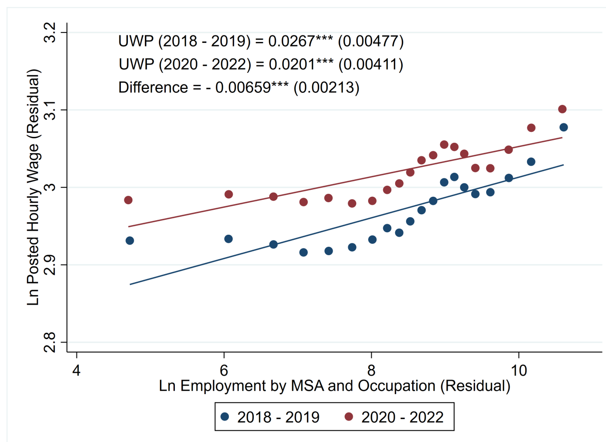
Figure 3: The Urban Wage Premium: 2018–2019 vs. 2020–2022



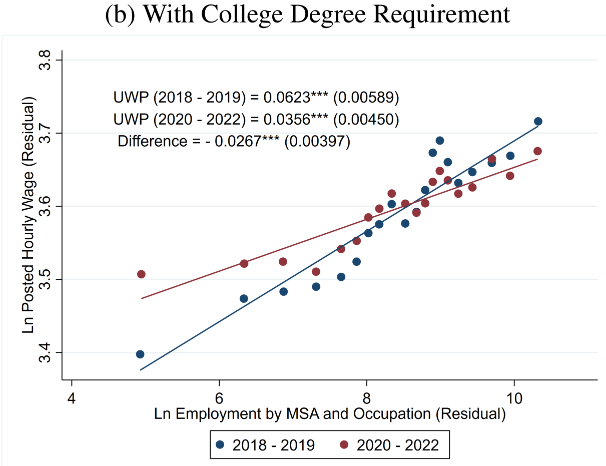
(a) All Jobs



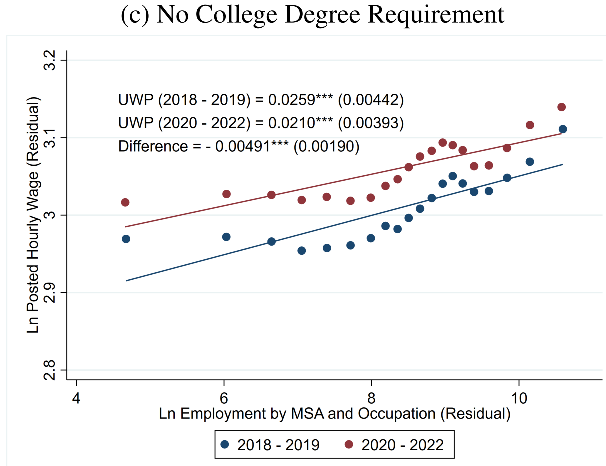
(b) With College Degree Requirement



(c) No College Degree Requirement



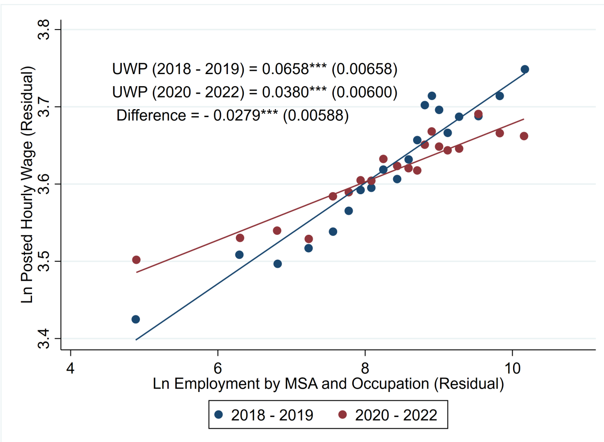
(d) High WFH Adoption



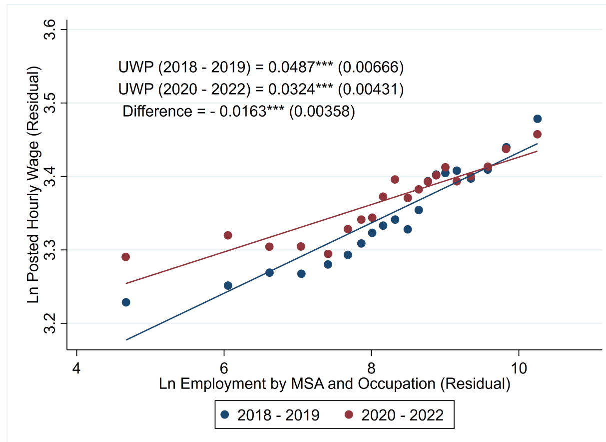
(e) Low or Moderate WFH Adoption

Note: The figures present the binned scatterplots of the residual log posted hourly wage against the residual log employment of the occupation and MSA of the job. We obtain the residualized log wage and the log employment by first regressing these variables on SOC-ONET occupation code, NAICS code, year of education required, salary type, full-/part-time status, tax terms, and the month of the posting date. We then add back the means of the origin variables. In each figure, we plot the relationship between the residual posted log wage and log employment separately for the jobs posted between 2018 and 2019 and for jobs posted between 2020 and the first 5 months of 2022. Figure 3a presents the plot for all jobs posted. Figure 3b presents the plot for jobs with college degree requirement (16 years of education). Figure 3c presents the plot for jobs without college requirement. Figure 3d presents the plot for jobs with high level of WFH adoption. Figure 3e presents the plot for jobs with low or moderate levels of WFH adoption. We use a 10% random sample of the Burning Glass data.

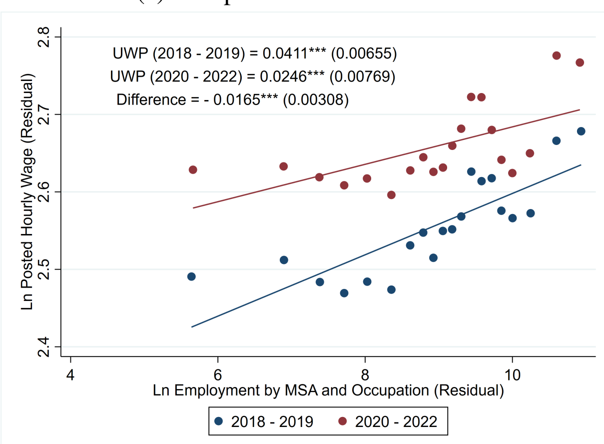
Figure 4: The Urban Wage Premium of Selected Occupation Groups



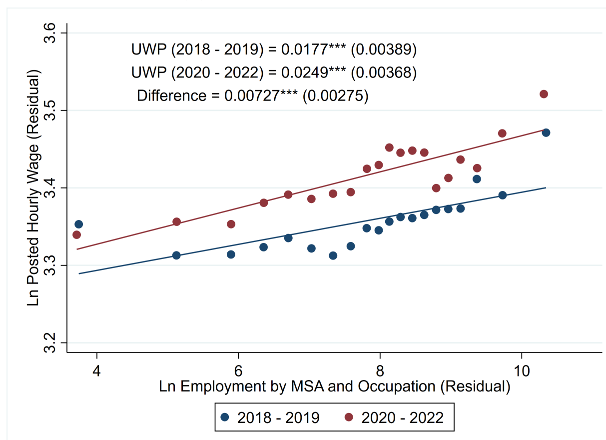
(a) Computer and Mathematical



(b) Business and Finance



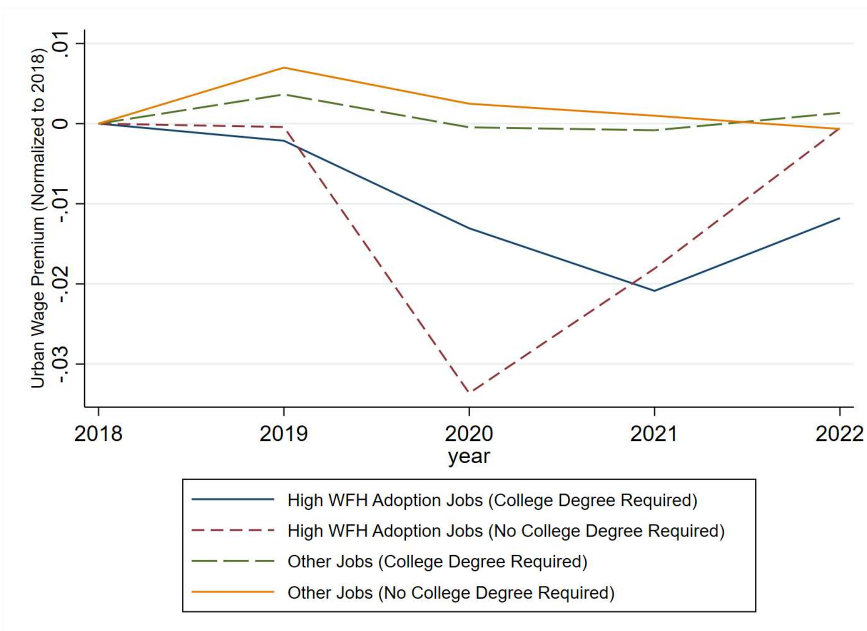
(c) Food Prep and Service



(d) Health

Note: The figures present the binned scatterplots of the residual log posted hourly wage against the residual log employment of the occupation and MSA of the job. We obtain the residualized log wage and the log employment by first regressing these variables on SOC-ONET occupation code, NAICS code, year of education required, salary type, full-/part-time status, tax terms, and the month of the posting date. We then add back the means of the origin variables. In each figure, we plot the relationship between the residual posted log wage and log employment separately for the jobs posted between 2018 and 2019 and for jobs posted between 2020 and the first 5 months of 2022. Figure 4a presents the plot for jobs categorized in the occupation family of "Computer and Mathematical Occupations." Figure 4b presents the plot for jobs categorized in the family of "Business and Financial Operations Occupations." Figure 4c presents the plot for jobs categorized in the family of "Food Preparation and Serving Related Occupations." Figure 4d presents the plot for jobs categorized in the family of "Healthcare Practitioners and Technical Occupations." We use a 10% random sample of the Burning Glass data.

Figure 5: The Urban Wage Premium by Year



Note: This figure presents the urban wage premium over years, by job types based on the education required and the level of WFH adoption during the pandemic. To estimate the yearly urban wage premium, we control for each job's SOC-ONET occupation code, NAICS code, years of education required, salary type, full-/part-time status, tax terms, and the month of the job posting. We allow the regression coefficients for log posted wages on log employment of the job's occupation and MSA to vary by year and by job type. We use a 10% random sample of the Burning Glass data.

Table 1: Testable Predictions during the COVID-19 Pandemic

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

Note: This table summarizes the changes in the urban wage premium (column 1) and employment in large (L) and small (S) cities (column 2) in occupations with low or moderation WFH adoption (upper panel) and high 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 the Urban Wage Premium by the Level of WFH Adoption

	Log Posted Hourly Wages			
	(1)	(2)	(3)	(4)
Log M	-0.0101***	0.0262***	0.0257***	0.0200***
	(0.00319)	(0.00414)	(0.00391)	(0.00386)
Log M $\times$ Post	0.00320**	-0.00296***	-0.00233***	-0.00237***
	(0.00139)	(0.00101)	(0.000863)	(0.000829)
Log M $\times$ High WFH	0.0694***	0.0342***	0.0256***	0.0187***
	(0.00566)	(0.00401)	(0.00335)	(0.00461)
Log M $\times$ High WFH $\times$ Post	-0.0253***	-0.0198***	-0.0154***	-0.0103***
	(0.00290)	(0.00259)	(0.00196)	(0.00142)
Measurement of M	Emp Size by Occ & MSA	Emp Size by Occ & MSA	Emp Size by Occ & MSA	Emp Density by Occ & County
Controls: Occupation, Industry, Education Requirement, Salary Type, Tax Term		X	X	X
Controls: Skills Requirements			X	X
Observations	3,862,606	3,862,599	3,848,098	3,848,096

Note: This table presents the estimates of the urban wage premiums before and after the start of the COVID-19 pandemic (i.e., α_0, α_1, α_2, and α_3 in Equation 5). The sample comprises the job postings from the Burning Glass data from 2018 to the first five months of 2022. The dependent variable is the log posted hourly wage of each job posting. M is defined as the size of employment of the occupation in the county of the posted job (Columns 1–2) or the employment density (employment divided by the county area) of the occupation in the county of the posted job (Column 3–4). $Post$ indicates the pandemic period (i.e., the years of 2020–2022). $High\ WFH$ is an indicator which is equal to 1 if the occupation of the posted job has a high level of WFH adoption. Column 1 does not include any control variables. Column 2 controls for the indicators of occupation code (SOC-ONET), industry code (3-digit NAICS), years of education required by the job, salary type, part-/full-time status, tax term, and job posting month. Columns 3 and 4 further control for indicators of 20 skill requirements. We use a 10% random sample of the Burning Glass data. Standard errors are clustered at the MSA level. *** $p < 0.01$, ** $p < 0.05$, *$p < 0.1$.

Table 3: Changes in the Urban Wage Premium by the Level of WFH Adoption:
Alternative Measurements of WFH Adoption

	Log Posted Hourly Wages		
	(1)	(2)	(3)
Log M	0.0186***	0.0248***	0.0195***
	(0.00382)	(0.00400)	(0.00383)
Log M × Post	-0.00151	-0.00378***	-0.00263**
	(0.00107)	(0.000963)	(0.00107)
Log M × High WFH		0.0276***	0.0168***
		(0.00407)	(0.00254)
Log M × High WFH × Post		-0.00925***	-0.00162*
		(0.00234)	(0.000846)
Log M × WFH ($0.1 \leq \Delta < 0.15$)	0.00905***		
	(0.00205)		
Log M × WFH ($0.15 \leq \Delta < 0.2$)	0.0143***		
	(0.00202)		
Log M × WFH ($0.2 \leq \Delta < 0.25$)	0.0120***		
	(0.00295)		
Log M × WFH ($\Delta \geq 0.25$)	0.0397***		
	(0.00455)		
Log M × WFH ($0.1 \leq \Delta < 0.15$) × Post	-0.00398***		
	(0.00103)		
Log M × WFH ($0.15 \leq \Delta < 0.2$) × Post	0.000713		
	(0.000898)		
Log M × WFH ($0.2 \leq \Delta < 0.25$) × Post	-0.00303***		
	(0.00116)		
Log M × WFH ($\Delta \geq 0.25$) × Post	-0.0169***		
	(0.00239)		
Measurement of WFH Adoption	Baseline	Business and Finance Computer and Mathematics	Dingel and Neiman
Observations	4,812,826	5,090,324	4,822,575

Note: This table presents estimates of Equation 5, with the same specification of Table 2 Column 2, but alternative measurements of WFH adoption. In Column 1 , we use the same imputed change in the prevalence of WFH by occupation, but define three additional categories based on the change in the percentage of the prevalence of WFH (Δ) between 2019 and 2020. In Column 2, we define occupations as high WFH adoption if the occupations belong to the occupation groups of business and finance or computer and mathematics. In Column 3, we use Dingel and Neiman (2020)'s measure of teleworkability for each occupation. We use a 10% random sample of the Burning Glass data. 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 2020 for Different Occupation Groups

	Changes in Log Number of Jobs		
	(1)	(2)	(3)
Log M $\times$ 1/2019–1/2020 $\times$ Low WFH	-0.0201***		-0.00515**
	(0.00639)		(0.00238)
Log M $\times$ 1/2020–8/2021 $\times$ Low WFH	-0.0351***		-0.0211***
	(0.00564)		(0.00232)
Log M $\times$ 1/2019–1/2020 $\times$ High WFH	-0.0192***		-0.00367
	(0.00615)		(0.00259)
Log M $\times$ 1/2020–8/2021 $\times$ High WFH	-0.0315***		-0.0172***
	(0.00538)		(0.00354)
Log M $\times$ 1/2019–1/2020 $\times$ Other Occ		-0.0187***	
		(0.00648)	
Log M $\times$ 1/2020–8/2021 $\times$ Other Occ		-0.0338***	
		(0.00599)	
Log M $\times$ 1/2019–1/2020 $\times$ Computer & Business		-0.00174***	
		(0.00641)	
Log M $\times$ 1/2020–8/2021 $\times$ Computer & Business		-0.0281***	
		(0.00589)	
Measurement of M	Emp Size by Occ & MSA	Emp Size by Occ & MSA	Emp Density by Occ & County
Observations	3,447,993	3,762,677	3,445,828

Note: This table presents the estimates of changes in employment with respect to the employment size or density of a MSA separately for different types of occupations. Specifically, Columns 1 and 3 present the estimates of Equation 6 and Column 2 presents the estimates of Equation 7. The sample comprises employment numbers from the Quarterly Census of Employment and Wages (QCEW) over two periods: from January 2019 to January 2020, and from January 2020 to August 2021. The dependent variable is the change in log employment by occupation and MSA between January 2019 and January 2020, or between January 2020 and August 2021. The independent variables are log employment of same occupation and MSA in January 2019 (Columns 1–2) or log employment density of the same occupation in the same county in January 2019 (Column 3), interacted with period dummies and occupation group dummies. Each estimate represents how employment growth varies with respect to initial employment size or density, by time period and occupation group. In each regression, we control for the occupation $\times$ period fixed effects and MSA fixed effects. 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 Premiums to the Decrease in the Urban Wage Premium among High-WFH Jobs

Skill Cluster Family	β	Γ	Contribution	Contribution Share
	(1)	(2)	(3)	(4)
Building Relationship	-0.0074253	0.3692392	-0.00274	12.38%
Information Technology	-0.0021337	0.8839056	-0.00189	8.52%
Marketing and Public Relations	-0.0026919	0.4948321	-0.00133	6.02%
Sales	-0.0031725	0.4190814	-0.00133	6.00%
Customer and Client Support	-0.0116636	0.1084517	-0.00126	5.71%
Finance	-0.0079618	0.15231	-0.00121	5.48%
Business	-0.0015145	0.5673476	-0.00086	3.88%
Legal	0.0157841	-0.0374079	-0.00059	2.67%
Public Safety and National Security	0.0194709	-0.0134763	-0.00026	1.19%
Environment	0.0177919	-0.0131623	-0.00023	1.06%
Education and Training	0.004016	-0.038441	-0.00015	0.70%
Agriculture, Horticulture, and the Outdoors	0.0381407	-0.002726	-0.0001	0.47%
Economics, Policy, and Social Studies	0.0183028	-0.0044734	-8.2E-05	0.37%
Physical Abilities	0.0029959	-0.0137042	-4.1E-05	0.19%
Supply Chain and Logistics	-0.0001862	0.0713502	-1.3E-05	0.06%
Engineering	0.0000219	0.0580872	1.27E-06	-0.01%
Architecture and Construction	0.0070308	0.0013742	9.66E-06	-0.04%
Manufacturing and Production	0.0002339	0.0810596	0.000019	-0.09%
Personal Care and Services	0.0134388	0.001547	2.08E-05	-0.09%
Maintenance, Repair, and Installation	0.0082365	0.0041734	3.44E-05	-0.16%
Energy and Utilities	0.0268742	0.003359	9.03E-05	-0.41%
Health Care	0.0112902	0.0082688	9.34E-05	-0.42%
Human Resources	0.0025423	0.0541127	0.000138	-0.62%
Media and Writing	0.0029203	0.0681733	0.000199	-0.90%
Administration	0.0026286	0.1802215	0.000474	-2.14%
Science and Research	0.0068385	0.0839379	0.000574	-2.59%
Industry Knowledge	0.0076343	0.1287657	0.000983	-4.44%
Organizational Skills	0.0131825	0.1271825	0.001677	-7.57%
Design	0.0140009	0.1202573	0.001684	-7.60%
Communications	0.0047153	0.492551	0.002323	-10.49%
Analysis	0.0063902	0.4449412	0.002843	-12.84%

Note: This table presents the Gelbach decomposition results. Column 1 presents the estimates of β_2^s in Equation 9, where s is the corresponding skill cluster family. Column 2 presents the estimates of Γ_2^s in Equation 10. Column 3 presents the estimates of π^s according to Equation 11. Column 4 presents the contribution shares based on the estimates in Column 3.

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Appendix

A1 Comparative Statics of the Model

In this section, we provide the derivation of the comparative statics shown in section based on the spatial equilibrium model.

We proceed from the equalized utility levels in equilibrium:

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

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

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

To make sure that we can feasibly solve for the comparative statics, we reduce the number of equations by taking the difference between the first and second equations and the difference between the third and the second equations. We also plug in the equilibrium wage and rent equations:

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

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

We are interested in the values of $\frac{\partial N_{HH}}{\partial \phi}$ and $\frac{\partial N_{HL}}{\partial \phi}$. Since $N_{HH} + N_{HL} + N_{LL} = 1$, we do not need to compute the comparative static for N_{LL}. From the two equations above, there are endogenous variables N_{HH} and N_{HL} and one exogenous variable ϕ. The functional forms in the two equations are also smooth and differentiable. We apply the implicit function theorem to solve for 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 IFT,

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

If we expand the matrices, we get:

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

By plugging in each derivative terms, 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 working long-distance. Therefore, the effect of reducing the cost of working long distance should be obtained by adding a negative sign in front of each derivative.

A2 Data Appendix

A2.1 Urban Wage premium by ACS data vs. Burning Glass Data - pre-pandemic

We provide a validation of the urban wage premium estimated from the Burning Glass data by bringing in data from the American Community Survey (ACS) surveyed in the pre-pandemic year - 2019. In Figure A3a, we plot the relationship between the log posted hourly wage as measured in the 2019 Burning Glass data and the jobs' MSAs' total employment, while controlling for the SOC-ONET occupation codes of the posted jobs. In the same figure, we similarly plot the relationship between the log hourly wage measured in the American Community Survey and the surveyed respondents' MSAs' total employment, while controlling for the occupation code (occ2010) assigned to the survey respondents. We see that the urban wage premiums as manifested by the wage gradient with respect to local employment size are quite comparable between the two datasets. In Figure A3b, A3c, A3d, and A3e, we conduct the comparisons for the four occupation groups separately. The urban wage premia produced by the two datasets compare well by occupations. Notably, the urban wage premium is lower in health care occupations, which can be reproduced by both ACS and Burning Glass data.

A2.2 The Definitions and Skills and Skill Cluster Family

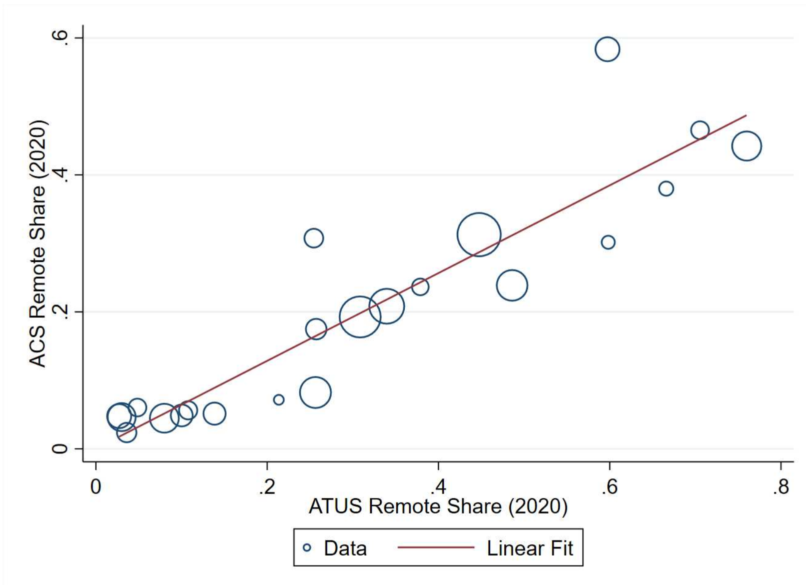
The Burning Glass data provide a vector of skills for each distinct posted job. There are more than 13,000 distinct skills included in the data. These skills are strings extracted from actual job descriptions. The skill vectors have two uses in our paper. The first is to provide extremely detailed job-level controls when we estimate the change in the urban wage premium. The second use is to allow us to estimate the change in the urban wage premium by skill and conduct the Gelbach decomposition described in section 5.

The challenge pertaining to this data is that the lengths of the skill vectors are different. Some jobs have only one or two listed skills while others have close to 20. To construct the full set of skill controls for each job, we control for the first 20 skills associated with each job. To fill in the skill variables for each job, we rank the skills within each job by each skill's overall frequency of appearance in the data. Stata will automatically create dummy variables for each skill in each of the 20 skill variables (the "reghdfe" command). We do so for the ease of implementation in Stata. Alternatively, we can define 13,000 distinct dummy variables for each skill, which can get very computationally burdensome. We believe this should not pose a problem to the validity of our study because our method of control is actually much more stringent (13,000 $\times$ 20 dummy variables).

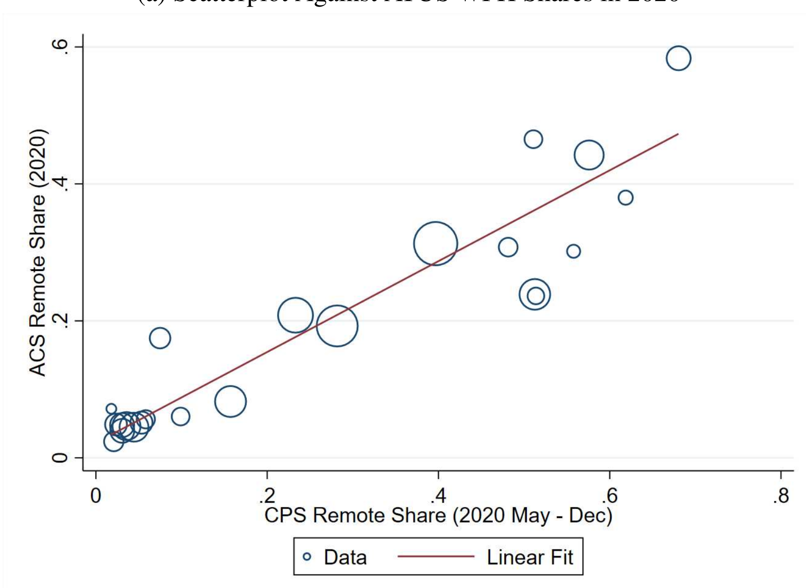
To dissect the decline in the urban wage premium in the high-WFH jobs, we need to interact $\ln M$ with skill dummies. However, for feasibility, we do not use the detailed skill dummies as the skill unit to analyze. Instead, we use a much higher level of skill groups. The Burning Glass data group skills into skill clusters and skill cluster families. There are more than 650 skill clusters, which is still too many. But there are only 29 skill cluster families. We use the skill cluster families as the units for our Gelbach decomposition exercise.

Because skill cluster families only cover a subset of skills, a subset of skills are not assigned to a skill cluster family. We manually assign some very commonly listed skills that are unassigned. Table A3 is a crosswalk that list our manual assignment of the unassigned skills.

Figure A1: Validation of the ACS WFH Share by Occupation Group with the ATUS and CPS



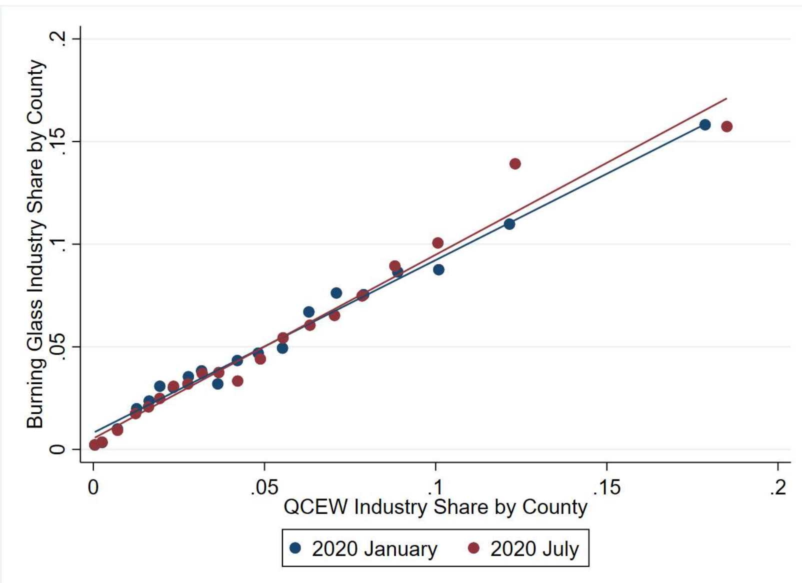
(a) Scatterplot Against ATUS WFH Shares in 2020



(b) Scatterplot Against CPS WFH Shares in 2020 (May - Dec)

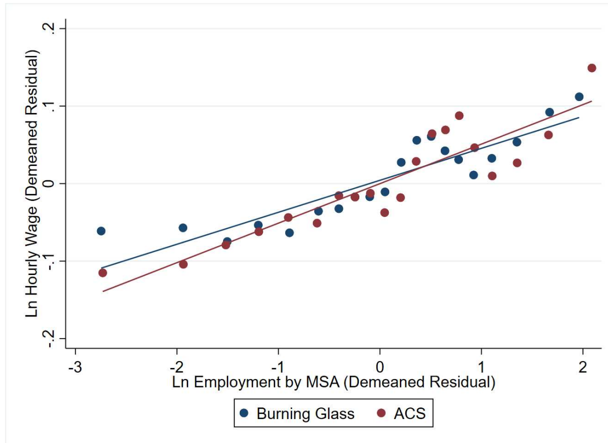
Note: These figures validate the WFH shares observed in the ACS data. We compute the share of workers who worked from home in 2020 (post Q1) for each occupation group. We perform the same calculations using the 2020 (post Q1) ATUS data and the 2020 (May to December) CPS data. Figure A1a plots the share of WFH workers by occupation group using the ACS vs. the ATUS. Figure A1b plots the share of WFH workers by occupation group using the ACS vs. the CPS.

Figure A2: Industry Share within MSAs in the Burning Glass Data vs. the Quarterly Census of Employment and Wages

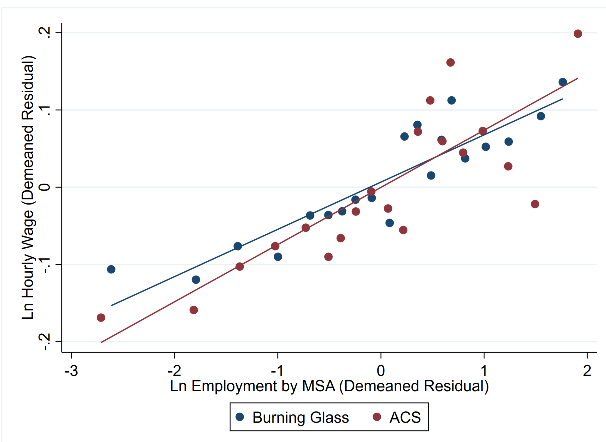


Note: This figure is designed to validate that the geographic distribution of job postings reflect employers' location. The y-axis represents the two-digit NAICS industry share within each MSA in the Burning Glass job postings, and the x-axis represents the two-digit NAICS industry share within each MSA in the Quarterly Census of Employment and Wages (QCEW) data, which is based on the employers' locations. We plot the statistics extracted from January and July of 2020.

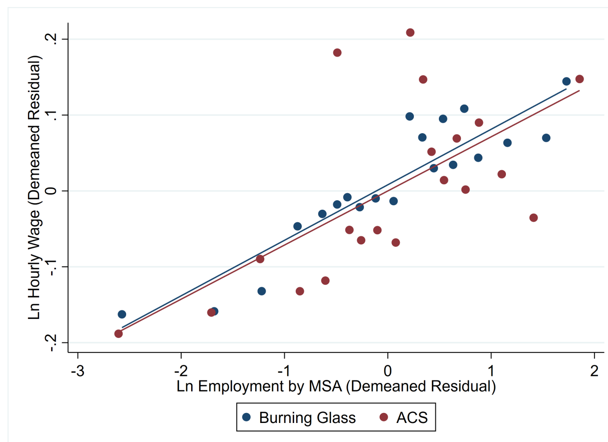
Figure A3: Urban Wage Premium in Burning Glass Data vs. in the American Community Survey (ACS) in the year 2019



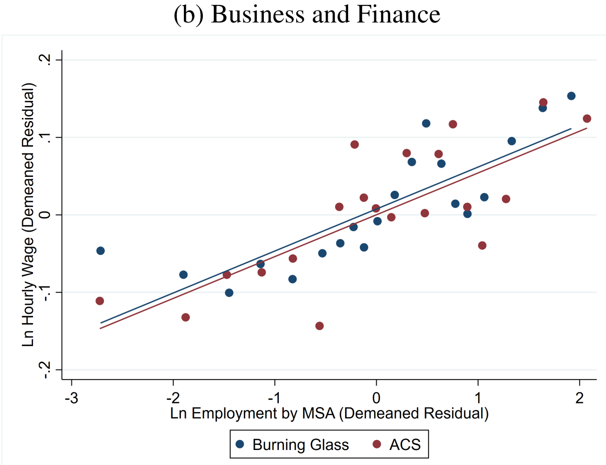
(a) All Jobs



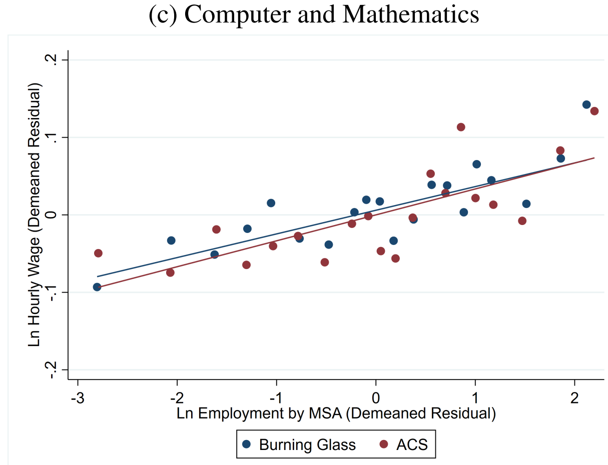
(b) Business and Finance



(c) Computer and Mathematics



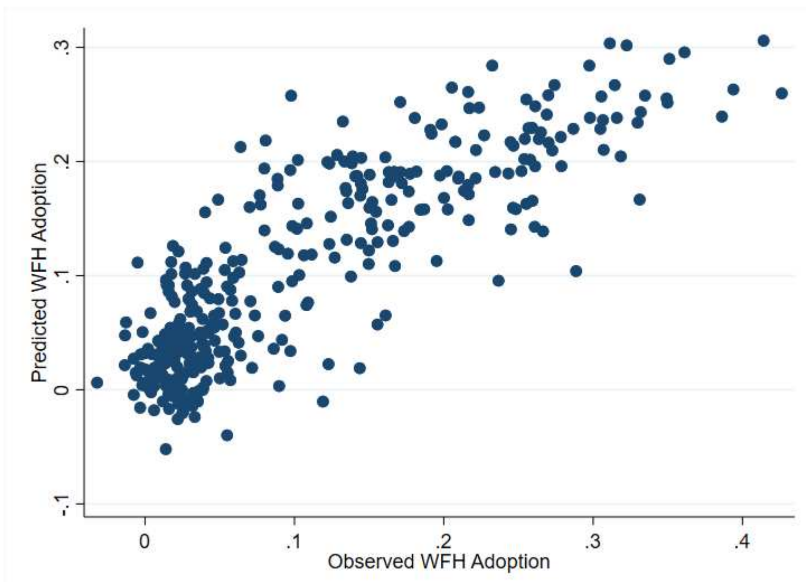
(d) Food Services



(e) Health Care

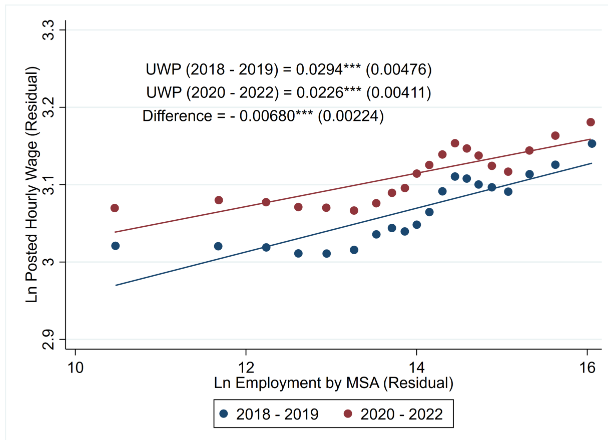
Note: In this set of graphs, we attempt to provide some external validation for the urban wage premium (UWP) estimated from the Burning Glass data by bringing in the American Community Survey (ACS) data. We estimate the UWP with the Burning Glass data by regressing the log posted wages in 2019 on the log total employment size of the MSA of the jobs in question, while controlling for the occupation code fixed effects (SOC-ONET). Then, we estimate the UWP with the ACS data by regressing the log hourly wage in 2019 on the log total employment size of the MSA, while controlling for the occupation code fixed effects in the ACS (occ2010). We plot the demeaned binned scatterplots of both micro datasets of the full sample in Figure A3a. In Figure A3b, A3c, A3d, and A3e, we plot the results from subsamples of each respective occupation group.

Figure A4: Predicted Adoption of WFH vs. Observed Adoption of WFH

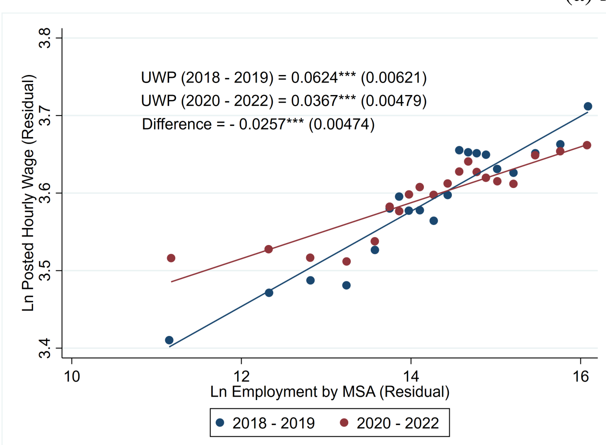


Note: This graph is to validate the predicted adoption of WFH with the observed adoption of WFH. We use the subset of occupations with vectors of O*NET occupational characteristics that can be matched to the ACS occupation code. We calculate the change in the share of WFH workers per occupation and use the collection of O*NET work context characteristics as predictors. We first apply the Lasso selection method to reduce the dimension of the work context characteristics. We then regress the change in the WFH share by occupation on the work context characteristics selected by the Lasso method. The predicted adoption of WFH is the predicted change in the WFH share based on the work context characteristics. The observed adoption of WFH is the observed change in the WFH share based on ACS data.

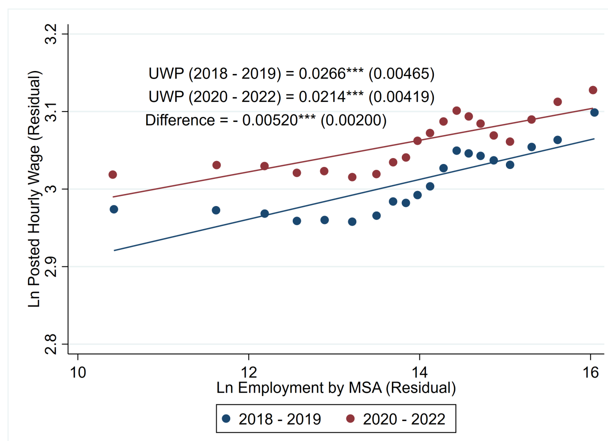
Figure A5: The Urban Wage Premium With Respect to MSAs' Total Employment: 2018-2019 vs. 2020-2022



(a) All Jobs



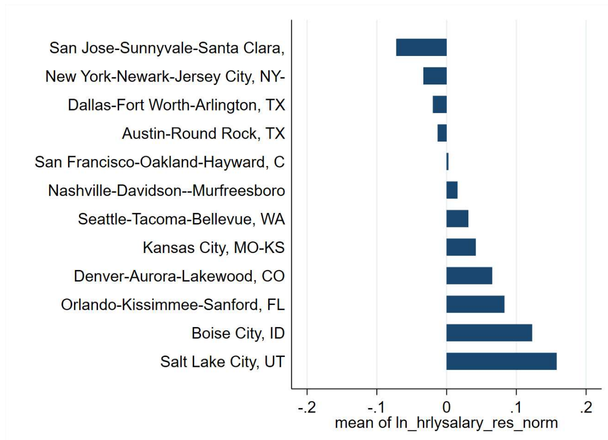
(b) High WFH Adoption



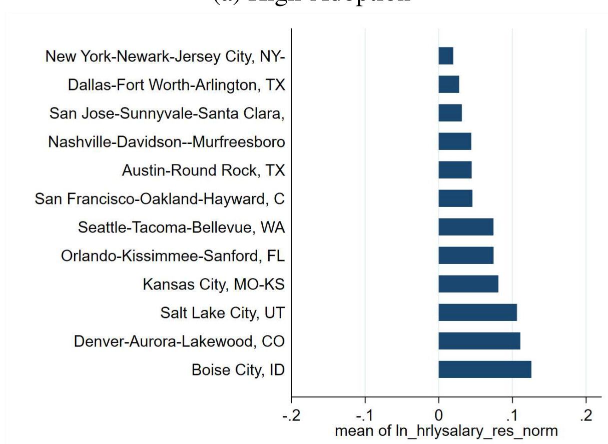
(c) Low or Moderate WFH Adoption

Note: We show the binned scatterplot of the residual log posted wage against the residual log employment number of the MSA of the job. We obtain the residualized log posted wage and the log employment number by first regressing these variables on SOC-ONET occupation code, NAICS code, year of education required, salary type, full-/part-time status, tax terms, and the month of the posting date. We then add back the means of the origin variables. For each subfigure, we plot the relationship between the residual posted log wage and log employment separately for the jobs posted in 2018-2019 and for jobs posted between 2020 and the first five months of 2022. Figure A5a shows the plot for all jobs posted. Figure A5b shows the plot for jobs with high level of WFH adoption. Figure A5c shows the plot for jobs with low or moderate levels of WFH adoption. We use a 10% random sample of the Burning Glass data.

Figure A6: Residual Wage Growth of High-Adoption Occupations vs. Low-Adoption Occupations



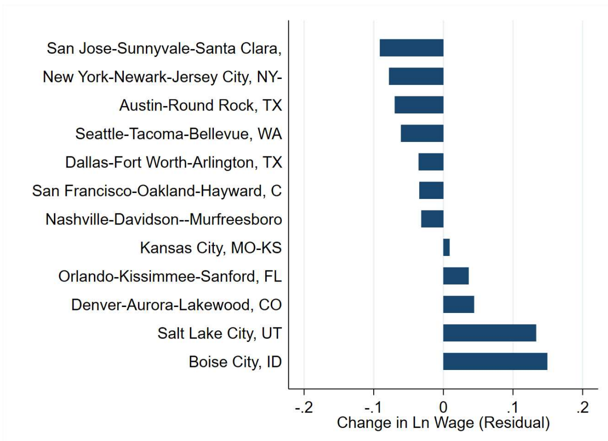
(a) High-Adoption



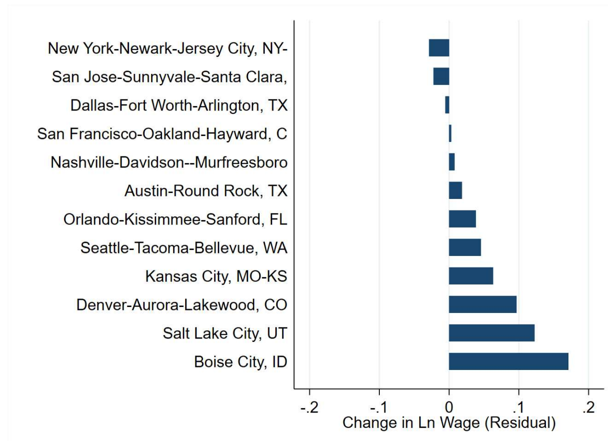
(b) Low-Adoption

Note: In the figures, we plot the change in residual log posted wages by MSA between the pandemic period (2020 - 2022 Q1) and the pre-pandemic period (2018 - 2019). We obtain the residualized log posted wage by first regressing it on SOC-ONET occupation code, NAICS code, year of education required, salary type, full-/part-time status, tax terms, and the month of the posting date. We then add back the mean of the origin variable. Figure A6a displays the sample of jobs with high levels of WFH adoption. Figure A6b displays the sample of jobs with low levels of WFH adoption.

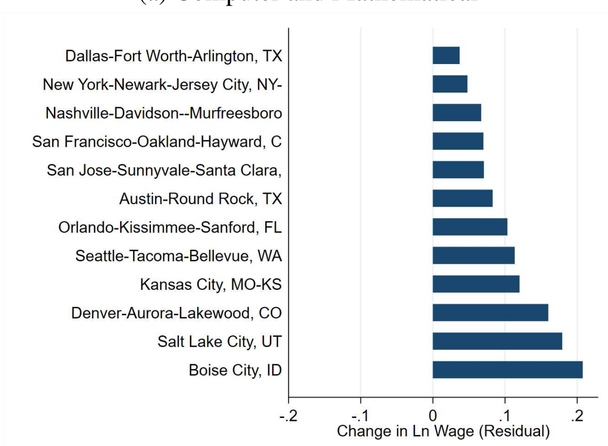
Figure A7: Residual Wage Growth of Selected Occupation Groups



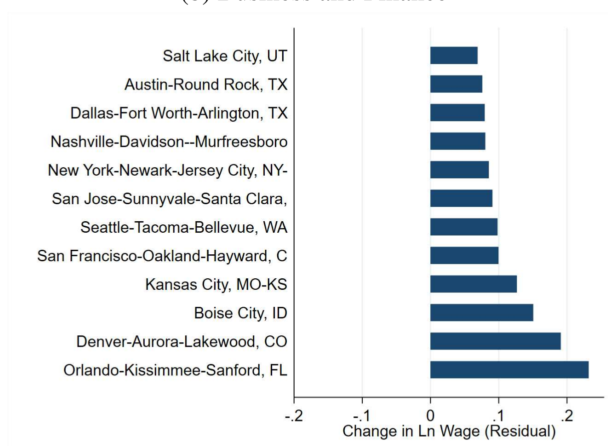
(a) Computer and Mathematical



(b) Business and Finance



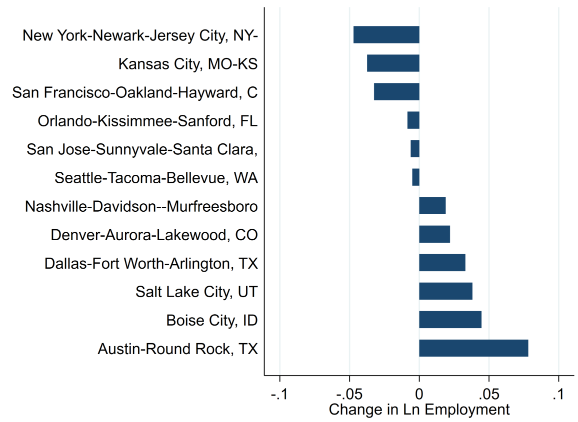
(c) Food Prep and Service



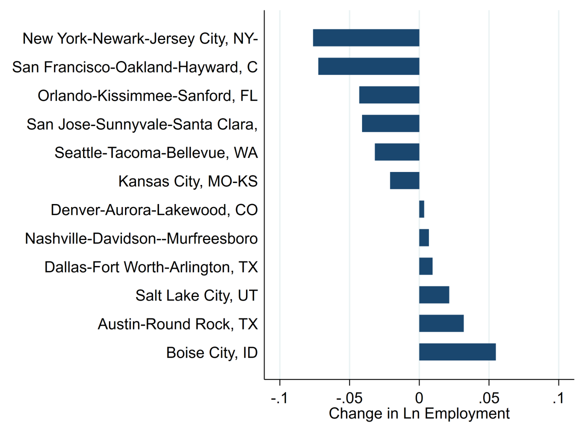
(d) Health

Note: In the figures, we plot the change in residual log posted wages by MSA between the pandemic period (2020 - 2022 Q1) and the pre-pandemic period (2018 - 2019). We obtain the residualized log posted wage by first regressing it on SOC-ONET occupation code, NAICS code, year of education required, salary type, full-/part-time status, tax terms, and the month of the posting date. We then add back the mean of the origin variable. Figure A7a displays the sample of jobs in the occupation family of “Computer and Mathematical Occupations”. Figure A7b displays the sample of jobs in the occupation family of “Business and Financial Operations Occupations”. Figure A7c displays the sample of jobs in the occupation family of “Food Preparation and Serving Related Occupations”. Figure A7d displays the sample of jobs in the occupation family of “Healthcare Practitioners and Technical Occupations”.

Figure A8: Employment Growth of High-Adoption Occupations vs. Low-Adoption Occupations



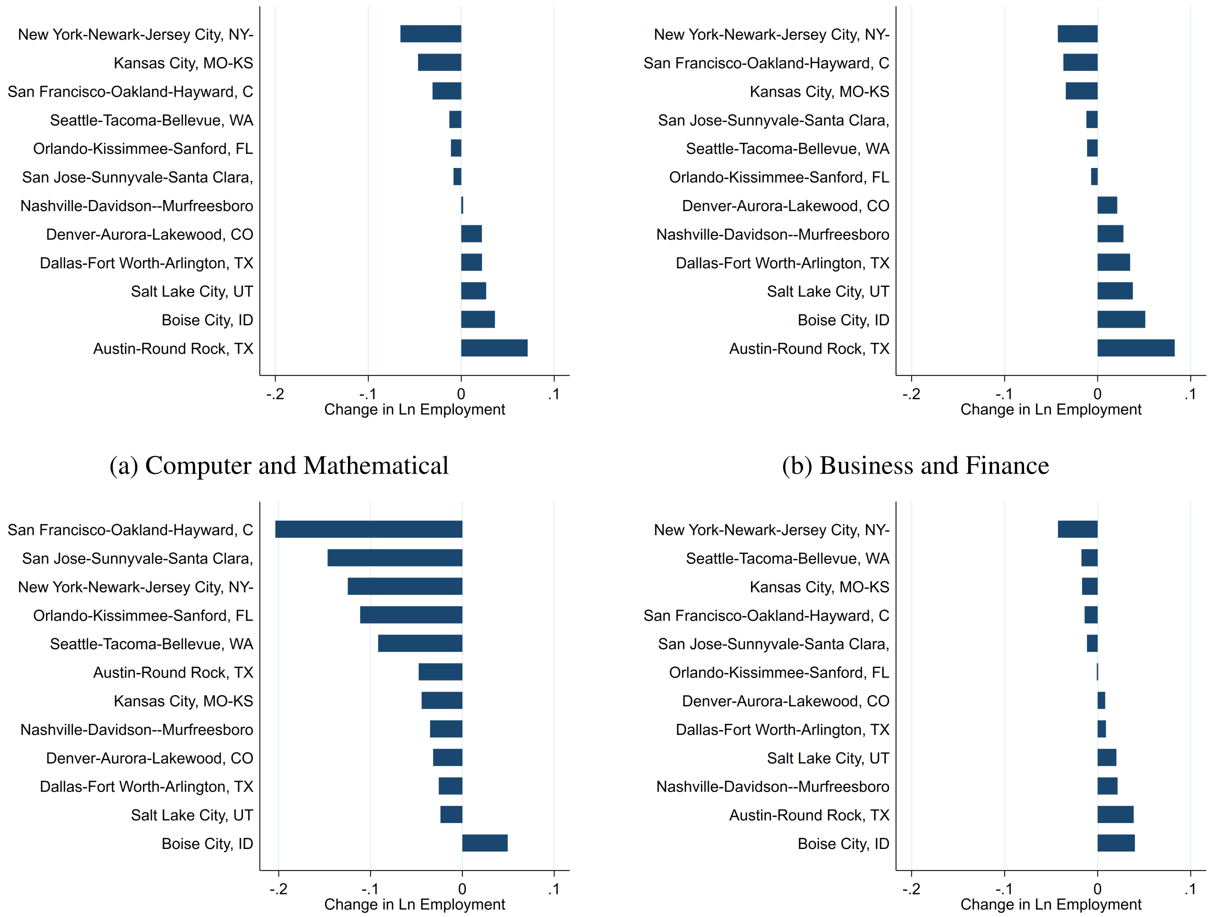
(a) High-Adoption



(b) Low-Adoption

Note: In the figures, we plot the change in log employment by MSA and levels of WFH adoption during the pandemic (from 2020 Q1 to 2021 Q3). Figure A6a displays the sample of jobs with high levels of WFH adoption. Figure A6b displays the sample of jobs with low levels of WFH adoption. The source of the data is the Quarterly Census of Employment and Wages.

Figure A9: Employment Growth of Selected Occupation Groups



(a) Computer and Mathematical

(b) Business and Finance

(c) Food Prep and Service

(d) Health

Note: In the figures, we plot the change in log employment by MSA during the pandemic (from 2020 Q1 to 2021 Q3). Figure A7a displays the sample of jobs in the occupation family of "Computer and Mathematical Occupations". Figure A7b displays the sample of jobs in the occupation family of "Business and Financial Operations Occupations". Figure A7c displays the sample of jobs in the occupation family of "Food Preparation and Serving Related Occupations". Figure A7d displays the sample of jobs in the occupation family of "Healthcare Practitioners and Technical Occupations". The source of the data is the Quarterly Census of Employment and Wages.

Table A1: Lasso Selection Results:
Work Context Characteristics as Predictors for WFH Adoption During the Pandemic

	Lasso	OLS
Deal With External Customers	-0.0089	-0.0181***
		(0.00507)
Deal With Physically Aggressive People	-0.01028	-0.0119
		(0.00915)
Deal With Unpleasant or Angry People	-0.00421	-0.00428
		(0.00752)
Electronic Mail	0.006438	0.00691*
		(0.00379)
Exposed to Contaminants	-0.011	-0.0102**
		(0.00481)
Exposed to Disease or Infections	-0.00229	-0.00406
		(0.00408)
Exposed to Minor Burns, Cuts, Bites, or Stings	-0.0029	-0.00375
		(0.00542)
Level of Competition	0.013591	0.0175***
		(0.00562)
Pace Determined by Speed of Equipment	-0.00207	-0.00913*
		(0.00480)
Physical Proximity	-0.01062	-0.0131**
		(0.00629)
Public Speaking	0.009759	0.0137**
		(0.00590)
Responsible for Others' Health and Safety	-0.02696	-0.0317***
		(0.00621)
Spend Time Bending or Twisting the Body	-0.00088	-0.000222
		(0.00719)
Spend Time Sitting	0.009258	0.00730
		(0.0105)
Spend Time Standing	-0.01237	-0.0132
		(0.0114)
Spend Time Using Your Hands to Handle, Control, or Feel Objects, Tools, or Controls	-0.01788	-0.0150***
		(0.00550)
Work With Work Group or Team	0.01448	0.0284***
		(0.00796)

Note: This table shows the result of the Lasso regression and the OLS regression after the selection of variables. We use the O*NET work context characteristics as predictors for the change in the WFH share 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 A2: Changes in the Urban Wage Premium by the Level of WFH Adoption - Cross-County and Within-MSA

	Log Posted Hourly Wages			
	(1)	(2)	(3)	(4)
Log M	0.0177***	0.0123***	0.0173***	0.0137***
	(0.000210)	(0.000315)	(0.000191)	(0.000282)
Log M $\times$ Post	-6.53e-05	-0.000845***	-0.00175***	-0.00122***
	(0.000218)	(0.000272)	(0.000205)	(0.000261)
Log M $\times$ High WFH	0.0168***	0.0189***	0.0163***	0.0135***
	(0.000468)	(0.000724)	(0.000395)	(0.000595)
Log M $\times$ High WFH $\times$ Post	-0.00415***	-0.00253***	-0.00385***	-0.00111**
	(0.000483)	(0.000595)	(0.000432)	(0.000555)
MSA FE $\times$ High WFH $\times$ Post	No	Yes	No	Yes
Measurement of M	Emp Size by Occ and County	Emp Size by Occ and County	Emp Density by Occ and County	Emp Density by Occ and County
Observations	5,228,603	5,153,403	5,228,603	5,153,403

Note: This table presents the estimates of the urban wage premiums before and after the start of the COVID-19 pandemic (i.e., α_0, α_1, α_2, and α_3 in Equation 5). The sample comprises the job postings from the Burning Glass data from 2018 to the first five months of 2022. The dependent variable is the log posted hourly wage of each job posting. M is defined as the size of employment of the occupation in the county of the posted job (Columns 1–2) or the employment density (employment divided by the county area) of the occupation in the county of the posted job (Column 3–4). $Post$ indicates the pandemic period (i.e., the years of 2020–2022). $High\ WFH$ is an indicator which is equal to 1 if the occupation of the posted job has a high level of WFH adoption. All columns control for the indicators of occupation code (SOC-ONET), industry code (3-digit NAICS), years of education required by the job, salary type, part-/full-time status, tax term, and job posting month. Columns 2 and 4 include the interaction of the MSA FE, indicator of whether the posted job has a high level of WFH adoption, and the indicator of the pandemic period (i.e., the years of 2020–2022). We use a 10% random sample of the Burning Glass data. Standard errors are clustered at the MSA level. *** $p <$ 0.01, ** $p <$ 0.05, *$p <$ 0.1.

Table A3: 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
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
Decision Making	Business
Planning	Business
Leadership	Business
Organizational Skills	Organizational Skills
People Management	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 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 A4: Most Frequently Listed Skills Under Key Skill Cluster Families (Part 1)

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

Table A5: Most Frequently Listed Skills Under Key Skill Cluster Families (Part 2)

rank	Sales	Information Technology	Analysis
1	Sales	Microsoft Office	Data Analysis
2	Product Sales	Microsoft Powerpoint	Data Collection
3	Merchandising	SQL	Tableau
4	Sales Goals	Software Development	Data Science
5	Business Development	Python	Machine Learning
6	Product Knowledge	Spreadsheets	Business Intelligence
7	Prospective Clients	Software Engineering	SAS
8	Retail Sales	Java	Data Visualization
9	Description and Demonstration of Products	Technical Support	Statistics
10	Sales Management	Microsoft Outlook	Statistical Analysis
11	Negotiation Skills	Software as a Service (SaaS)	Pipeline (Computing)
12	Account Management	Information Systems	Data Mining
13	Outside Sales	SAP	Requirements Verification and Validation
14	Business-to-Business	Enterprise Resource Planning (ERP)	Data Governance
15	E-Commerce	Oracle	MATLAB
16	Upselling Products and Services	JavaScript	Ad Hoc Reporting
17	Inside Sales	Microsoft Azure	Geometry
18	Cross Sell	Scrum	R
19	Sales Support	Word Processing	Algebra
20	Retail Management	Linux	Behavior Analysis
21	Articulating Value Propositions	DevOps	Data Validation
22	Cold Calling	Data Management	Quantitative Analysis
23	Sales Strategy	Atlassian JIRA	Predictive Models
24	Sales Planning	Git	Alteryx
25	Insurance Recommendation	Telecommunications	Business Metrics
26	Insurance Sales	Information Security	Cognos Impromptu
27	Sales Calls	Microsoft Windows	Big Data Analytics
28	Visual Merchandising	Microsoft Sharepoint	Statistical Methods
29	Sales Cycle	Microsoft C#	Data Manipulation
30	Sales Training	Microsoft Access	SAP BusinessObjects
31	Direct Sales	Microsoft Project	Deep Learning
32	Lead Generation	ServiceNow	Natural Language Processing
33	Account Closing	Agile Development	SPSS
34	Overcoming Objections	Systems Engineering	Data Capture
35	Sales Leadership	Amazon Web Services (AWS)	Data Reports
36	Sales Reporting	C++	Predictive Analytics
37	Telemarketing	Kubernetes	Business Intelligence Reporting
38	Sales Meetings	Troubleshooting Technical Issues	Qlikview
39	Sales Prospecting	Systems Development Life Cycle (SDLC)	Statistical Process Control (SPC)
40	Consultative Sales	Network Hardware/Software Maintenance	Qlik
41	Sales Administration	System Design	Calculus
42	Sales Channels	Debugging	trigonometry
43	New Business Development	Relational Databases	Ad Hoc Analysis
44	Complex Sales	Unit Testing	Computer Vision
45	Closing Sales	System Administration	Microstrategy
46	Product and Service Information	UNIX	Data Trending
47	Sales Principles	SQL Server	Data Verification
48	Technical Sales	Extraction Transformation and Loading (ETL)	Model Building
49	Sales Development	Data Warehousing	Decision Trees
50	Life Insurance Sales	Big Data	Pandas

Table A6: Gelbach Decomposition: Contribution of Changes in Skill-Specific Urban Wage Premiums to the Decrease in the Urban Wage Premium among High-WFH Jobs - Jobs Requiring College Education

Skill Cluster Family	β	Γ	Contribution	Contribution Share
	(1)	(2)	(3)	(4)
Business	-0.009948	0.6552911	-0.0065188	43.75%
Building Relationship	-0.0071532	0.4362624	-0.0031207	20.94%
Customer and Client Support	-0.0139438	0.1475065	-0.0020568	13.80%
Engineering	-0.0125198	0.0817247	-0.0010232	6.87%
Communications	-0.0014427	0.6029444	-0.0008699	5.84%
Finance	-0.0035053	0.1963087	-0.0006881	4.62%
Education and Training	0.0121326	-0.0427101	-0.0005182	3.48%
Legal	0.0114919	-0.0347027	-0.0003988	2.68%
Environment	0.0133503	-0.0164243	-0.0002193	1.47%
Public Safety and National Security	0.0107764	-0.017954	-0.0001935	1.30%
Agriculture, Horticulture, and the Outdoors	0.0335211	-0.0027691	-0.0000928	0.62%
Economics, Policy, and Social Studies	0.0145573	-0.0052441	-0.0000763	0.51%
Human Resources	-0.0007784	0.0624638	-0.0000486	0.33%
Physical Abilities	0.0031597	-0.0071981	-0.0000227	0.15%
Administration	-0.00009	0.2408115	-0.0000217	0.15%
Personal Care and Services	-0.0030477	0.0012513	-3.81E-06	0.03%
Energy and Utilities	0.0044138	0.0006934	3.06E-06	-0.02%
Media and Writing	0.0010354	0.0676898	0.0000701	-0.47%
Marketing and Public Relations	0.0002039	0.4904028	0.0001	-0.67%
Architecture and Construction	0.0082786	0.0133645	0.0001106	-0.74%
Maintenance, Repair, and Installation	0.0107667	0.0142901	0.0001539	-1.03%
Information Technology	0.0001666	0.9285307	0.0001547	-1.04%
Industry Knowledge	0.0018065	0.1401459	0.0002532	-1.70%
Supply Chain and Logistics	0.0034513	0.0831463	0.000287	-1.93%
Analysis	0.0007782	0.4979387	0.0003875	-2.60%
Manufacturing and Production	0.0038417	0.1013248	0.0003893	-2.61%
Science and Research	0.0037418	0.1084927	0.000406	-2.72%
Health Care	0.0080358	0.0639552	0.0005139	-3.45%
Design	0.0076283	0.1270839	0.0009694	-6.51%
Organizational Skills	0.0090132	0.1517637	0.0013679	-9.18%
Sales	0.0047558	0.4361944	0.0020745	-13.92%

Note: This table presents the Gelbach decomposition results similar to Table 5. This table uses the sample of job postings that require college education.

Table A7: Gelbach Decomposition: Contribution of Changes in Skill-Specific Urban Wage Premiums to the Decrease in the Urban Wage Premium among High-WFH Jobs - Jobs Not Requiring College Education

Skill Cluster Family	β	Γ	Contribution	Contribution Share
	(1)	(2)	(3)	(4)
Information Technology	-0.0075657	0.8377702	-0.0063383	29.19%
Sales	-0.0067045	0.3865255	-0.0025915	11.94%
Marketing and Public Relations	-0.0028468	0.4843286	-0.0013788	6.35%
Building Relationship	-0.004091	0.3011343	-0.0012319	5.67%
Legal	0.0253815	-0.0350095	-0.0008886	4.09%
Finance	-0.0113555	0.0774084	-0.000879	4.05%
Customer and Client Support	-0.0087441	0.0684798	-0.0005988	2.76%
Supply Chain and Logistics	-0.0072616	0.0496138	-0.0003603	1.66%
Public Safety and National Security	0.0395662	-0.0089626	-0.0003546	1.63%
Architecture and Construction	0.0167482	-0.0133037	-0.0002228	1.03%
Physical Abilities	0.0050157	-0.0294784	-0.0001479	0.68%
Environment	0.0144511	-0.0098667	-0.0001426	0.66%
Agriculture, Horticulture, and the Outdoors	0.0385638	-0.0028898	-0.0001114	0.51%
Maintenance, Repair, and Installation	0.0072489	-0.0097931	-0.000071	0.33%
Economics, Policy, and Social Studies	-0.0018678	-0.0099465	0.0000186	-0.09%
Personal Care and Services	0.0282552	0.0019123	0.000054	-0.25%
Media and Writing	0.0012411	0.0570896	0.0000709	-0.33%
Human Resources	0.0021229	0.0529169	0.0001123	-0.52%
Manufacturing and Production	0.0023591	0.0614268	0.0001449	-0.67%
Science and Research	0.0051364	0.0554355	0.0002847	-1.31%
Education and Training	-0.0088758	-0.0327903	0.000291	-1.34%
Health Care	0.0213469	0.0146093	0.0003119	-1.44%
Engineering	0.0108175	0.0374829	0.0004055	-1.87%
Energy and Utilities	0.0522504	0.008327	0.0004351	-2.00%
Administration	0.0054825	0.1107273	0.0006071	-2.80%
Organizational Skills	0.0107535	0.0834136	0.000897	-4.13%
Industry Knowledge	0.0117489	0.1035725	0.0012169	-5.60%
Business	0.0031731	0.464642	0.0014743	-6.79%
Design	0.0193391	0.1034363	0.0020004	-9.21%
Analysis	0.0061521	0.3437929	0.002115	-9.74%
Communications	0.0079507	0.3529117	0.0028059	-12.92%

Note: This table presents the Gelbach decomposition results similar to Table 5. This table uses the sample of job postings that do not require college education.