Work from Home and Spatial Misallocation

please click here for the latest version

Mikhail Zavarzin[1]

December 2025

Abstract

I study whether the recent shift towards work from home (WFH) in the US alleviates or exacerbates the impact of existing policy distortions—progressive taxation and housing supply restrictions—on the aggregate level of output and inequality. These policies divert labour towards less productive locations, hurting aggregate productivity. In principle, WFH can alleviate this misallocation by allowing workers to supply their labour to high-productivity cities while living in more affordable areas and paying lower income taxes. In turn, firms in high-productivity cities can substitute in-person labour with cheaper remote workers. However, WFH may also exacerbate the misallocation, as remote work remains subject to relatively high tax rates and is complementary to in-person labour. Using a spatial equilibrium model calibrated with US Census data, I find that the shift to WFH does not change the distortionary effect of housing regulations, but it increases the distortionary effect of progressive taxation. In particular, adopting a flat tax scheme yields an additional 0.5pp output increase in the economy with the WFH shift, relative to the economy in 2019. However, this greater productivity gain comes at the cost of additional inequality between college- and non-college-educated workers, compared to the 2019 economy, as lower-skilled workers have less access to remote work. Thus, WFH intensifies the spatial equity-productivity trade-off, underscoring the need for more nuanced tax policy.

Keywords: remote work, tax progressivity, housing supply, labour mobility
JEL Codes: E24, H21, R13, R31

1. HEC, University of Lausanne, and Department of Economics, University of Pittsburgh, mikhail.zavarzin@unil.ch. I am incredibly grateful to my advisors, Daniele Coen-Pirani and Marla Ripoll, and to Laurence Ales, David DeJong, Eric Donald, Douglas Hanley, Mike Mei, Randall Walsh, Octavio Aguilar, Leonardo Urrea, Zebang Xu, and Ruiyu Zhu for many great suggestions and comments. I also thank conference and seminar participants at Remote Work Conference, HEC Lausanne Macroeconomics Workshop, Midwest Macroeconomics Meeting, and University of Pittsburgh Macroeconomics Brownbag and Applied Micro/Urban Brownbag. All errors are mine.

1 Introduction

Progressive income taxation reduces incentives for workers to locate in areas that offer higher wages. As a result, fewer people choose to work in high-productivity, high-wage cities such as San Francisco or New York, which in turn suppresses aggregate productivity. In addition, many of these productive areas face inelastic housing supply, partially due to local regulations, further discouraging workers from locating there. Recently, Colas and Hutchinson (2021) estimate that the output losses due to the progressive US income tax amount to 0.25% while Hsieh and Moretti (2019) calculate that restrictive housing regulations in the most constrained cities can generate a 36.3% loss in output.

The recent shift to remote work, which allowed more than 22% of full-time college-educated workers to work from home as of 2023 compared to just 6% in 2019 according to the US Census American Community Survey (ACS), has the potential to affect the extent of spatial misallocation caused by income tax progressivity and housing regulations.[2] In particular, as more jobs in highly productive areas that previously required physical presence can now be done from anywhere, more workers can supply their labour to these locations without paying high rents or sacrificing access to amenities.[3] In turn, employers in more productive places also benefit from the shift to remote work, as the WFH wage discount and reduced need for office space allow them to cut costs and expand production by taking advantage of the national pool of remote labour. This way, the WFH shift induces a reallocation of labour from less productive to more productive firms, generating a "winner takes most" effect and increasing aggregate productivity.

However, by suppressing the supply of remote and in-person labour in the most productive cities, policy can restrain the "winner takes most" effect, widening the gap between actual and potential output. A priori, it is not clear whether the post-WFH increase in output will keep pace with the increase in potential output, so spatial misallocation may actually increase in relative terms.

One concern related to the shift to remote work is that it has been concentrated mostly in high-skill jobs requiring a college degree, whereas many low-skill jobs, such as truck drivers and store clerks, must still be done in person. For workers without a college education, the

2. These numbers are consistent with, e.g., Barrero, Bloom, and Davis (2021) survey and its follow-ups.

3. Working remotely also allows workers to avoid higher marginal income tax rates in high-productivity locations if the remote wage is lower than their in-person wage. Workers may be willing to accept this wage discount because working remotely can, first, increase consumption by enabling relocation to areas with cheaper housing, and second, provide access to more amenities, including the amenity of remote work itself, as demonstrated by Bagga et al. (2023). In addition, the wage discount can also result from increased competition in the remote labour market, as employers may perceive remote workers as more replaceable than in-person workers.

share of remote workers increased by a much smaller margin: from about 4% in 2019 to 9% in 2023. As such, the shift to WFH can exacerbate inequality resulting from the reduction of tax progressivity and the relaxation of housing supply restrictions.[4]

To account for both the direct and general equilibrium effects that the shift to remote work may have on spatial misallocation and inequality associated with correcting it, I develop and quantify a spatial general equilibrium model with a progressive national income tax and local housing supply restrictions, in which workers decide where to reside and whether to work from home or commute in person. The model allows me to construct long-run counterfactual economies that have fully adjusted to the WFH shift and policy changes. Using the model calibrated with ACS data, I calculate how much more output is gained or lost in the long-run WFH economy compared to 2019 due to progressive taxation (relative to a flat tax system) and housing supply constraints (compared to a counterfactual in which all locations have at least the median supply elasticity). I also assess how much more or less inequality results from correcting these distortions in the post-WFH world.

I find that compared to 2019, the shift to remote work *increases* the output loss from progressive taxation by at least 0.5pp (50%) but does not robustly affect the output loss from inelastic housing. I emphasise three channels that generate these results. First, tax progressivity directly reduces the attractiveness of remote work, which still offers above-average wages, thus limiting the productivity advantages of the "winner takes most" effect: when fewer WFH workers are available, firms in the most productive cities cannot substitute enough in-person labour with cheaper remote work and expand less. In addition, with fewer remote workers leaving expensive cities, fewer in-person workers can move into their place and contribute to production there. Second, both tax progressivity and housing supply constraints directly suppress in-person labour supply in the most productive areas. With fewer in-person workers, the WFH-driven expansion of firms there is constrained when remote and in-person work are complementary. Third, housing supply constraints push remote workers out of productive areas with expensive housing, and an increase in housing supply there will bring some remote workers back. However, because they do not need to physically be in these places to be productive, the productivity benefits from increasing housing supply elasticities are reduced in the post-WFH world.

Note that housing regulations directly constrain the supply of in-person labour (second channel), whereas tax progressivity directly limits the supply of *both* remote and in-person labour (first and second channels). As a result, the WFH shift is more likely to increase

4. Moreover, in the presence of skill complementarity, the uneven access to remote work across skills may affect the degree of spatial misallocation itself. E.g., as high skill workers relocate towards lower housing prices and better amenities, housing prices may decline in higher productivity areas and rise in lower productivity areas with high amenities, pushing low-skill workers away from low- to high-productivity locations.

the misallocation caused by tax progressivity than by housing restrictions. Additionally, the first and second channels ensure that reducing tax progressivity leads to extra output growth in the post-WFH world, regardless of the degree of complementarity between WFH and in-person work. In contrast, for relaxed housing supply restrictions to generate additional output growth after the WFH shift, the second channel must dominate the third, and the degree of WFH-in-person complementarity must be sufficiently high.

In terms of inequality, measured as the difference in equivalent variation for each skill group, flattening tax progressivity in the post-WFH world will hurt low-skill workers more than in 2019 and increase inequality between high- and low-skill workers by 1.6pp (12%) more. Raising housing supply elasticities to the median level will also benefit low-skill workers disproportionately less in the post-WFH world, increasing inequality by an additional 0.6pp (6%). This additional inequality is generated by the interaction of the "winner takes most" effect, skill complementarity, and the limited access to WFH among low-skill workers compared to high-skill workers. Less productive places lose high-skill in-person workers who switch to working remotely for firms in the most productive cities. Through skill complementarity, this weakens the demand for local low-skill workers and depresses their wages. Since they have limited access to remote work, it is more difficult for them to escape lower wages in less productive places, which reduces their welfare and increases skill inequality. Consequently, removing policy distortions in the post-WFH world would further increase the number of high-skill remote workers and widen skill inequality even more.

Together, these results imply that the shift to WFH intensifies the equity-productivity trade-off in a spatial context, underscoring the need for more nuanced tax policy going forward. In the post-WFH world, governments should be aware that easing inequality through progressive taxation can become even more costly in terms of productivity.

My paper contributes to several strands of literature: the new literature studying the effects of the recent shift to remote work; the literature on spatial misallocation, particularly that caused by the national progressive income tax and housing supply restrictions; and the literature examining the concentration of economic activity within "superstar" firms and cities.

The spatial literature studying the WFH shift finds that cities can become less centralised and productive (Monte, Porcher, and Rossi-Hansberg 2023), and that inequality within cities may widen (Davis, Ghent, and Gregory 2024 show this with a static CBD-suburb model calibrated to US data, while Richard 2024 finds similar results using a dynamic version calibrated to UK data). At the same time, inequality and concentration of talent across regions may decline (Delventhal and Parkhomenko 2023 demonstrate this in a spatial model calibrated to US data; Gokan et al. 2022 and Brueckner, Kahn, and Lin 2023 document this empirically in UK and US data respectively).[5] This literature also shows that WFH reduces rent differentials within cities and across regions; in particular, the shift to WFH has lowered the demand for commercial real estate in downtown areas (Gupta, Mittal, and Van Nieuwerburgh 2022). Additionally, data suggest that workers have become more sensitive to local taxes since the WFH shift (Agrawal and Brueckner 2022). In this paper, I build a spatial model of regions similar to Monte, Redding, and Rossi-Hansberg (2018) and Delventhal and Parkhomenko (2023), which also incorporates a progressive national income tax in the spirit of Heathcote, Storesletten, and Violante (2017). I use this framework to study the spatial reallocation of workers induced by the shift to remote work and changes in policy. My focus is on how the WFH shift affects the *aggregate* outcomes in the presence of spatial distortions created by national income tax progressivity and local housing regulations.

Note that this paper presents a more optimistic perspective on the aggregate impacts of WFH compared to some of the existing literature I mentioned, in particular, Gupta, Mittal, and Van Nieuwerburgh (2022) (who discuss the potential collapse of downtown commercial real estate) and Monte, Porcher, and Rossi-Hansberg (2023) (who highlight a reduction in productivity due to declining concentration in downtown areas and the associated agglomeration effects). My model shows that as firms in high-productivity areas save on labour costs and commercial real estate by switching to remote work, they expand and actually need to hire more in-person workers and provide office space for them over the longer run, counterbalancing the effects of the short-run departure of in-person workers from downtowns as they start remote work. In my model, WFH can have similarly beneficial effects to those of commuting documented by Monte, Redding, and Rossi-Hansberg (2018), by allowing more people to work in more productive and constrained cities.

The literature on spatial misallocation of labour documents that taxation (Albouy 2009, Colas and Hutchinson 2021, Coen-Pirani 2025) and housing supply constraints (Herkenhoff, Ohanian, and Prescott 2018, Hsieh and Moretti 2019) reduce aggregate output and welfare by making high-productivity locations more expensive. My contribution is to evaluate how these negative effects are impacted by the shift to work from home.

Finally, a strand of literature documents the increasing concentration of economic activity within "superstar" firms and cities. Autor et al. (2020) argue that greater product market competition or advances in information technology generate a "winner takes most" effect, reallocating market share to the most productive firms and increasing market concentration. Moretti (2012) describes the "great divergence" between American cities and attributes it

5. Interestingly, earlier theoretical work on WFH (dating back to Gaspar and Glaeser 1998 and Safirova 2002) has documented many of the effects explored in the recent quantitative spatial literature, albeit with more stylised models.

to the greater importance of agglomeration forces in the innovation and knowledge economy, with innovation hubs like San Francisco concentrating human capital and economic opportunity while places like Cleveland are left behind. This paper emphasises that WFH can be another economic mechanism contributing to increased economic concentration by enabling the reallocation of labour from less productive firms and cities to more productive ones.[6]

The rest of the paper is organised as follows. In the next section, I document several facts about the shift to remote work. Section 3 presents the model. Section 4 describes the counterfactual analysis setup and model calibration. In Section 5, I run the counterfactual experiments and discuss how the aggregate implications of national income tax progressivity and inelastic housing supply change as the economy shifts to more work done remotely. Section 6 examines the sensitivity of the results to the degree of complementarity between WFH and in-person work, the amount of commercial space per worker, and the inclusion of agglomeration effects. Section 7 concludes. Appendix describes the data and counterfactual experiments in more detail and presents some additional robustness checks.

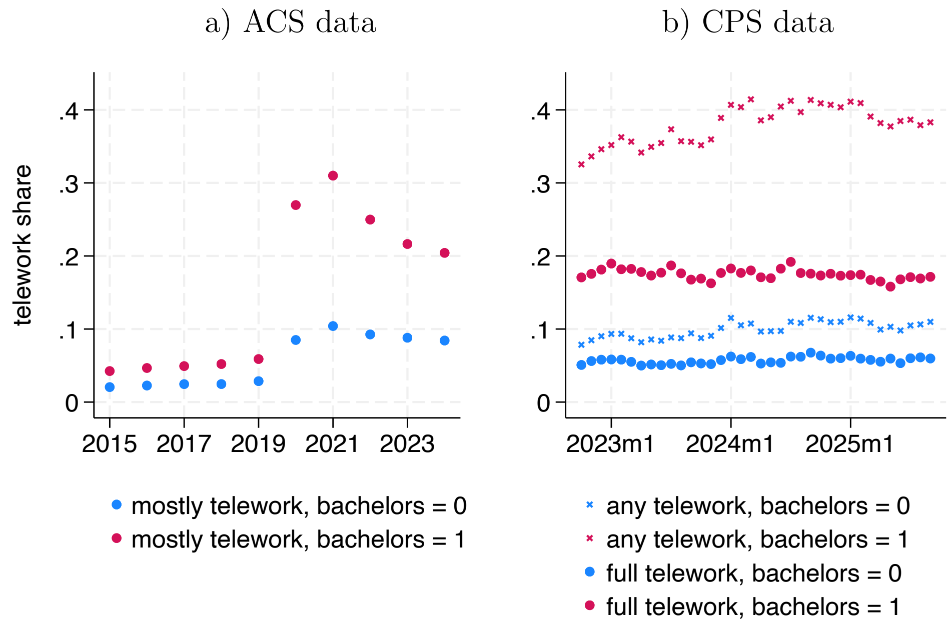
2 Work-from-Home Shift in the Data

Figure 1 presents recent trends in telework. Initially, the shift to remote work was a necessary response to the Covid-19 pandemic. Since then, the share of remote workers has declined slightly, but it remains well above the pre-pandemic levels. According to ACS, as of 2023, roughly 22% and 9% of full-time workers with and without a college degree, respectively, mostly worked from home—a dramatic increase compared to 6% and 4% in 2019. To compensate for the lack of more recent data in ACS, I turn to the US Community Population Survey (CPS) which currently provides telework data through April 2025. Despite differences in how remote work is defined across the two sources, CPS data suggest that the shares of remote workers has at least stabilised at the new levels. These observations are complemented by Barrero, Bloom, and Davis (2021) who have been conducting a comprehensive survey of remote work in the US, documenting that the share of paid full days worked from home has stabilised above 25% through April 2025; they also list reasons why WFH is likely to stick. Altogether, it appears that remote work is here to stay, making the analysis of its long-run consequences a highly relevant endeavour.

Another empirical pattern that Figure 1 documents is the heterogeneity of the WFH shift across worker types. Since college-educated workers are much more likely to do jobs that can

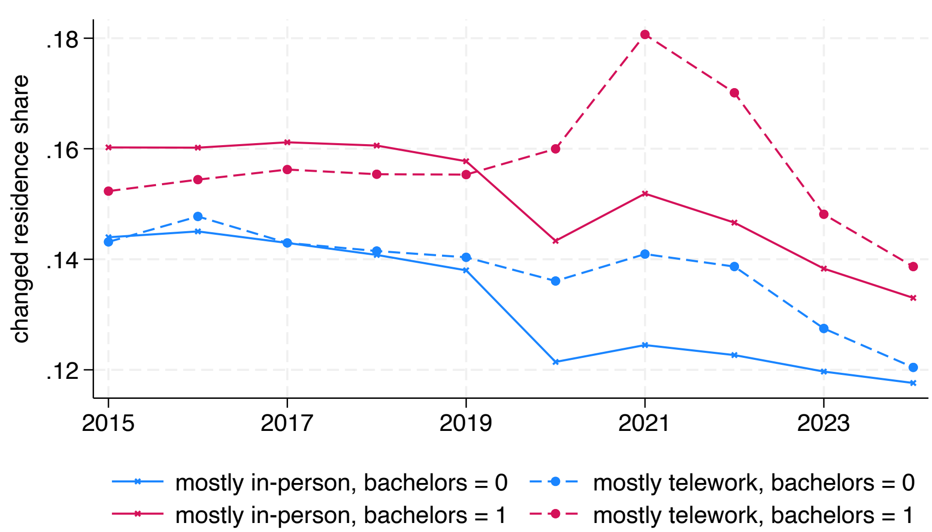
6. There is an interesting parallel between the shift to WFH and the rise of e-commerce: just as remote workers don't need to be physically present near employers, online retailers don't need to be near consumers to sell goods. Li (2025) explores the e-commerce shock using a quantitative model and finds that it leads to a reallocation of economic activity that widens regional disparities.

Figure 1: **Persistent Rise of Work from Home**



Notes: Full-time workers, averages by education group. ACS definition of WFH: "worked mostly from home last week". Unlike ACS, CPS provides detailed hours teleworked last week, and I define "any telework" as "worked at least one hour from home last week" and "full telework" as "worked at least forty hours from home last week".

Figure 2: **Work from Home and Propensity to Change Residence**



Notes: Full-time workers; averages by education group and indicator whether a worker changed residence last year. Source: ACS.

be done remotely (in industries like IT and finance), they now work remotely far more often than high-school-educated workers (who are more likely to work, e.g., in transportation, construction, and social services).

Despite stable WFH shares since 2023, the economy can still take a long time to reach a new equilibrium, as workers face migration costs, firms face adjustment costs, housing takes time to build, etc. The data provide support for increased spatial mobility of remote workers, as shown in Figure 2, suggesting that remote workers have started relocating to areas with lower housing prices and better amenities. Compared to in-person workers, WFH workers are consistently more likely to change residences after the shift, regardless of education. This aligns with Bick et al. (2024) who use quasi-panel data on changes in employers' WFH policies to document that WFH induces increased interstate migration. Interestingly, the only group that became more mobile after 2019 is college-educated remote workers—perhaps because they face lower migration costs. However, the fact that remote workers remain more mobile than in-person workers as of 2024 (despite being less mobile before 2019) suggests that the economy may still be adjusting to the WFH shock. Moreover, new housing may take more than just three years to build in places where the WFH shift increased housing demand. Therefore, a model is necessary to assess how policy changes would play out in a world that has fully adjusted to WFH.

3 The Model

I build a spatial equilibrium model that includes a remote work option for workers in addition to commuting to in-person workplaces. To capture the heterogeneity in the extent of the WFH shift across high- and low-skill workers, the model allows for several exogenous agent types. It also features a national progressive income tax as in Heathcote, Storesletten, and Violante (2017) and constrained supply of rental housing as sources of spatial misallocation.

There are $j = 1, \ldots, J$ locations in the economy, each characterised by production and residential amenities, a housing supply function, type-specific commuting costs to all other locations, and a type-specific cost of working remotely from that location.

A CES sector in each location produces the freely tradeable consumption good, combining local and remote labour of all household types with floor space. The national government collects taxes to fund redistribution and government spending.

Households. The economy is populated by the total mass L^a of type a households, where $a = 1$ refers to low-skill workers and $a = 2$ to high-skill workers. Households choose in which location j to live and whether to work in person in any location $i \geq 1$, or to work from home, which corresponds to the choice of $i = 0$. There are local markets for in-person labour of each type which clear at wage w_i^a. If a worker chooses to work remotely, they join a *national* market for remote labour of their type that clears at wage w_0^a.[7]

Each worker receives an idiosyncratic taste shock for each workplace-residence pair s_{ij}^a, distributed Frechét(θ^a).[8] The national government collects taxes and pays transfers to households so that the post-tax/transfer income of workers working in i is $\chi(w_i^a)^{1-\mu}$. I assume each worker's preferences over the consumption good and housing are Cobb-Douglas, so agents spend a fraction γ of their post-tax/transfer income on the consumption good (the price of which is normalised to 1 in all locations). Workers rent local housing at price q_j. Workers' overall utility function is given by the Cobb-Douglas component, multiplied by the taste shock, s_{ij}^a, the cost of commuting or remote work, $(1-\kappa_{ij}^a)$, and local residential amenities, B_j, which depend on resident density via agglomeration effects. Then, the indirect utility function of a worker of type a for a workplace-residence pair i, j is

$$U_{ij}^a = s_{ij}^a\,(1-\kappa_{ij}^a)B_j\chi(w_i^a)^{1-\mu}(q_j)^{\gamma-1}. \tag{1}$$

Given individual realisations of the taste shocks, we can calculate the fractions of agents of each type a choosing option i, j:

$$\pi_{ij}^a = \frac{\left((1-\kappa_{ij}^a)B_j\chi(w_i^a)^{1-\mu}(q_j)^{\gamma-1}\right)^\theta}{\sum_e\sum_h\left((1-\kappa_{eh}^a)B_h\chi(w_e^a)^{1-\mu}(q_h)^{\gamma-1}\right)^\theta}. \tag{2}$$

Then, the number of residents in each location is $R_j^a \equiv \sum_i \pi_{ij}^a L^a$, and the number of in-person workers in location $i \geq 1$ or the national number of remote workers, $i = 0$, is given by $L_i^a \equiv \sum_j \pi_{ij}^a L^a$.

Production. There are three goods produced by firms in the economy: local housing, national remote services that can be costlessly assigned to any location, and the final consumption good that can be freely traded across locations.

7. Of course, it is possible to model WFH labour markets as local. However, due to the limitations of ACS data, which don't show the physical location of employers for remote workers, it is impossible to match such a model to these data. The assumption of national WFH markets seems reasonable, as firms can hire remote workers from anywhere in the economy, so they have to compete with other employers at the level of the whole economy as well.

8. Setting $\theta^1 < \theta^2$ accounts for the fact that college-educated workers are more mobile than non-college-educated. In addition, I assume the same distribution of the shock for both in-person workplace-residence ($i \geq 1$) pairs and WFH-residence pairs ($i = 0$). However, it is reasonable to think that it is easier for workers to switch between in-person work and WFH (keeping the place of residence fixed) than between in-person work in different locations. I modify the structure of the iid shock to reflect this fact and find that the main quantitative results are robust to alternative specifications. Details are available upon request.

The competitive national remote work sector hires remote workers of each type a at wage w_0^a and sells remote work services at price p_0^a:

$$y_0^a = A_0^a \ell_0^a, \qquad p_0^a = w_0^a / A_0^a. \tag{3}$$

The local CES final good sector hires in-person labour ℓ_i^a, rents floor space for in-person workers h_i^a, and purchases remote services y_{0i}^a from the national market. First, an in-person work composite of each type a combines floor space with in-person labour:

$$\tilde{\ell}_i^a = \min\{\ell_i^a, \rho^a h_i^a\}, \qquad \ell_i^a = \rho^a h_i^a. \tag{4}$$

Then, a type-a composite combines $\tilde{\ell}_i^a$ with remote services y_{0i}^a:

$$y_i^a = A_i^a \left[(\alpha^a)^{1-\sigma^a} (\tilde{\ell}_i^a)^{\sigma^a} + (1-\alpha^a)^{1-\sigma^a} (y_{0i}^a)^{\sigma^a} \right]^{\frac{1}{\sigma^a}}, \quad \sigma^a < 1. \tag{5}$$

Finally, the consumption good is produced by combining the composites of all types:

$$y_i = A_i \left\{ \nu^{1-\delta} (y_i^1)^\delta + (1-\nu)^{1-\delta} (y_i^2)^\delta \right\}^{\frac{1}{\delta}}, \quad \delta < 1. \tag{6}$$

The consumption good is freely traded across locations, so it is sold at the same price everywhere which I normalise to 1. Then, the aggregate final good output is $Y^c \equiv \sum_i y_i$. Because the CES sector earns zero profit, the total revenue must equal the total wage and commercial rent bill: $Y^c = \sum_a L^a \left[\sum_j \sum_i \pi_{ij}^a \left(w_i^a + \frac{q_i}{\rho^a} \right) + \pi_{0j}^a w_0^a \right]$. In the above expressions, A_0^a is the relative productivity of remote work, A_i^2 is the relative productivity of high-skill workers ($A_i^1 = 1$), A_i is a location-specific productivity subject to agglomeration effects in the density of in-person workers, $1/\rho^a$ is the amount of floor space required per worker, $1/(1-\sigma^a)$ is the type-specific elasticity of substitution between in-person composite and remote services, $1/(1-\delta)$ is the elasticity of substitution between the low-skill and high-skill services, α^a determines the expenditure share of in-person services relative to remote, and ν determines the expenditure share of low-skill ($a = 1$) services relative to high-skill ($a = 2$) in production of the consumption good.

After solving the cost-minimisation problem for a local final good sector and plugging in the optimal input ratios, I maximise its profit to derive the unit cost expression:

$$A_i = \left\{ \sum_a \nu^a (A_i^a)^{\frac{\delta}{1-\delta}} \left[\alpha^a \left(w_i^a + \frac{q_i}{\rho^a} \right)^{-\frac{\sigma^a}{1-\sigma^a}} + (1-\alpha^a) \left(p_0^a \right)^{-\frac{\sigma^a}{1-\sigma^a}} \right]^{\left(-\frac{1-\sigma^a}{\sigma^a}\right)\left(-\frac{\delta}{1-\delta}\right)} \right\}^{-\frac{1-\delta}{\delta}}, \tag{7}$$

where $\nu^1 = \nu, \nu^2 = 1 - \nu, A_i^1 = 1$.

Local housing in each location is supplied by competitive developers who rent land from absentee land owners and purchase the final good to produce housing services

$$H_j = A_j^h (Y_j^h)^{\lambda_j} (Z_j)^{1-\lambda_j}, \tag{8}$$

where A_j^h is a local housing productivity shifter, Y_j^h denotes final good input, and Z_j is land input, which is in fixed supply $\bar{Z}_j$, bounded by the maximum amount of buildable land $\bar{Z}_j^m$. Land markets are competitive. Solving the profit-maximisation problem of local developers, I obtain the housing supply function in each location j:

$$H_j = \bar{H}_j \, q_j^{\xi_j}, \tag{9}$$

where $\xi_j \equiv \frac{\lambda_j}{1-\lambda_j}$ is the local elasticity of housing supply with respect to rent, and $\bar{H}_j \equiv A_j^h \bar{Z}_j \lambda_j^{\frac{\lambda_j}{1-\lambda_j}}$ is the location-specific parameter capturing the amount of developable land and housing sector productivity. Land owners earn a share $1 - \lambda_j$ of local housing sales, so their earnings are $(1 - \lambda_j) q_j H_j$.

Aggregate Outcomes. The GDP of the whole economy is then the aggregate wage bill plus the earnings of absentee land owners:

$$Y = \sum_a L^a \sum_j \sum_i \pi_{ij}^a w_i^a + \sum_j (1 - \lambda_j) q_j H_j. \tag{10}$$

$U^a = \mathrm{E}\left[\max_{ij} U_{ij}^a\right] = \Gamma\left(\frac{\theta^a - 1}{\theta^a}\right) \left[\sum_i \sum_j \left((1 - \kappa_{ij}^a) B_j \chi (w_i^a)^{1-\mu} q_j^{\gamma-1}\right)^{\theta^a}\right]^{\frac{1}{\theta^a}}$ is the ex-ante expected welfare for each skill type. Using equation (2), it can be rewritten as

$$U^a = \Gamma\left(\frac{\theta^a - 1}{\theta^a}\right) \left[\left((1 - \kappa_{ij}^a) B_j \chi (w_i^a)^{1-\mu} q_j^{\gamma-1}\right)^{\theta^a} / \pi_{ij}^a\right]^{\frac{1}{\theta^a}}. \tag{11}$$

The earnings of absentee land owners are not part of domestic welfare.

Closing the Model. To close the model, I specify the market clearing conditions in local in-person and national remote labour markets, local housing markets, as well as the national budget constraint.[9]

9. The final good national market clearing follows from the balanced national budget: its output is split between the housing sector, absentee landlords, workers (equal to post-tax wages minus rents), and the government (equal to government spending).

First, given the CES production function for the local consumption good, the local market for one type of labour, say, low-skill in-person, clears given any prices $\{w_i^a\}$ and $\{q_j\}$:

$$L_i^1 = \ell_i^1. \tag{12}$$

Remember that $L_i^a = \sum_j \pi_{ij}^a L^a$. Then, we can use the solution to the cost minimisation problem to express the other labour market clearing conditions in terms of $\{L_i^1\}$. For in-person high-skill workers it is

$$L_i^2 = \ell_i^2 = \frac{1-\nu}{\nu}\frac{\alpha^2}{\alpha^1}\left[(A_i^2)^{\delta}\frac{(C_i^2)^{\delta-\sigma^2}}{(C_i^1)^{\delta-\sigma^1}}\frac{w_i^1+\frac{q_i}{\rho^1}}{w_i^2+\frac{q_i}{\rho^2}}\right]^{\frac{1}{1-\delta}}\ell_i^1, \tag{13}$$

$$C_i^a \equiv \left[\alpha^a + (1-\alpha^a)\left(\frac{w_i^a+\frac{q_i}{\rho^a}}{p_0^a}\right)^{\frac{\sigma^a}{1-\sigma^a}}\right]^{\frac{1}{\sigma^a}}$$

and for remote workers, the national market clearing conditions are given by

$$L_0^a = \sum_{i\geq 1}\frac{y_{0i}^a}{A_0^a} = \sum_{i\geq 1}\frac{1-\alpha^a}{\alpha^a}\left(\frac{w_i^a+\frac{q_i}{\rho^a}}{w_0^a}\right)^{\frac{1}{1-\sigma^a}}\frac{\ell_i^a}{A_0^a}. \tag{14}$$

Note that the supply and demand for remote workers are aggregated across all physical locations $i = 1, \ldots, J$ to the national level.

Local rents adjust so that the local quantity supplied is equal to the local quantity demanded by firms, who require $1/\rho^a$ units of space per in-person worker of each type, and by households, who spend fraction $1-\gamma$ of their income on housing:

$$\bar{H}_j q_j^{\xi_j} = \sum_a \left[\frac{L_j^a}{\rho^a} + \frac{1-\gamma}{q_j}\sum_i \chi(w_i^a)^{1-\mu}\pi_{ij}^a L^a\right]. \tag{15}$$

Finally, the national government collects taxes from and provides transfers to workers, $w_i^a - \chi(w_i^a)^{1-\mu}$, and maintains government expenditure, G.[10] Together with equations (2), (7), and (12)-(15), the balanced budget condition closes the model:

$$G = \sum_a\sum_i\left(w_i^a - \chi(w_i^a)^{1-\mu}\right)L_i^a. \tag{16}$$

I assume that G enters all agents' indirect utility from equation (1) multiplicatively. However, because G is the same for all agents, it does not affect the choice probabilities in equation

10. If $\mu = 0$ (income tax is proportional), $1-\chi$ corresponds to the flat tax rate.

(2).

The government can set any two of the three parameters (μ, χ, G), and the remaining one will be pinned down by the balanced budget. Because the goal of this paper is to study the effects of national tax progressivity, the counterfactual experiments focus on changing the parameter μ while holding government spending G fixed. This means that the parameter χ must adjust with μ to keep the budget balanced.

Agglomeration Effects. The productivity of the local final good sector and the value of local amenities are subject to agglomeration economies in the density of in-person workers and residents respectively:

$$A_i = \bar{A}_i \left(\frac{\sum_a L_i^a}{\bar{Z}_i^m} \right)^{\eta^L}, \quad B_j = \bar{B}_j \left(\frac{\sum_a R_j^a}{\bar{Z}_j^m} \right)^{\eta^R}, \tag{17}$$

where $\bar{A}_i$ and $\bar{B}_j$ summarise the exogenous determinants of local productivity and amenity, and η^L and η^R are the elasticities of productivity and amenity with respect to the local density of in-person workers and residents. In this formulation, I assume that remote workers do not contribute to local productivity externalities, but do contribute to local amenity externalities to the same extent as in-person workers.

Heblich, Redding, and Sturm (2020) estimate that, in the context of 19th-century London boroughs, both η^L and η^R are positive, suggesting that on net, agglomeration forces dominate congestion effects. With knowledge of η^L and η^R, I can group exogenous parameters into $\tilde{A}_i \equiv \bar{A}_i/(\bar{Z}_i^m)^{\eta^L}$ and $\tilde{B}_j \equiv \bar{B}_j/(\bar{Z}_j^m)^{\eta^R}$.

Competitive Equilibrium. Given exogenous parameters, local fundamentals, and government policy parameters (μ, G), a competitive equilibrium for this economy is defined as national remote and local in-person wages, prices of remote services, and local rents, $\{w_i^a, p_0^a, q_j\}$, an allocation $\{\pi_{ij}^a\}$, and a government policy χ such that

1. Given prices, the allocation satisfies household optimisation, i.e., $\{\pi_{ij}^a\}$ are given by equation (2).
2. Given prices, the WFH sector maximises profit, i.e., prices satisfy equation (3).
3. Given prices, local final good sectors maximise profit, i.e., prices satisfy equation (7).
4. Given prices, local housing developers maximise profit, i.e., prices satisfy equation (9).
5. Local in-person labour markets clear, i.e., prices and allocation satisfy equation (13).
6. National remote labour markets clear, i.e., prices and allocation satisfy equation (14).

7. Local housing markets clear, i.e., prices, allocation, and policy satisfy equation (15).
8. The policy χ is such that the national government's budget in equation (16) is balanced.

4 Counterfactual Analysis

In this section, I first describe how I set up the counterfactual experiments to run with the model in order to evaluate spatial distortions due to policy and how they change with the shift to WFH. Then, I show how to quantitatively implement these experiments, with a detailed description relegated to Appendix B. For clarity of exposition, here and in Section 5, I abstract from commercial housing and agglomeration effects, setting $\rho^a \to \infty$ and $\eta^L = \eta^R = 0$; I report the main results of this paper, which include $\rho^a < \infty$ and $\eta^L, \eta^R > 0$, in Sections 6.2 and 6.3.

To evaluate how WFH impacts the aggregate output loss and inequality due to progressive taxation and housing regulations, I run two types of counterfactual experiments, implementing the following "difference-in-differences" approach with the model. The first difference is between the 2019 baseline economy and a counterfactual economy with the WFH shift, but with all other parameters held constant as in the baseline economy. The second difference is between the initial economy (either 2019 baseline or WFH counterfactual) and a counterfactual economy with a policy change (again, with all other parameters fixed as in the initial economy). Then, I compare changes in output and each skill type's welfare from the second difference for the 2019 baseline economy ($Y_{2019}^{\text{new policy}}/Y_{2019}$, $(U^a)_{2019}^{\text{new policy}}/U^a_{2019}$) with those for the WFH economy ($Y_{\text{WFH}}^{\text{new policy}}/Y_{\text{WFH}}$, $(U^a)_{\text{WFH}}^{\text{new policy}}/U^a_{\text{WFH}}$).

In performing the WFH counterfactual, I assume that both demand for remote labour and its supply increase. This assumption is motivated by the data: while the national shares of remote workers in total employment have increased dramatically since 2019, their real wages have remained largely stagnant. To increase the demand for remote labour in the model, I raise the expenditure shares on remote labour in production, $\{1-\alpha^a\}$; to increase the supply, I reduce the cost of WFH in workers' utility function, $\{1-\kappa^a_{0j}\}$ (which is equivalent to an increase in the preference for remote work). I assume that this cost decreases by the same factor $\{1 \hat{-} \kappa^a_0\}$ in each location j and calibrate the rates of change $\{1 \hat{-} \alpha^a\}$ and $\{1 \hat{-} \kappa^a_0\}$ to match observed growth rates in the national share of remote workers in full-time employment and their national real wages over 2019-2022: 3.78 and 1.04 for workers without a college degree, and 5.07 and 1 for college-educated workers.[11] The calibrated parameter values are reported in Table 1.

11. In Appendix C, I show that the aggregate implications are similar if I instead directly match the change in the cost of WFH $\{1 \hat{-} \kappa^a_{0j}\}$ to the change in the number of WFH workers in each location j.

TABLE 1: **Model Calibration**

Parameter	Description	Value	Target/Source
	Change in in-person expenditure share		Change in national WFH wage, ACS
$\hat{\alpha}^1$	non-college	0.81	1.04
$\hat{\alpha}^2$	college	0.72	1
	Change in preference towards WFH		Change in national share of WFH, ACS
$1 - \hat{\kappa}_0^1$	non-college	1.34	3.78
$1 - \hat{\kappa}_0^2$	college	1.35	5.07
	Initial production weight on in-person work		National WFH expenditure share, ACS 2019
α^1	non-college	0.03	among non-college
α^2	college	0.06	among college
	Elasticity of substitution b.w. in-person and WFH labour		
$\frac{1}{1-\sigma^1}$	non-college	3.89	Delventhal and Parkhomenko (2023)
$\frac{1}{1-\sigma^2}$	college	3.03	
$\frac{1}{1-\delta}$	Elasticity of substitution b.w. non-college and college labour	3.63	Colas and Hutchinson (2021)
ν	Production weight on low-skill labour	0.44	National expenditure share, ACS 2019
	Frechét shape parameter		
θ^1	non-college	3.5	$\theta^2 = 1.5\theta^1$, Colas and Hutchinson (2021)
θ^2	college	5.25	$L^1\theta^1 + L^2\theta^2 = 4$, Monte, Redding, and Rossi-Hansberg (2018)
L^2/L^1	Ratio of college to non-college labour	0.54	ACS 2019
$1-\gamma$	Share of housing in labour income	0.3	ACS 2019
G/Y	Share of government spending in GDP	0.07	Share of federal spending in GDP, BEA 2019
ξ_j	Price elasticity of housing supply		Baum-Snow and Han (2024)
μ	Degree of tax progressivity	0.18	Heathcote, Storesletten, and Violante (2017)

Notes: Targets calculated using ACS data in 2022 and 2019. Policy parameter χ is calculated using equation (16) and local exogenous productivity parameter $\{\tilde{A}_i\}$ using (7) and (17).

The tax policy counterfactual involves manipulating the tax progressivity parameter μ. Heathcote, Storesletten, and Violante (2017) estimate that the US federal income tax rates (at least pre-pandemic) can be approximated with the value of the tax progressivity parameter $\mu = 0.18$ which I take as the 2019 baseline; note that proportional taxation corresponds to the case $\mu = 0$. The housing policy counterfactual involves manipulating the local housing supply elasticities $\{\xi_j\}$. I use the estimates provided by Baum-Snow and Han (2024) as the baseline values.

Table 1 reports all other parameters necessary to implement the counterfactual analysis with the model. I use the same set of parameter values from this table for all experiments I run (except for $\{\alpha^a\}$, μ, and $\{\xi_j\}$). Most of them are directly taken from the literature.

In particular, I select the Frechét shock parameters for non-college- and college-educated workers based on Colas and Hutchinson (2021). However, since their estimates are larger in magnitude (7.15 for non-college and 12.54 for college, implying greater economic mobility among college-educated workers) than the estimates in the regional literature that do not distinguish between agent types (Monte, Redding, and Rossi-Hansberg 2018, Delventhal and Parkhomenko 2023), I scale them so that the average of the two parameters, weighted by the national share of each skill type, is equal to 4.

The data for the implementation come from ACS. The lowest level of aggregation at which both the individual's place of residence and the place of in-person employment are reported in ACS is the place-of-work PUMA.[12] As the model considers individual choices of both residence and work locations, I use place-of-work PUMAs as its spatial units. In 2019, there are 975 workplace PUMAs with a positive population of both residents and workers.

From ACS, I take data on $\{\pi_{ij}^a\}$ (shares of non-college/college-educated workers living in workplace PUMA j and working remotely, $i = 0$, or in workplace PUMA $i \geq 1$), $\{w_i^a\}$ (average wages of in-person non-college/college workers by employment location, $i \geq 1$, or national average wages of remote workers, $i = 0$), and $\{q_j\}$ (average housing rents of all workers by residence location). I use the 5-year 2019 ACS sample, provided by Ruggles et al. (2021); more details are available in Appendix A.

The final piece of data comes from Baum-Snow and Han (2024) who provide local housing supply elasticities at the census tract level within US metropolitan areas. I aggregate them to the model location level, workplace PUMAs, using the number of occupied housing units as weights, as proposed by the authors. Whenever ξ_j is not available in Baum-Snow and Han (2024), I set it to the highest value from their dataset, 1.4, because such places are rural or outside metropolitan areas and are thus most likely unconstrained.

After running the WFH counterfactual using the 2019 data, $\{\widehat{1 - \alpha^a}\}$, and $\{\widehat{1 - \kappa_0^a}\}$, I record the counterfactual data D', consisting of $\{(\pi_{ij}^a)'\}$, $\{(w_i^a)'\}$, and $\{q_j'\}$, which describe the economy that fully adjusts to the calibrated WFH shift. Then, I run both the tax progressivity and housing supply policy counterfactuals twice: once using the original 2019 ACS data, and once using the WFH counterfactual data D'.

In Appendix D, Figure 5, I plot the counterfactual data D' on a map at the workplace-PUMA level. We can observe the "winner takes most" effect: in-person employment decreases everywhere except in the most productive places. Low-skill and some high-skill residents follow this reallocation of employment and move closer to the most productive cities; since high-skill workers have more remote work opportunities, a significant fraction of

12. It is usually equivalent to a county, except for counties with fewer than 100,000 workers which are grouped into a single workplace PUMA.

them move outside major cities to the suburbs and across regions to places like Colorado or Florida. Overall, this pattern of geographic reallocation is consistent with Delventhal and Parkhomenko (2023), as reported in their maps, Figure F.1.

5 Aggregate Implications and Discussion

In this section, I run the policy counterfactuals with the model to evaluate the implications of the WFH shift for spatial misallocation caused by progressive national taxation and local housing regulations, as well as its implications for inequality arising from correcting these distortions. I also explore the intuition behind the results and decompose them into channels.

5.1 Tax Progressivity Counterfactual

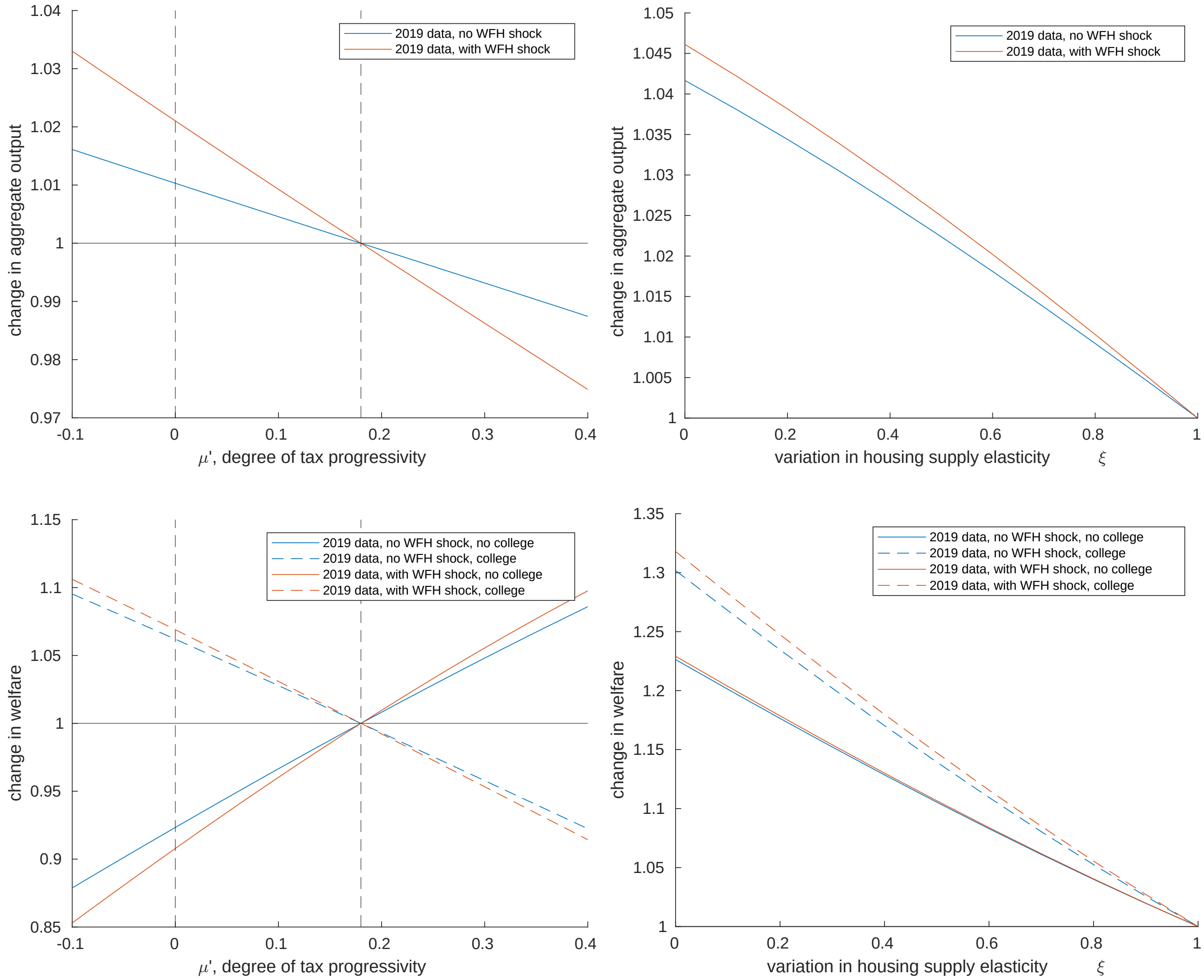
Output. Figure 3 shows the change in aggregate output in the experiments with the counterfactual degree of tax progressivity μ' in the baseline 2019 economy and the 2019 economy that adjusted to the WFH shift, described by data D'. The shift to WFH steepens the gradient of output loss relative to the degree of tax progressivity. In particular, moving from the current degree of tax progressivity to flat taxation increases aggregate output by 1% in 2019. The magnitude of this number is in line with existing pre-WFH literature.[13] However, after the economy adjusts to the WFH shift, the output gain from moving towards flat taxation increases by an additional 1pp.

Why does progressive taxation cause a larger aggregate output loss in the counterfactual post-WFH economy? To answer this question, I decompose the full effect of flattening tax progressivity into two components: a direct effect on productive in-person work and a direct effect on WFH; within each of these two channels, I also extract the contribution of in-person and remote workers sorting across locations. The results of this decomposition are presented in Table 2.

First, in both the baseline 2019 economy and the economy with the WFH shift, flattening tax progressivity increases output due to its *direct effect* on the attractiveness of *in-person work* in more productive locations through reduced tax rates on local wages (while tax rates increase in less productive places). Note that the WFH shift raises the attractiveness of *both* in-person and remote work (national remote wages are relatively high and thus experience the reduction in rates as well). Thus, to isolate the direct effect on just in-person work, I restrict workers from switching between WFH and in-person modes, fixing the number of remote

13. In particular, Colas and Hutchinson (2021) estimate a 0.2% gain, and Coen-Pirani (2025) estimates 1.2% when excluding idiosyncratic matches.

Figure 3: **Counterfactual Changes in Aggregate Outcomes**



Notes: Policy counterfactuals with the new degree of tax progressivity μ' (left) or increased housing supply elasticities $\{\xi'_j\}$ (right). Blue lines correspond to the experiment based on the 2019 data; red lines correspond to the experiment based on the WFH counterfactual data D'. Percent change in GDP Y (up) and skill-specific welfare U^1, U^2 (down), relative to the initial GDP in 2019 data or D'. Initial $\mu = 0.18$, counterfactual μ' is on the horizontal axis. $\mu' = 0$ corresponds to the flat tax rate. $\{\xi'_j\}$ for locations with less than median ξ_j are calculated as a convex combination of ξ_j from Baum-Snow and Han (2024) and median$(\xi_j) = 0.77$; the coefficient on ξ_j is on the horizontal axis.

workers in the entire economy at the initial level (either in 2019 or post-WFH). To control for the impact of sorting of remote and in-person workers across locations, I also prohibit WFH workers from changing residence locations, further fixing the number of remote workers in each location. Workers can still switch between in-person workplaces. Then, I re-run the counterfactual experiment. The second row of Table 2 reports the results. The direct effect on in-person work is responsible for almost the entire change in output in the baseline 2019

TABLE 2: **Contributions of Model Mechanisms, Output**

	% Change in Y			
	$\mu' = 0$		$\xi_j' = \text{med}\ \xi_j$	
	2019	2019+WFH	2019	2019+WFH
Full effect	1.03	2.02	4.17	4.61
Direct effect, in-person work				
no sorting	0.90	1.25	4.13	4.50
with sorting	0.92	1.32	4.07	4.20
Direct effect, WFH				
no sorting	0.27	0.82	—	—
with sorting	0.56	1.18	—	—

Notes: Counterfactual change in output relative to 2019 data or 2019 counterfactual data with WFH shift D'. First two columns show results for flat tax counterfactual, $\mu' = 0$, and the latter two show results for median housing elasticity counterfactual, $\xi_j' = \mathbf{1}\{\xi_j > \text{med}\,\xi_j\}\,\xi_j + \mathbf{1}\{\xi_j \leq \text{med}\,\xi_j\}\,\text{med}\,\xi_j$. Direct effect on in-person work is measured by running the experiment with the fixed number of remote workers in each location $\{\pi_{0j}^a\}$ from the initial data; allowing for sorting instead fixes only the total number of remote workers $\sum_j \pi_{0j}^a$. Direct effect on WFH is measured by fixing the number of residents in each location who work in high- or low-productivity areas $\{\sum_{i \notin S^a} \pi_{ij}^a\}$ and $\{\pi_{ij}^a\}_{i \in S^a}$ from the initial data, where S^a is the set of workplaces with $w_i^a > w_0^a$; allowing for sorting instead fixes only the total number of workers in high- or low-productivity areas $\sum_j \sum_{i \notin S^a} \pi_{ij}^a$ and $\sum_j \sum_{i \in S^a} \pi_{ij}^a$.

economy, but only about half of the change in the WFH-adjusted economy.[14]

I can further study how the spatial *sorting* of remote workers interacts with this direct effect by allowing remote workers to change their residential locations in response to the change in policy, while their total mass is still fixed at the initial level. As remote workers can now escape high rents in more productive areas, they free up space for more in-person workers to move in, thus further increasing aggregate production. This effect is negligible in 2019 because the number of remote workers is small; however, the increased number of remote workers in the counterfactual data makes this effect more prominent, although still modest.

Second, removing tax progressivity *directly* alters workers' incentives to choose *WFH*. This channel must lie at the root of the extra output gain in the counterfactual WFH economy because remote work now has an increased weight in production.

Intuitively, the shift to WFH has the potential to reduce the aggregate output loss caused by tax progressivity: since national WFH wages are lower than in-person wages in the most

14. Because some of the workers who could switch to WFH in the unrestricted experiment can now only switch between in-person work, the sum of the direct effects on in-person work and WFH will yield a number that exceeds the full effect. While this decomposition is not exact, it is still informative of the relative importance of each channel.

productive locations, the tax rate on WFH wages is also lower than on in-person wages in such locations. As a result, some workers who previously chose to work in lower-productivity places due to lower tax rates will now switch to WFH. These WFH services are then consumed by high-productivity places, as they benefit the most from substituting expensive local in-person labour with cheaper WFH services. Cheaper labour costs allow firms in the most productive places to expand production despite the constraints of the progressive tax system. As a result, output in more productive places grows, while output in less productive places falls (the "winner takes most" effect), and spatial misallocation decreases.

However, WFH wages are still relatively high compared to the distribution of in-person wages, so they are subject to higher marginal tax rates, which pushes some workers away from WFH towards lower-tax less productive work. With fewer WFH workers available, high-productivity locations cannot expand enough by substituting expensive in-person labour with cheaper WFH services. Thus, with the shift to WFH, high-productivity places produce much less than they could if the progressive tax system were replaced with a flat one.

Altogether, because there is more employment in locations that offer wages below the WFH wage than above, the negative effect of WFH on output loss dominates the positive effect as the economy adjusts to the WFH shift. As such, flattening tax progressivity (and reducing the tax rate on WFH) attracts more workers to remote work, allowing higher productivity locations to substitute more expensive in-person labour with cheaper remote services and expand further.

I isolate the overall *direct effect* of flattening tax progressivity on attractiveness of *WFH* by fixing the number of in-person workers who work in the most productive cities at the initial level, prohibiting workers from less productive cities from switching to high-productivity in-person work as tax rates on it fall. To prevent sorting, I also fix workers' residential choices. I re-run the counterfactual experiment and report the results in the fourth row of Table 2. While the direct effect on WFH can generate only a quarter of the full effect in the 2019 economy, in the WFH economy, it alone can generate more than 40% of the full effect. This explains the additional gain in productivity in the counterfactual economy with the WFH shift as it moves towards flat taxation.[15]

In addition, to study how the spatial *sorting* of remote and in-person workers interacts with this direct effect, I relax workers' residential choices. Remote workers will sort into cheaper residence locations characterised by low productivity, freeing up space for more in-person workers to move in. This allows output in the most productive places to expand even more, creating additional productivity gains of about 0.3pp on top of the direct effect. This

15. This effect may be understated, since I prohibit a large mass of workers from more productive places from switching to WFH.

number, however, understates the full extent of the sorting effect because I do not allow agents to switch their workplace between the rest of the economy and the group of the most productive places as more space becomes available in the latter.[16]

Finally, the magnitudes of these channels are affected by how complementary or substitutable WFH and in-person work are. The more WFH and in-person work are substitutes, the weaker the direct effect on the attractiveness of in-person work and sorting effect, and the stronger the direct effect on the attractiveness of WFH, and vice versa. Higher substitutability allows firms in the most productive locations to substitute more in-person workers with cheaper remote workers, increasing demand for remote workers and decreasing demand for in-person workers in those areas. Since progressive taxation suppresses the supply of both kinds of labour, a reduction in progressivity leads to extra output growth in the post-WFH world, regardless of the degree of complementarity between WFH and in-person work. However, when WFH and in-person work are more complementary, housing congestion in the most productive cities plays a bigger role by limiting the direct effect on in-person work, thus reducing the output gain from flattening tax progressivity. In Section 6, I re-do the counterfactual experiments under different degrees of substitutability between WFH and in-person work. Overall, the extra output gain in the economy with the WFH shift still persists as I increase or decrease WFH-in-person work complementarity, albeit falling from 1pp to 0.6pp in the case of higher complementarity.

Welfare and Inequality. The counterfactual change in the ex-ante expected welfare is measured as the equivalent variation for each skill type:

$$\phi^a = \frac{(U^a)'}{U^a} - 1 = \left(\frac{1}{\hat{\pi}^a_{ij}}\right)^{\frac{1}{\theta^a}} \frac{\chi'}{\chi} (\hat{w}^a_i)^{1-\mu'} (w^a_i)^{\mu-\mu'} \hat{q}_j^{\gamma-1} - 1,\text{[17]} \tag{18}$$

where x' denotes the counterfactual value, $\hat{x} \equiv \frac{x'}{x}$ denotes the counterfactual change, and the ex-ante expected welfare U^a is given by equation (11). Following Colas and Hutchinson (2021), I measure the change in inequality across the two skill types as the difference in equivalent variation across skills $\phi^2 - \phi^1$. The earnings of absentee land owners are not part of domestic welfare.

The bottom panel of Figure 3 shows the change in welfare and inequality in the exper-

16. The problem with doing so is that the sorting effect cannot be identified separately from the direct effect on in-person work, since both effects push agents towards high-productivity locations.

17. If agents are not allowed to sort, i.e., $\hat{\pi}^a_{ij}$ is fixed at 1, the equivalent variation becomes

$$\phi^a = \frac{\sum_i \sum_j (\pi^a_{ij})^{\frac{1+\theta^a}{\theta^a}} \frac{\chi'}{\chi} (w^a_i)^{\mu-\mu'} q_j^{\gamma-1}}{\sum_i \sum_j (\pi^a_{ij})^{\frac{1+\theta^a}{\theta^a}}}.$$

iments with the counterfactual degree of tax progressivity μ' in the baseline 2019 economy and the counterfactual 2019 economy with the WFH shift. In particular, moving the 2019 economy towards a flat income tax system raises the welfare of college-educated workers by 6.2% and decreases the welfare of high-school-educated workers by 7.7% in 2019, increasing inequality by 13.9pp.[18] Yet, after the economy adjusts to the WFH shift, the welfare of college-educated workers increases by an additional 0.6pp, whereas the welfare of high-school-educated workers falls by 1.4pp more, increasing inequality by an additional 2pp compared to the baseline economy that experienced the same reduction in tax progressivity.

To pinpoint the source of this additional increase in inequality in the economy with the WFH shift, I follow the structure of the equivalent variation in equation (18) and decompose the full change in welfare as the mechanical effect of changed tax rates, $\frac{\chi'}{\chi}(w_i^a)^{\mu-\mu'}\hat{q}_j^{\gamma-1}$, the sorting effect, $\left(\frac{1}{\hat{\pi}_{ij}^a}\right)^{\frac{1}{\theta^a}}$, the effect of changes in remote wages, $(\hat{w}_0^a)^{1-\mu'}$, and finally, the effect of changes in in-person wages, $(\hat{w}_i^a)^{1-\mu'}, i \geq 1$. The results of this decomposition are reported in Table 3.

To isolate the *mechanical effect* of changes in tax rates on welfare, I perform the tax counterfactual with residential and workplace choices fixed as in the original data (either 2019 or WFH counterfactual D'). In this setting, there are no labour market movements, so wages remain the same, and the only channel through which workers' welfare is affected is the change in tax rates, plus the mechanical change in local rents due to changes in the after-tax incomes of local residents. As the after-tax/redistribution income of low-skill workers falls and that of high-skill workers rises, inequality increases. Notably, this mechanical effect covers almost the entire effect of removing tax progressivity on inequality in the baseline 2019 economy (as in Colas and Hutchinson (2021)) but falls short of covering the entire effect in the economy with the WFH shift by about 1.2pp. The mechanical effect alone can explain approximately half of the gap in inequality growth between the baseline and WFH economies resulting from flattening tax progressivity. This is due to the fact that the WFH shift is heavily skewed towards college-educated workers: while all WFH workers benefit from reduction in tax rates, in-person workers in less productive locations, who are disproportionately non-college-educated, have to pick up the larger tax bill.

The remaining half of the gap comes from an additional negative effect on non-college-educated workers in the 2019 economy with the WFH shift. This negative effect can arise from agents sorting across the economy (thus affecting local housing prices), changes in WFH wages, and changes in in-person wages. To explore the effect of sorting and changes in WFH wages, I first allow for sorting and then relax WFH wages. Both *sorting* and *WFH*

18. These results are also of the same order of magnitude as Colas and Hutchinson (2021) estimates of 2 and −3.7%.

Table 3: **Contributions of Model Mechanisms, Welfare and Inequality**

	% Change in U^a			
	$\mu' = 0$		$\xi_j' = \text{med}\ \xi_j$	
	2019	2019+WFH	2019	2019+WFH
Mechanical effect				
college	6.54	6.64	29.67	30.68
non-college	−7.06	−7.93	26.60	27.48
difference	13.61	14.57	3.08	3.20
Mechanical + Sorting				
college	5.99	6.06	29.00	29.99
non-college	−7.09	−8.00	24.57	25.39
difference	13.08	14.07	4.43	4.61
Mechanical + Sorting + WFH Wages				
college	5.92	5.83	29.19	31.29
non-college	−7.12	−8.15	24.62	25.70
difference	13.04	13.98	4.57	5.59
Full effect (+ In-Person Wages)				
college	6.20	6.77	30.18	31.80
non-college	−7.67	−9.02	22.63	22.91
difference	13.86	15.79	7.55	8.88

Notes: Counterfactual change in ex-ante welfare relative to 2019 data or 2019 counterfactual data with WFH shift D'. First two columns show results for flat tax counterfactual, $\mu' = 0$, and the latter two show results for median housing elasticity counterfactual, $\xi_j' = \mathbf{1}\{\xi_j > \text{med}\,\xi_j\}\,\xi_j + \mathbf{1}\{\xi_j \leq \text{med}\,\xi_j\}\,\text{med}\,\xi_j$. Mechanical effect is measured by fixing all residence/workplace choices $\{\pi_{ij}^a\}$ and wages $\{w_i^a\}$ as in initial data, but allowing housing prices $\{q_j\}$ to adjust. The sorting effect is measured by allowing all agents to freely choose residence/workplace and housing prices to adjust while keeping all wages fixed. The effect of sorting and WFH wage adjustment is measured by allowing all agents to freely choose their residence/workplace, housing prices, and WFH wages to adjust while still keeping in-person wages fixed. The full effect is measured by allowing all endogenous variables to adjust, including all wages.

wage adjustment negatively affect agents through increased rents in high-productivity places and decreased WFH wages. However, both changes disproportionately hurt college-educated agents, who are more likely to live in high-productivity places and work remotely, so these effects cannot explain the *increase* in the inequality observed in the full effect. Since the only endogenous variables that remain fixed are in-person wages, they are fully responsible for the additional negative effect on non-college-educated workers' welfare.

As *in-person wages* are relaxed, the wages of low-skill workers decline while those of high-skill workers rise in both the baseline and WFH economies. However, this effect is much more pronounced in the latter, picking up the remaining 1pp gap in inequality growth unaccounted for by the mechanical effect. The intuition for this result involves the complementarity of high- and low-skill work and the differential access to remote work. Under the flat tax, high-skill workers are more induced to switch to WFH (especially in the economy with the WFH shift) and to in-person work in higher productivity locations than low-skill workers. Therefore, in many less productive locations, the number of high-skill in-person workers declines much more than the number of low-skill in-person workers. However, because of skill complementarity in production, a decline in supply of one type of labour causes a decline in demand for the other type, raising in-person wages for high-skill workers and reducing in-person wages for low-skill workers. The higher the skill complementarity, the greater the increase in inequality in addition to the mechanical effect. Yet, since the imbalance in skill composition primarily affects less productive areas, it doesn't have an impact on aggregate productivity.

In Section 6, I also show that the effect of skill complementarity on inequality is amplified by a higher degree of substitutability between WFH and in-person work: as the demand for high-skill remote workers increases, fewer high-skill workers work in-person in less productive locations, further depressing the demand for low-skill in-person workers and their wages.

5.2 Housing Supply Elasticity Counterfactual

In this section, I describe the results of the housing supply counterfactual in which I increase local housing supply elasticities in more constrained places (with elasticities below the median of 0.77) by replacing them with a convex combination of their original values and the median.

Output. Figure 3 shows the change in aggregate output in the experiments with counterfactual values of housing supply elasticities $\{\xi_j'\}$ in the baseline 2019 economy and the counterfactual 2019 economy that adjusted to the WFH shift. The convex combination coefficient on the original elasticity is on the horizontal axis. The shift to WFH slightly steepens the output loss gradient relative to the degree of housing supply restrictions. In particular, moving the 2019 economy from the current values of housing supply elasticities in the more constrained places towards the median elasticity increases aggregate output by 4.2% in 2019.[19] After the economy adjusts to the WFH shift, the output gain from moving towards flat taxation increases by an additional 0.4pp—a more modest figure compared to the tax progressivity counterfactual in the post-WFH economy.

19. The magnitude of this number is lower than a 36.3% increase reported in Hsieh and Moretti (2019), despite my experiment being broader in scope: I change the values of elasticities themselves to the median as opposed to changing just the housing regulations component of the elasticities. After I include commercial real estate and agglomeration effects, the output increase goes up to 21.8%, see Section 6, Figure 4.

To understand the intuition for this smaller difference, note that more elastic housing supply in more productive places reduces the local cost of living which directly increases the attractiveness of in-person work but does not alter the attractiveness of WFH relative to in-person work.[20] Since there is no direct effect on WFH in this case, the differences between the housing supply experiments in the 2019 economy and the post-WFH economy must be smaller than those in the tax progressivity experiments from Section 5.1. As in Section 5.1, I further evaluate the contributions of the direct effect on the attractiveness of in-person work and the sorting effect to the full effect of increasing housing supply elasticity on output. The results of this decomposition are presented in Table 2.

In both the baseline economy and the WFH economy, increased housing supply elasticities in more productive locations reduce rent differentials across locations, *directly* making *in-person work* in more productive locations more attractive relative to in-person work in lower-paying locations. To partially isolate the effect of sorting and WFH-in-person work complementarities, I prohibit agents from switching between in-person work and WFH and fix the number of remote agents in each location as in the initial data in 2019 or 2019 with the WFH shift (D'). The second row of Table 2 shows the results of this restricted experiment. The direct effect alone can cover almost the entire full effect.

There is an important qualification to this result, however. After I allow WFH agents to *sort* across residences (still keeping their total mass fixed), more WFH agents come to high-productivity areas, attracted by reduced rents. As they do so, they start competing for space with in-person workers, pushing some of them out of high-productivity areas and reducing aggregate output, as reflected in the third row of Table 2. That is, in the housing supply experiment, the sorting effect pushes both WFH and in-person agents towards the same high-productivity places. This is in contrast to the tax-progressivity experiment, in which the sorting effect guided WFH and in-person agents in opposite directions. Because there are more WFH workers in the WFH economy, the negative effect of sorting on aggregate output is stronger there, narrowing the gap in the counterfactual output change between the baseline and WFH economies.

As I relax the number of WFH workers, the force that restores this gap back to the level of the full effect is WFH-in-person work complementarity. As more people come to work in-person in high-productivity places attracted by lower rents, local firms will require more WFH services to expand. Relaxing the supply of WFH work allows that expansion to happen, particularly in the WFH economy, generating the full gap in the counterfactual

20. The direct effect on attractiveness of WFH shows up in my experiments with $\rho^a < \infty$ in Section 6, but it is actually negative, since cheaper housing reduces the cost of in-person work for firms, raising the relative cost of WFH. As a result, spatial misallocation due to inelastic housing can actually decrease after the WFH shift, in contrast to spatial misallocation induced by income tax progressivity.

output change between the 2019 economy and the WFH economy. In Section 6.1, I re-run the experiment in this section under the assumption that WFH and in-person work are less complementary. In this case, the counterfactual output growth gap between the baseline and WFH economies disappears (or even turns slightly negative).

Welfare and Inequality. The bottom panel of Figure 3 shows the change in welfare ϕ^a as defined in equation (18) and inequality as measured by $\phi^2 - \phi^1$ in the experiments with counterfactual values of housing supply elasticities $\{\xi_j'\}$ in the economy in 2019 and the 2019 economy that experienced the WFH shift. In particular, increasing local housing supply elasticities in the more constrained locations all the way to the median level raises the welfare of college-educated workers in the 2019 economy by 30.1% and high-school educated workers by 22.6%, increasing inequality by 7.6pp.[21] However, after the economy experiences the WFH shift, the welfare of college-educated workers increases by an additional 1.6pp, whereas the welfare of high-school-educated workers increases only by 0.3pp, skewing the benefit from more relaxed housing supply towards college-educated workers by an additional 1.3pp compared to the economy in 2019 without the WFH shift that experienced the same increase in housing supply elasticities.

To analyse why more elastic housing supply benefits high-skill workers disproportionately more in the 2019 economy with the WFH shift, I perform the same decomposition of the full change in welfare as in Section 5.1 into the mechanical effect of increased housing supply elasticities, $\frac{\chi'}{\chi}\hat{q}_j^{\gamma-1}$, the sorting effect, $\left(\frac{1}{\hat{\pi}_{ij}^a}\right)^{\frac{1}{\theta^a}}$, the effect of changes in remote wages, $(\hat{w}_0^a)^{1-\mu}$, and the effect of changes in in-person wages, $(\hat{w}_i^a)^{1-\mu}, i \geq 1$. The results of this decomposition are reported in the right panel of Table 3.

By fixing the residential and workplace choices as in the original data, I isolate the *mechanical effect* of increased supply elasticities on welfare. As high-skill workers are more likely to reside in the most constrained and productive cities, they will disproportionately benefit from reduced rents. Interestingly, the mechanical effect generates less than half of the full effect of increased supply elasticities on inequality in the 2019 economy, and even less in the post-WFH economy. The mechanical effect alone is also not able to explain the inequality gap between the counterfactual economy in 2019 with and without the WFH shift. This is because in the model, the WFH shift does not change the proportion of high-to-low-skilled residents in the most restricted locations in the 2019 economy, as remote workers leave, but in-person workers come into their place.

Relaxing workers' residential and workplace choices while keeping wages fixed enables

21. These results are larger than Hsieh and Moretti (2019) estimates of 13.1%, which is to be expected, since my experiment is much larger in scope (see footnote 13).

the *sorting effect*. High-skill workers have higher incentives to move to now cheaper high-productivity places because their wage differentials are greater than those of low-skill workers. As they bid up rents in higher productivity places by more than low-skill agents alone would, the welfare of low-skill workers declines by more than that of high-skill workers. The inequality increases in the 2019 economy and the WFH economy by the same amount due to the same reason that the WFH shift doesn't affect the skill distribution of residents in the most restricted locations.

Allowing *WFH wages* to adjust while still keeping in-person wages fixed actually increases the welfare of all agents, but disproportionately more for high-skilled agents in the WFH economy than for low-skilled agents. Their wages increase the most because all high-skill workers, who moved to the most productive cities that are now cheaper, create demand for more WFH services by firms due to WFH-in-person work complementarity. This effect can explain 1pp of the 1.3pp additional inequality generated in the counterfactual with the WFH economy relative to the 2019 economy, so the remaining 0.3pp must come from the differences in the adjustment of *in-person wages*. As in the tax progressivity experiment, this effect arises because of skill complementarity and the fact that high-skill workers respond more to increased housing supply in more productive places and to the resulting increased demand for high-skill WFH. As more high-skill workers leave in-person work in less productive locations, the demand for low-skill labour and their wages fall. The strength of this effect depends on how strongly the demand for high-skill WFH increases. In Section 6.1, I show that under increased substitutability between in-person and remote labour (which increases the demand for WFH), the effect of in-person wages on the change in inequality is smaller in the economy with the WFH shift than in the baseline 2019 economy. Therefore, the benefits from the increase in housing supply elasticities are even less skewed to high-skilled workers in the economy with the WFH shift than without, mirroring the reversed gap in the aggregate output changes.

6 Sensitivity Analysis

In this section, I document how sensitive my results are to the estimates of WFH-in-person work complementarity σ^a, the amount of commercial space per worker ρ^a, and the inclusion of agglomeration effects $\eta^L, \eta^R > 0$.

6.1 WFH-in-Person Work Complementarity

Below, I show that eliminating tax progressivity in the world with WFH still induces substantial additional aggregate productivity gains at the cost of increased inequality when I consider different degrees of complementarity between in-person work and WFH services compared to Delventhal and Parkhomenko (2023). I also show that the results of the housing supply counterfactual crucially depend on the degree of WFH-in-person work complementarity.

Higher substitutability between WFH and in-person work increases the full effect of reduced tax progressivity due to the higher pure direct effect on WFH: it allows firms in the most productive locations to substitute more in-person workers with cheaper remote workers and increase production. At the same time, it decreases the significance of direct effect on in-person work (lower tax rates invite more in-person workers to most productive areas) and sorting effect (WFH workers leave most productive and expensive cities, allowing more in-person workers to move in) because most productive firms need less in-person workers.

Table 4, Panel A, shows that in case when $\sigma^1 = \sigma^2 = 0.9$, the increase in the direct effect on WFH outweighs the decreases in the two other effects, increasing the full effect of eliminating tax progressivity on output both in 2019 and 2019 with the WFH shift, such that the gap between the output gains remains equal to 1pp as in Table 2.

This logic is reversed when WFH is more complementary to in-person work. Indeed, Table 4, Panel B shows that in case when $\sigma^1 = \sigma^2 = 0.2$, the direct effect on WFH *decreases*, while the sorting effect and effect on in-person work *increase*. However, the decrease in the direct effect on WFH is not fully compensated by the increase in the two other effects because the direct effect on in-person work creates higher congestion in the most productive cities, as they typically have more restricted housing supply. The full effect on output decreases, and the gap between the output gains is reduced to 0.6pp.

In the housing supply experiment, higher substitutability between WFH and in-person work reduces the full effect of increased housing supply through a reduced direct effect on in-person work, while the counterbalancing direct effect on WFH is absent. The negative sorting effect is slightly mitigated, as now WFH workers who come to expensive cities and crowd out in-person workers are more productive, but it is not enough to compensate for the absence of a positive direct effect on WFH. See Table 4, Panel A. The residual effect is generated by the adjustment in the number of remote and in-person workers. In this case, this adjustment is small because the most productive firms will not need even more remote workers, as they have already substituted away almost all of the in-person workers.

The opposite is true in the case of higher complementarity: the positive direct effect on in-person work increases, while the negative sorting effect becomes slightly stronger. The direct effect on WFH is still absent. See Table 4, Panel B. The residual effect is generated by

TABLE 4: **WFH and In-Person Work Complementarity, Output**

	% Change in Y			
	$\mu' = 0$		$\xi'_j = \text{med } \xi_j$	
	2019	2019+WFH	2019	2019+WFH
Panel A. $\sigma^1 = \sigma^2 = 0.9$				
Full effect	1.17	2.20	4.05	3.97
Direct effect, in-person work				
no sorting	0.90	1.14	3.99	4.06
with sorting	0.92	1.20	3.92	3.81
Direct effect, WFH				
no sorting	0.37	1.23	—	—
with sorting	0.68	1.50	—	—
Panel B. $\sigma^1 = \sigma^2 = 0.2$				
Full effect	0.97	1.54	4.15	4.41
Direct effect, in-person work				
no sorting	0.91	1.23	4.18	4.54
with sorting	0.92	1.30	4.11	4.23
Direct effect, WFH				
no sorting	0.22	0.56	—	—
with sorting	0.51	0.92	—	—

Notes: Counterfactual change in output relative to 2019 economy or 2019 counterfactual economy with the WFH shift. All parameters are as in Table 1, except for $\sigma^1 = \sigma^2 = 0.9$ (Panel A) or $\sigma^1 = \sigma^2 = 0.2$ (Panel B) and recalibrated $\{\hat{\alpha}^a\}$ and $\{1 - \hat{\kappa}^a_{0j}\}$. See Notes for Table 2 in Section 5.

the adjustment in the number of remote and in-person workers. As firms need to complement increased numbers of in-person workers, the adjustment will be stronger than in the case of increased substitutability. However, the full gap in the output growth between the 2019 economy and the 2019 economy with the WFH shift is smaller because the expansion in more productive and housing-restricted cities due to the increased supply of in-person workers is more limited by housing congestion.

Table 5 presents the decomposition of the full change in welfare that follows the structure of equation (18). Higher substitutability of WFH and in-person work increases the number of remote workers in the post-WFH shift economy, making the mechanical effect of eliminating tax progressivity more pronounced. In addition, the higher number of remote workers further reduces the number of high-skill in-person workers in lower productivity locations, decreasing low-skill in-person wages and increasing inequality. On the other hand, the higher substitutability of WFH and in-person work reduces the skewness of gains towards high-skill workers in the housing supply experiment with the WFH economy compared to 2019. This

Table 5: **WFH and In-Person Work Complementarity, Welfare**

	% Change in U^a			
	$\mu' = 0$		$\xi'_j = \text{med } \xi_j$	
	2019	2019+WFH	2019	2019+WFH
Panel A. $\sigma^1 = \sigma^2 = 0.9$				
Mechanical effect				
college	6.54	6.89	29.67	30.12
non-college	−7.06	−8.41	26.60	27.23
difference	13.59	15.30	3.08	2.88
Mechanical + Sorting				
college	5.99	6.35	29.00	29.60
non-college	−7.09	−8.42	24.57	25.19
difference	13.08	14.77	4.43	4.41
Mechanical + Sorting + WFH Wages				
college	6.01	6.58	29.27	31.09
non-college	−7.11	−8.51	24.64	25.62
difference	13.12	15.09	4.63	5.48
Full effect (+ In-Person Wages)				
college	6.28	7.24	30.37	30.82
non-college	−7.73	−9.64	22.26	22.85
difference	14.01	16.87	8.11	7.97
Panel B. $\sigma^1 = \sigma^2 = 0.2$				
Mechanical effect				
college	6.54	6.53	29.67	30.90
non-college	−7.06	−7.65	26.60	27.44
difference	13.59	14.19	3.08	3.46
Mechanical + Sorting				
college	5.99	5.96	29.00	30.08
non-college	−7.09	−7.75	24.57	25.33
difference	13.08	13.71	4.43	4.75
Mechanical + Sorting + WFH Wages				
college	5.87	5.33	29.10	30.93
non-college	−7.14	−7.94	24.59	25.51
difference	13.00	13.27	4.51	5.42
Full effect (+ In-Person Wages)				
college	6.19	6.52	30.14	31.76
non-college	−7.63	−8.50	22.69	23.01
difference	13.82	15.02	7.45	8.75

Notes: Counterfactual change in ex-ante welfare relative to 2019 economy or 2019 counterfactual economy with the WFH shift. All parameters are as in Table 1, except $\sigma^1 = \sigma^2 = 0.9$ (Panel A) or $\sigma^1 = \sigma^2 = 0.2$ (Panel B) and recalibrated $\{\alpha^a\}$ and $\{1 - \hat{\kappa}^a_{0j}\}$. See Notes for Table 3 in Section 5.

occurs entirely due to the reduced wages of in-person workers: when they are more substitutable, the demand for their labour declines in the most productive and constrained locations, while additional housing reduces compensating differentials.

6.2 Commercial Housing

In this section, I discuss how the results change if firms must purchase office space for their in-person employees, $\rho^a < \infty$. I do not have the data that would allow me to properly estimate the space per in-person worker parameter $1/\rho^a$. For now, I rely on Squarefoot Office Space Calculator estimates, and set the office space per college-educated worker $1/\rho^2$ to 0.5 to match the average annual office rent per employee q_j/ρ^2 in Manhattan in 2019, which was about \$12,500.[22] I also set $1/\rho^1 = 0.4$ to reflect the fact that low-skill workers may get lower amount of dedicated workspace (e.g., a cash register station at the supermarket vs. a cubicle in the office). Since commercial housing plays a crucial role in firms' incentives to substitute in-person labour with WFH, I treat the results obtained with these office space parameters as the main results of this paper, despite the data limitations. I also test my results under the assumption that both types of workers require twice as much office space.

Theoretically, as space becomes a factor of production, the distortive impact of progressive income tax on labour is reduced, while that of housing supply constraints increases. As for the theoretical channels, first, with high rents in the most productive places, firms will be more eager to substitute in-person labour with WFH when employing in-person labour requires renting (more) office space. This means that a lot of substitution will occur as the WFH shift occurs and before the counterfactual policy changes, reducing the relevance of the direct effect of eliminating tax progressivity on in-person work. Second, the benefits due to complementarity of in-person and remote work are limited as in-person work becomes inherently more costly. Third, the negative effect of remote labour returning to the most constrained and productive cities as housing restrictions are relaxed is exacerbated by the fact that WFH workers now not only take the space away from in-person workers, but also from offices. Altogether, this should lead to smaller output gains in policy experiments with the 2019 economy after the WFH shift.

The effects of eliminating tax progressivity and relaxing housing supply restrictions on output when firms must buy office space are shown in Table 6. In this table, I also perform the same decomposition of the full effect into direct effects through in-person work and WFH and study the impact of sorting. The results reported in the table are consistent with the logic described above. Yet, remarkably, in the tax progressivity experiment, the

22. https://www.squarefoot.com/leasopedia/dollars-cents-much-cost-rent-office-space/.

Table 6: **Commercial Housing, Output**

	% Change in Y			
	$\mu' = 0$		$\xi'_j = \text{med } \xi_j$	
	2019	2019+WFH	2019	2019+WFH
Panel A. $\rho^1 = 2.5, \rho^2 = 2$				
Full effect	1.02	1.52	7.22	7.14
Direct effect, in-person work				
no sorting	0.94	1.14	7.30	7.52
with sorting	0.95	1.19	7.21	7.16
Direct effect, WFH				
no sorting	0.23	0.51	0.09	−0.02
with sorting	0.43	0.69	3.40	3.22
Panel B. $\rho^1 = 1.25, \rho^2 = 1$				
Full effect	0.81	1.08	8.82	8.67
Direct effect, in-person work				
no sorting	0.77	0.91	8.94	9.16
with sorting	0.78	0.95	8.85	8.80
Direct effect, WFH				
no sorting	0.12	0.29	0.08	−0.02
with sorting	0.21	0.38	1.12	1.67

Notes: Counterfactual change in ex-ante welfare relative to 2019 economy or 2019 counterfactual economy with the WFH shift. All parameters are as in Table 1, except for $\rho^1 = 2.5, \rho^2 = 2$ (Panel A) or $\rho^1 = 1.25, \rho^2 = 1$ (Panel B) and recalibrated $\{\hat{\alpha}^a\}$ and $\{1 - \hat{\kappa}^a_{0j}\}$. See Notes for Table 2 in Section 5.

gap in output gains between the 2019 economy and the 2019 economy with the WFH shift still persists, albeit reduced to 0.5pp, whereas in the housing supply experiment, the gap in output gains is reduced with the WFH shift, but only slightly.

Table 7 presents the decomposition of the full change in welfare following the structure of equation (18). In both policy experiments, a higher office space requirement per in-person worker reduces inequality in the post-WFH economy compared to the 2019 economy. This reduction is generated almost entirely by the adjustment in in-person wages and reflects the higher amount of office space required per high-skill worker than per low-skill worker.

6.3 Agglomeration Effects

In this section, I show that the increased sensitivity of aggregate output losses in the WFH economy is robust to the inclusion of both agglomeration effects and commercial housing. For the strength of agglomeration forces in local productivity and amenity, I rely on Heblich,

Table 7: **Commercial Housing, Welfare**

	% Change in U^a			
	$\mu' = 0$		$\xi'_j = \text{med } \xi_j$	
	2019	2019+WFH	2019	2019+WFH
Panel A. $\rho^1 = 2.5, \rho^2 = 2$				
Mechanical effect				
college	6.58	6.74	48.61	49.29
non-college	−7.06	−7.95	43.37	43.69
difference	13.64	14.69	5.24	5.60
Mechanical + Sorting				
college	5.98	6.20	50.19	50.97
non-college	−7.07	−7.87	42.07	42.53
difference	13.05	14.07	8.12	8.44
Mechanical + Sorting + WFH Wages				
college	5.90	6.14	50.28	52.06
non-college	−7.11	−8.00	41.96	42.28
difference	13.01	14.14	8.32	9.78
Full effect (+ In-Person Wages)				
college	6.17	6.67	61.25	60.85
non-college	−7.45	−8.58	51.78	50.83
difference	13.62	15.25	9.47	10.02
Panel B. $\rho^1 = 1.25, \rho^2 = 1$				
Mechanical effect				
college	6.61	6.80	52.97	53.00
non-college	−7.07	−7.92	47.16	47.05
difference	13.67	14.73	5.81	5.95
Mechanical + Sorting				
college	5.98	6.31	55.13	55.22
non-college	−7.05	−7.77	46.2	46.11
difference	13.03	14.08	8.93	9.11
Mechanical + Sorting + WFH Wages				
college	5.91	6.42	55.03	55.40
non-college	−7.08	−7.84	45.91	45.27
difference	13.00	14.26	9.11	10.13
Full effect (+ In-Person Wages)				
college	6.03	6.57	76.59	73.24
non-college	−7.45	−8.45	69.53	66.71
difference	13.49	15.02	7.06	6.53

Notes: Counterfactual change in ex-ante welfare relative to 2019 economy or 2019 counterfactual economy with the WFH shift. All parameters are as in Table 1, except $\rho^1 = 2.5, \rho^2 = 2$ (Panel A) or $\rho^1 = 1.25, \rho^2 = 1$ (Panel B) and recalibrated $\{\alpha^a\}$ and $\{1 - \hat{\kappa}^a_{0j}\}$. See Notes for Table 3 in Section 5.

Redding, and Sturm (2020) estimates based on data for 19th-century Greater London boroughs.

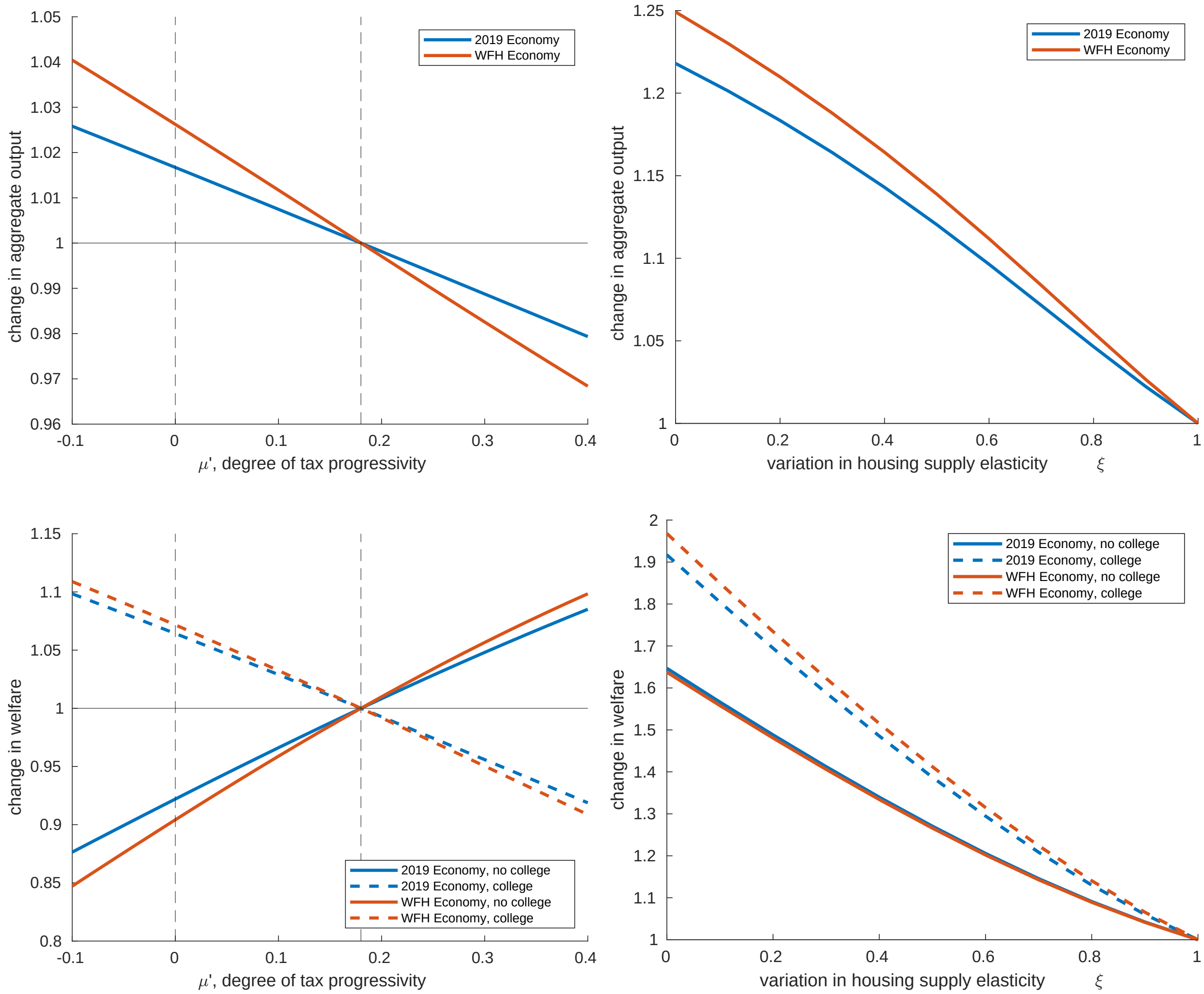
Agglomeration effects in production can increase the distorting effect of tax progressivity in the WFH economy, despite the fact that remote work allows workers to move away from productive but expensive cities. As explored in the previous sections, if WFH-in-person-work complementarity is sufficiently high, with a higher number of remote workers turning to work for more productive firms, the number of in-person workers in the more productive cities can actually increase, and through the agglomeration forces in production, this will increase productivity even more. Agglomeration forces in amenities will reinforce the impact of agglomeration effects in production by attracting even more workers toward productive cities that grow with the shift to WFH.

Agglomeration effects also make restrictive housing supply policies more costly. In the WFH economy, restrictive housing polices constrain the inflow of in-person workers necessary for firms in the most productive cities to expand. The interaction between these two effects in the WFH economy will make removing housing supply restrictions more beneficial for aggregate productivity compared to the baseline. However, the result will still be sensitive to the parameter specification (in particular, the elasticity of substitution between in-person and remote work and office space per worker).

Figure 4 and Table 8 show that the shift to WFH increases misallocation, even when accounting for agglomeration effects and commercial housing. This increase (1pp and 3.1pp for tax and housing distortion respectively) is larger compared to the case with only commercial housing (0.5pp and -0.1pp), Table 6. In the case of tax progressivity, the increased misallocation is attributed to the in-person work effect, while that of remote work does not change. This is not surprising, since agglomeration effects increase the productivity of in-person work but not remote work. The sorting of remote workers out of expensive cities is now also more important for productivity because it allows for more agglomeration effects to occur as in-person workers move into their place.

In terms of inequality arising from adopting the flat taxation scheme, agglomeration effects in production reinforce the effect of in-person wages on higher inequality in the WFH world relative to the baseline economy. This is because, first, disproportionately more high-skill workers come to work in more productive cities than low-skill workers, so high-skill workers benefit from agglomeration effects in production much more; and second, as high-skill workers shift to remote work in less productive areas, they stop contributing to agglomeration effects in production in less productive places, negatively impacting local low-skill workers for whom WFH options are more limited. The effect of amenity externalities is more ambiguous, as the number of residents can increase in both more and less productive cities to which

FIGURE 4: **Aggregate Counterfactual Changes, Agglomeration Effects and Commercial Housing**



Notes: Counterfactual change in output and ex-ante welfare relative to the 2019 economy or counterfactual economy with the WFH shift. All parameters are as in Table 1, except for office space per worker $\rho^1 = 2.5, \rho^2 = 2$, recalibrated WFH parameters $\{\hat{\alpha}^a\}$, $\{1 -\hat{}\kappa^a_{0j}\}$, and agglomeration effects elasticities $\eta^L = 0.086, \eta^R = 0.172$ which I take from Heblich, Redding, and Sturm (2020).See Notes for Table 3 in Section 5.

remote workers move. Figure 4 and Table 9 confirm that when accounting for agglomeration economies, the WFH shift indeed generates slightly more inequality when correcting for misallocation induced by policies (2.5pp and 6.1pp vs. 1.6pp and 0.6pp in the case with no externalities).

Table 8: **Agglomeration Effects, Output**

	% Change in Y			
	$\mu' = 0$		$\xi'_j = \text{med } \xi_j$	
	2019	2019+WFH	2019	2019+WFH
Full effect	1.66	2.61	21.84	24.96
Direct effect, in-person work				
no sorting	1.58	2.13	21.90	24.63
with sorting	1.59	2.18	21.66	24.13
Direct effect, WFH				
no sorting	0.25	0.51	—	—
with sorting	0.65	0.94	—	—

Notes: Counterfactual change in output relative to 2019 economy or 2019 counterfactual economy with the WFH shift. All parameters are as in Table 1, except for office space per worker $\rho^1 = 2.5, \rho^2 = 2$, recalibrated WFH parameters $\{\hat{\alpha}^a\}$, $\{1 - \hat{\kappa}^a_{0j}\}$, and agglomeration effects elasticities $\eta^L = 0.086, \eta^R = 0.172$ which I take from Heblich, Redding, and Sturm (2020). See Notes for Table 2 in Section 5.

Table 9: **Agglomeration Effects, Welfare and Inequality**

	% Change in U^a			
	$\mu' = 0$		$\xi'_j = \text{med } \xi_j$	
	2019	2019+WFH	2019	2019+WFH
Mechanical effect				
college	6.58	6.8	48.79	50.47
non-college	−7.06	−8.19	43.53	44.53
difference	13.64	14.98	5.26	5.94
Mechanical + Sorting				
college	6.15	6.42	65.28	68.57
non-college	−7.07	−8.07	49.31	51.23
difference	13.21	14.49	15.97	17.34
Mechanical + Sorting + WFH Wages				
college	6.08	6.55	65.58	71.62
non-college	−7.1	−8.18	49.23	51.24
difference	13.18	14.73	16.34	20.39
Full effect (+ In-Person Wages)				
college	6.46	7.23	93.63	98.77
non-college	−7.76	−9.51	66.26	65.32
difference	14.22	16.74	27.37	33.45

Notes: Counterfactual change in ex-ante welfare relative to 2019 economy or counterfactual economy with the WFH shift. All parameters are as in Table 1, except for office space per worker $\rho^1 = 2.5, \rho^2 = 2$, recalibrated WFH parameters $\{\hat{\alpha}^a\}$, $\{1 - \hat{\kappa}^a_{0j}\}$, and agglomeration effects elasticities $\eta^L = 0.086, \eta^R = 0.172$ which I take from Heblich, Redding, and Sturm (2020). See Notes for Table 3 in Section 5.

7 Conclusion

In this paper, I document the impact of work from home on the spatial misallocation of labour resulting from income tax progressivity and housing supply constraints. With a spatial equilibrium model calibrated using ACS data, I show that the post-pandemic shift to WFH generates additional productivity benefits to policies that create incentives for workers to work remotely and in-person in the most productive cities. These extra benefits come from the fact that WFH reduces real estate congestion and enables firms in the most productive cities to save on labour and housing costs and grow. Even without any government reinforcement, these positive long-run impacts of WFH can potentially counterbalance many of the immediate negative effects of remote work documented in the literature.

However, a simple productivity-increasing policy, such as eliminating tax progressivity or relaxing housing constraints in the most constrained cities, generates a mechanical increase in inequality (by eliminating redistribution or by disproportionately benefiting more well-off workers respectively) which is further exacerbated by the fact that low-skill workers have less access to remote work. Thus, WFH intensifies the spatial equity-productivity trade-off, creating scope for more nuanced socially optimal policy. Another interesting avenue for future research is to quantify the impact of WFH on *local* taxation and redistribution, which is omitted in this paper, as remote work gives workers the opportunity to move more freely across the economy to avoid high local taxes.

References

Agrawal, David R, and Jan K Brueckner. (2022). "Taxes and Telework: The Impacts of State Income Taxes in a Work-From-Home Economy." *SSRN 4162196.*

Albouy, David. (2009). "The Unequal Geographic Burden of Federal Taxation." *Journal of Political Economy* 117 (4): 635–667.

Autor, David, David Dorn, Lawrence F Katz, Christina Patterson, and John Van Reenen. (2020). "The fall of the labor share and the rise of superstar firms." *The Quarterly Journal of Economics* 135 (2): 645–709.

Bagga, Sadhika, Lukas Mann, Aysegül Sahin, and Giovanni L Violante. (2023). "Job amenity shocks and labor reallocation." *Working Paper.*

Barrero, Jose Maria, Nicholas Bloom, and Steven J Davis. (2021). "Why working from home will stick." *NBER Working Paper.*

Baum-Snow, Nathaniel, and Lu Han. (2024). "The Microgeography of Housing Supply." *Journal of Political Economy* 132 (6): 1897–1946.

Bick, Alexander, Adam Blandin, Karel Mertens, and Hannah Rubinton. (2024). "Work from Home and Interstate Migration." *Working Paper.*

Brueckner, Jan K, Matthew E Kahn, and Gary C Lin. (2023). "A new spatial hedonic equilibrium in the emerging work-from-home economy?" *American Economic Journal: Applied Economics* 15 (2): 285–319.

Coen-Pirani, Daniele. (2025). "Tax Progressivity and Mobility Costs." *Regional Science and Urban Economics,* forthcoming.

Colas, Mark, and Kevin Hutchinson. (2021). "Heterogeneous Workers and Federal Income Taxes in a Spatial Equilibrium." *American Economic Journal: Economic Policy* 13 (2): 100–134.

Davis, Morris A, Andra C Ghent, and Jesse Gregory. (2024). "The Work-from-Home Technology Boon and Its Consequences." *Review of Economic Studies,* forthcoming.

Delventhal, Matt, and Andrii Parkhomenko. (2023). "Spatial Implications of Telecommuting." *SSRN 3746555.*

Gaspar, Jess, and Edward L Glaeser. (1998). "Information technology and the future of cities." *Journal of Urban Economics* 43 (1): 136–156.

Gokan, Toshitaka, Sergei Kichko, Jesse A Matheson, and Jacques-François Thisse. (2022). "How the Rise of Teleworking Will Reshape Labor Markets and Cities." *Working Paper.*

Gupta, Arpit, Vrinda Mittal, and Stijn Van Nieuwerburgh. (2022). "Work from home and the office real estate apocalypse." *NBER Working Paper.*

Heathcote, Jonathan, Kjetil Storesletten, and Giovanni L Violante. (2017). "Optimal Tax Progressivity: An Analytical Framework." *The Quarterly Journal of Economics* 132 (4): 1693–1754.

Heblich, Stephan, Stephen J Redding, and Daniel M Sturm. (2020). "The Making of the Modern Metropolis: Evidence from London." *The Quarterly Journal of Economics* 135 (4): 2059–2133.

Herkenhoff, Kyle F, Lee E Ohanian, and Edward C Prescott. (2018). "Tarnishing the Golden and Empire States: Land-use Restrictions and the US Economic Slowdown." *Journal of Monetary Economics* 93:89–109.

Hsieh, Chang-Tai, and Enrico Moretti. (2019). "Housing Constraints and Spatial Misallocation." *American Economic Journal: Macroeconomics* 11 (2): 1–39.

Li, Elmer Zongyang. (2025). "E-commerce and Regional Inequality: A Trade Framework and Evidence from Amazon's Expansion." *Working Paper.*

Monte, Ferdinando, Charly Porcher, and Esteban Rossi-Hansberg. (2023). "Remote Work and City Structure." *NBER Working Paper.*

Monte, Ferdinando, Stephen J Redding, and Esteban Rossi-Hansberg. (2018). "Commuting, Migration, and Local Employment Elasticities." *American Economic Review* 108 (12): 3855–3890.

Moretti, Enrico. (2012). *The new geography of jobs.* Houghton Mifflin Harcourt.

Richard, Morgane. (2024). "The Spatial and Distributive Implications of Working-from-Home: A General Equilibrium Model." *Working Paper.*

Ruggles, Steven, Sarah Flood, Sophia Foster, Ronald Goeken, Jose Pacas, Megan Schouweiler, and Matthew Sobek. (2021). "IPUMS USA: Version 11.0."

Safirova, Elena. (2002). "Telecommuting, traffic congestion, and agglomeration: a general equilibrium model." *Journal of Urban Economics* 52 (1): 26–52.

Appendix

A Data Appendix

Sample. Most of the data in this paper come from ACS. I work with the 2015-2019 five-year sample made available by Ruggles et al. (2021). In my sample, I include individuals who reside in the 48 contiguous US states, did not come from abroad last year, are 18 to 65 years old, were at work last week, are not self-employed, don't work in the military, and earn more than 1,000 2019-dollars in wage income. I aggregate individual variables to the 2010 place-of-work PUMA and national levels with individual US population weights, separately for the two skill types. Workers are classified as non-college-educated, $a = 1$, if they do not have a completed bachelor's degree, and as college-educated, $a = 2$, otherwise. There are 975 workplace PUMAs in 2019 with both positive residential and worker populations.

I supplement this sample with Baum-Snow and Han (2024) housing supply elasticities (floorspace estimates predicted by the IV-FMM quadratic model) aggregated from 2000 census tracts to 2010 workplace PUMA level, using tract shares of occupied housing units in a workplace PUMA as weights. Whenever census tract estimates are unavailable, I set them to 1.4, the highest value in the Baum-Snow and Han (2024) dataset.

To calculate national shares and wages of remote workers in 2022, I use the 2022 one-year ACS sample with the same sample restrictions as for 2019. I aggregate the number of individuals who work remotely and their wages to the national level using individual US population weights. I convert 2022 wages to 2019 consumption units using the PCE nondurable goods index from BEA (2019-2022 growth rate in the index is 1.14). In the robustness appendix, I also consider the 2022 ACS data aggregated to the 2020 workplace PUMAs. There are 997 2020-workplace PUMAs with positive residential and worker populations in 2022. To convert housing supply elasticities for 2010 workplace PUMAs into ones for 2020 workplace PUMAs, I use a population-weighted crosswalk provided by the Census.

Variables.

- π^a_{ij}, share of workers of type a who live in workplace PUMA j and work in workplace PUMA i; if a worker reports usually working from home last week (means of transportation to work variable = "work from home"), they are assigned $i = 0$.

- w^a_i, average annual wage of workers of type a in workplace PUMA ($i \geq 1$) or who work remotely ($i = 0$) as given by the pre-tax wage and salary income for the previous year variable.

- q_j, average annual residential rent in workplace PUMA j as given by the monthly contract rent variable.

B Counterfactual Experiments

B.1 Counterfactual Equations

In this section, I compute counterfactual changes as growth rates. I use the standard hat algebra notation: $\hat{x} \equiv x'/x$, where x denotes the initial values of parameters or endogenous variables taken from the data, and x' denotes the new values of parameters or counterfactual values of endogenous variables under the new set of parameters. When computing growth rates, unobserved fundamentals $\{1-\kappa_{ij}^a, B_j, \bar{H}_j\}$ cancel out, so I do not need to estimate them.

There are three types of counterfactual experiments I conduct in this paper. In the work-from-home experiment, 1) I decrease the share of expenditure that goes to in-person labour in the production function, $\hat{\alpha}^a < 1$, which implies an increase in the share of remote services $1 \hat{-} \alpha^a = \frac{1-\alpha^a \hat{\alpha}^a}{1-\alpha^a} > 1$, and 2) increase the preference towards/reduce the cost of remote work, $1 \hat{-} \kappa_{0j}^a > 1$ (while μ is not changed, so $\mu' = \mu$). In the tax progressivity experiment, I change the degree of tax progressivity μ' (while $\hat{\alpha}^a = 1$ and $1 \hat{-} \kappa_{ij}^a = 1$). In the housing supply experiment, I increase the local elasticities of housing supply $\{\xi_j'\}$ (while $\hat{\alpha}^a = 1$ and $1 \hat{-} \kappa_{ij}^a = 1$). In all experiments, I keep the government expenditure G constant at the same level of 7% of total wage bill in the 2019 data, $\sum_a L^a \sum_j \sum_{i \geq 0} \pi_{ij}^a w_i^a$. With G fixed in all experiments, the tax policy parameter χ' must adjust according to equation (16), which I rewrite in terms of counterfactual values below.

Denote the per-unit expenditure on in-person labour $W_i^a \equiv w_i^a + \frac{q_i}{\rho^a}$. Taking the growth rates of equations (2), (7), and (12)-(15) in the main text, I obtain the following equations for the counterfactual changes in endogenous variables:

$$\hat{\tilde{w}}^a_{ij} = (\widehat{1-\kappa^a_{ij}})(\hat{w}^a_i)^{1-\mu'} w_i^{\mu-\mu'} \hat{q}_j^{\gamma-1} (\hat{R}_j)^{\eta^R}, \tag{19}$$

$$\hat{\pi}^a_{ij} = \frac{(\hat{\tilde{w}}^a_{ij})^{\theta^a}}{\sum_{i'} \sum_{j'} (\hat{\tilde{w}}^a_{i'j'})^{\theta^a} \pi^a_{i'j'}}, \qquad \hat{L}^a_i = \sum_j \hat{\pi}^a_{ij} \frac{\pi^a_{ij}}{\sum_j \pi^a_{ij}}, \qquad \hat{R}^a_j = \sum_i \hat{\pi}^a_{ij} \frac{\pi^a_{ij}}{\sum_i \pi^a_{ij}}, \tag{20}$$
$$\hat{L}_i = \frac{\sum_a L^a \, L^a_i \hat{L}^a_i}{\sum_a L^a \, L^a_i}, \qquad \hat{R}_j = \frac{\sum_a L^a \, R^a_j \hat{R}^a_j}{\sum_a L^a \, R^a_j},$$

$$\hat{w}^a_i = \left(\hat{W}^a_i - \frac{\hat{q}_i}{\frac{w^a_i}{q_i/\rho^a} + 1} \right) \left(\left(\frac{w^a_i}{q_i/\rho^a} \right)^{-1} + 1 \right), \quad i \geq 1 \tag{21}$$

$$\hat{C}^a_i = \left[\frac{\hat{\alpha}^a}{1 + \frac{1-\alpha^a}{\alpha^a} \left(\frac{W^a_i}{p^a_0} \right)^{\frac{\sigma^a}{1-\sigma^a}}} + \frac{(\widehat{1-\alpha^a}) \left(\frac{\hat{W}^a_i}{\hat{p}^a_0} \right)^{\frac{\sigma^a}{1-\sigma^a}}}{\left(\frac{1-\alpha^a}{\alpha^a} \left(\frac{W^a_i}{p^a_0} \right)^{\frac{\sigma^a}{1-\sigma^a}} \right)^{-1} + 1} \right]^{\frac{1}{\sigma^a}}, \quad i \geq 1 \tag{22}$$

$$\hat{W}^1_i = \frac{1}{W^1_i} \left\{ \frac{\left[\tilde{A}_i \, (L_i \hat{L}_i)^{\eta^L} \right]^{-\frac{\delta}{1-\delta}} - (1-\nu) \left[A^2_i \, (W^2_i \hat{W}^2_i)^{-1} (C^2_i \hat{C}^2_i)^{1-\sigma^2} \right]^{\frac{\delta}{1-\delta}}}{\nu \left[A^1_i (C^1_i \hat{C}^1_i)^{1-\sigma^1} \right]^{\frac{\delta}{1-\delta}}} \right\}^{-\frac{1-\delta}{\delta}}, \; i \geq 1 \tag{23}$$

$$\hat{W}^2_i = \left(\frac{\hat{\alpha}^2}{\hat{\alpha}^1} \frac{\hat{L}^1_i}{\hat{L}^2_i} \right)^{1-\delta} \frac{(\hat{C}^2_i)^{\delta-\sigma^2}}{(\hat{C}^1_i)^{\delta-\sigma^1}} \hat{W}^1_i, \quad i \geq 1 \tag{24}$$

$$\hat{p}^a_0 = \left(\frac{(\widehat{1-\alpha^a})}{\hat{\alpha^a}} \frac{1}{\hat{L}^a_0} \frac{\sum_{i\geq 1} (W^a_i \hat{W}^a_i)^{\frac{1}{1-\sigma^a}} L^a_i \hat{L}^a_i}{\sum_{i \geq 1} (W^a_i)^{\frac{1}{1-\sigma^a}} L^a_i} \right)^{1-\sigma^a}, \qquad \hat{p}^a_0 = \hat{w}^a_0, \tag{25}$$

$$\hat{q}_j = \left(q_j^{\xi_j - \xi'_j} \frac{\sum_a L^a \left(\frac{1}{\rho^a} \sum_{j'} \pi^a_{jj'} \hat{\pi}^a_{jj'} + \frac{1-\gamma}{q_j \hat{q}_j} \sum_i \chi' \, (w^a_i \hat{w}^a_i)^{1-\mu'} \pi^a_{ij} \hat{\pi}^a_{ij} \right)}{\sum_a L^a \left(\frac{1}{\rho^a} \sum_{j'} \pi^a_{jj'} + \frac{1-\gamma}{q_j} \sum_i \chi \, (w^a_i)^{1-\mu} \pi^a_{ij} \right)} \right)^{\frac{1}{\xi'_j}}, \tag{26}$$

$$\chi' = \frac{\sum_a L^a \sum_i \sum_j w^a_i \hat{w}^a_i \, \pi^a_{ij} \hat{\pi}^a_{ij} - G}{\sum_a L^a \sum_i \sum_j (w^a_i \hat{w}^a_i)^{1-\mu'} \pi^a_{ij} \hat{\pi}^a_{ij}}. \tag{27}$$

B.2 Computational Algorithm

Take the parameter values from Table 1 (as discussed in Section 4) and the initial values of $\{w_i^a, \pi_{ij}^a, q_j\}$ from the 2019 data or the 2019 data with the WFH shift D'. Calculate $\{\alpha^a\}$ using (14), ν using (13), $\tilde{A}_i$ using (7) and (17). Calculate Y as the total wage and commercial rent bill, and then find χ using (16). Choose $\hat{\alpha}^a$, $\widehat{1-\kappa}_{0j}^a$, μ', or ξ_j'.

1. Guess $\{(\hat{W}_i^a)^g, (\hat{\pi}_{ij}^a)^g, (\hat{q}_j)^g\}$.[23]

2. Plug the guess into equations (21), (22), and (25) to calculate $\{\hat{w}_i^a\}$ and $\{\hat{C}_i^a\}$.

3. Plug values from 2., into equations (23) and (24) to update the guess $\{(\hat{W}_i^a)^{g'}\}$.

4. Plug $\{\hat{w}_i^a\}$ from 2. and $\{(\hat{\pi}_{ij}^a)^g\}$ into (27) to calculate χ'.

5. Plug $\{\hat{w}_i^a\}$ from 2., χ' from 4., and $\{(\hat{\pi}_{ij}^a)^g\}$ in (26) to update the guess $\{(\hat{q}_j)^{g'}\}$.

6. Plug $\{\hat{w}_i^a\}$, χ', and $\{(\hat{q}_j)^g\}$, into equations (19) and (20) to update the guess $\{(\hat{\pi}_{ij}^a)^{g'}\}$

7. Check if $\max\{|(\hat{W}_i^a)^{g'} - (\hat{W}_i^a)^g|, |(\hat{\pi}_{ij}^a)^{g'} - (\hat{\pi}_{ij}^a)^g|, |(\hat{q}_j^a)^{g'} - (\hat{q}_j^a)^g|\} < \varepsilon$; if not, replace the guess g with the convex combination of the values g and g', and go back to 2.

B.3 Evaluating the Effect of WFH on Spatial Misallocation

First, for a range of $\mu' \neq \mu$ (while $\hat{\alpha}^a = 1$ and $\widehat{1-\kappa}_{ij}^a = 1$) and $\{w_i^a, \pi_{ij}^a\}$ taken from 2019 data, run the counterfactual experiment as described in the previous section and compute the counterfactual output $Y' \equiv Y(\mu', \{\alpha^a\}, \{1-\kappa_{ij}^a\}) = \sum_a L^a \sum_i \sum_j w_i^a \hat{w}_i^a \pi_{ij}^a \hat{\pi}_{ij}^a$. In particular, $Y'/Y_0 \equiv Y(0, \{\alpha^a\}, \{1-\kappa_{ij}^a\})/Y(0.18, \{\alpha^a\}, \{1-\kappa_{ij}^a\})$ is the extra output gain from removing national income tax progressivity after the WFH shift.

Second, select $\hat{\alpha}^a$ and $\widehat{1-\kappa}_{i0j}^a$ (while $\mu' = \mu = 0.18$) such that given $\{w_i^a, \pi_{ij}^a\}$ taken from 2019 data, the counterfactual experiment described in the previous section returns the national shares and wages of remote workers $\{\sum_j \pi_{0j}^a \hat{\pi}_{0j}^a, w_0^a \hat{w}_0^a\}$ that match the 2022 data. Record the counterfactual data $D(\mu, \{(\alpha^a)'\}, \{(1-\kappa_{ij}^a)'\}) \equiv \{w_i^a \hat{w}_i^a, \pi_{ij}^a \hat{\pi}_{ij}^a\}$ and the counterfactual output $Y'' \equiv Y(\mu, \hat{\alpha}^a, \widehat{1-\kappa}_{0j}^a) = \sum_a L^a \sum_i \sum_j w_i^a \hat{w}_i^a \pi_{ij}^a \hat{\pi}_{ij}^a$ after the shift to work from home, but with the current degree of national income tax progressivity.

Then, for the same range of $\mu' \neq \mu$ (keeping $\hat{\alpha}^a = 1$, $\widehat{1-\kappa}_{ij}^a = 1$), but now using the WFH counterfactual data $D(\mu, \{(\alpha^a)'\}, \{(1-\kappa_{ij}^a)'\})$, run the counterfactual experiment and compute the counterfactual output $Y''' \equiv Y(\mu', \{(\alpha^a)'\}, \{(1-\kappa_{ij}^a)'\}) = \sum_a L^a \sum_i \sum_j w_i^a \hat{w}_i^a \pi_{ij}^a \hat{\pi}_{ij}^a$. In particular, Y'''/Y'' is the relative output gain from removing national income tax progressivity after the shift to work from home.

23. In case $\rho^a \to \infty$, guessing $\{q_j\}$ is not necessary.

Finally, by comparing Y'/Y_0 with Y'''/Y'', we can evaluate the impact of the shift to WFH on spatial misallocation generated by tax progressivity. The experiments described in this section suggest that the shift to WFH generates an additional 1pp loss in output due to tax progressivity.

C Additional Robustness Checks

C.1 Local Productivity and the Number of WFH Residents

In this section, I show that my main quantitative result still holds if I directly match the growth in the number of remote workers in each location to the 2019-2022 change in ACS data by choosing $\{1 \hat{-} \kappa^a_{0j}\}$ individually for each location to target $\{\hat{\pi}^a_{0j}\}$ as opposed to the national change in the number of remote workers. The gap in output growth between the baseline 2019 and post-WFH economies even increases slightly for the housing supply counterfactual.

Next, I directly use the 2022 data for my experiments instead of the 2019 counterfactual data with the WFH shift matched to fit the 2019-2022 changes in national shares and wages of remote workers. See Tables 10 (output) and 11 (inequality). The direct effect of reduced taxation on WFH with sorting still generates a positive gap between the full effect in 2019 and 2022. However, the magnitude of the full effect gap is smaller because in 2022, in-person employment in more productive places is lower than in 2019 or 2019 with the WFH shift, reflecting the fact that workers converted to remote work but didn't move out of the most productive cities, as my model predicts. As more productive cities collect disproportionately more remote workers, the reduced tax rates on in-person work there cannot attract as many in-person workers.

I prefer not to use the 2022 ACS data in the main text experiments because first, the 2022 data use the 2020 workplace PUMAs as opposed to the 2010 workplace PUMAs in the 2019 data, so to compare results for the fixed spatial unit, I will have to rely on the crosswalk; second, the 2022 data are a one-year ACS sample with fewer observations as opposed to the five-year ACS sample I use for 2019; and third, the 2022 data have much more employed college-educated workers ($L^2/L^1 = 0.68$) as opposed to 2019 ($L^2/L^1 = 0.54$), reflecting the fact that post-Covid recovery is still not complete in 2022 data.

TABLE 10: **Contributions of Model Mechanisms, Output**

	% Change in Y			
	$\mu' = 0$		$\xi'_j = \text{med } \xi_j$	
	2019	2022	2019	2022
Full effect	1.03	1.21	4.17	3.67
Direct effect, in-person work				
no sorting	0.90	0.70	4.13	3.46
with sorting	0.92	0.75	4.07	3.19
Direct effect, WFH				
no sorting	0.27	0.62	—	—
with sorting	0.56	0.91	—	—

Notes: Counterfactual change in output relative to 2019 economy or 2022 economy. All parameters are as in Table 1. See Notes for Table 2 in the main text.

TABLE 11: **Contributions of Model Mechanisms, Welfare and Inequality**

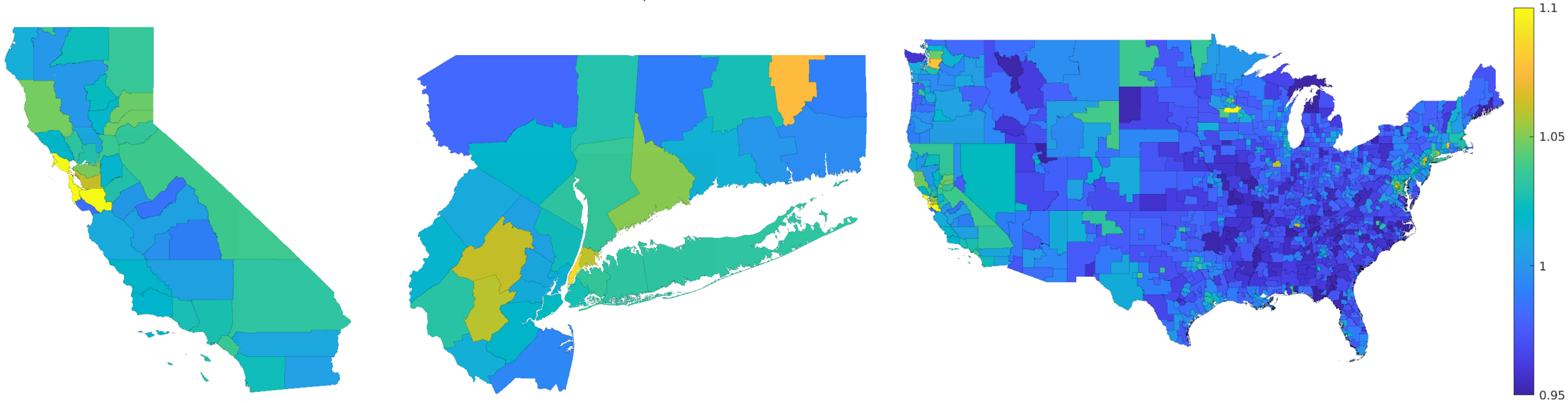
	% Change in U^a			
	$\mu' = 0$		$\xi'_j = \text{med } \xi_j$	
	2019	2022	2019	2022
Mechanical effect				
college	6.54	6.30	29.67	30.52
non-college	−7.06	−7.08	26.60	27.02
difference	13.61	13.38	3.08	3.50
Mechanical + Sorting				
college	5.99	5.84	29.00	29.85
non-college	−7.09	−7.08	24.57	25.06
difference	13.08	12.92	4.43	4.79
Mechanical + Sorting + WFH Wages				
college	5.92	5.47	29.19	30.40
non-college	−7.12	−7.20	24.62	25.15
difference	13.04	12.66	4.57	5.25
Full effect (+ In-Person Wages)				
college	6.20	6.17	30.18	31.52
non-college	−7.67	−7.72	22.63	22.95
difference	13.86	13.89	7.55	8.57

Notes: Counterfactual change in ex-ante welfare relative to 2019 economy or 2022 economy. All parameters are as in Table 1. See Notes for Table 3 in the main text.

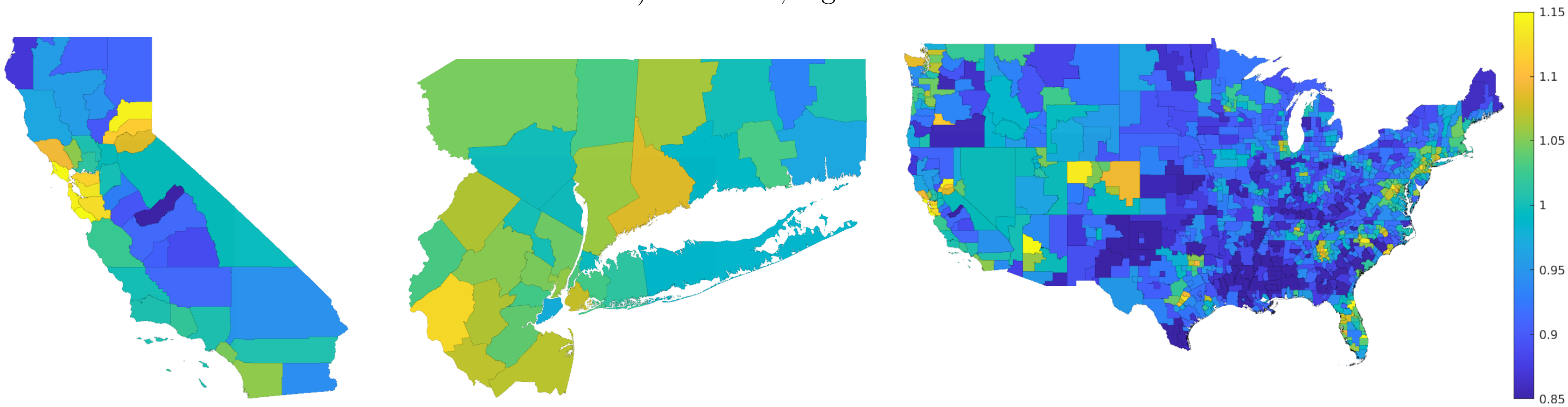
D Long-Run Geography of Work-from-Home Shift

Figure 5: **Counterfactual Changes in WFH experiment**

a) Residents, low-skill

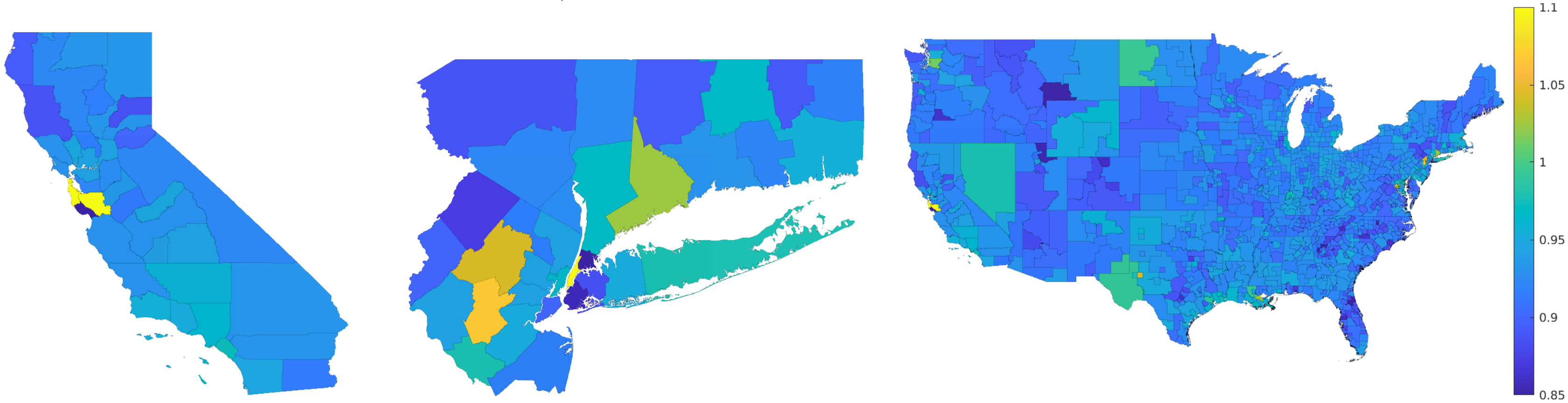


b) Residents, high-skill

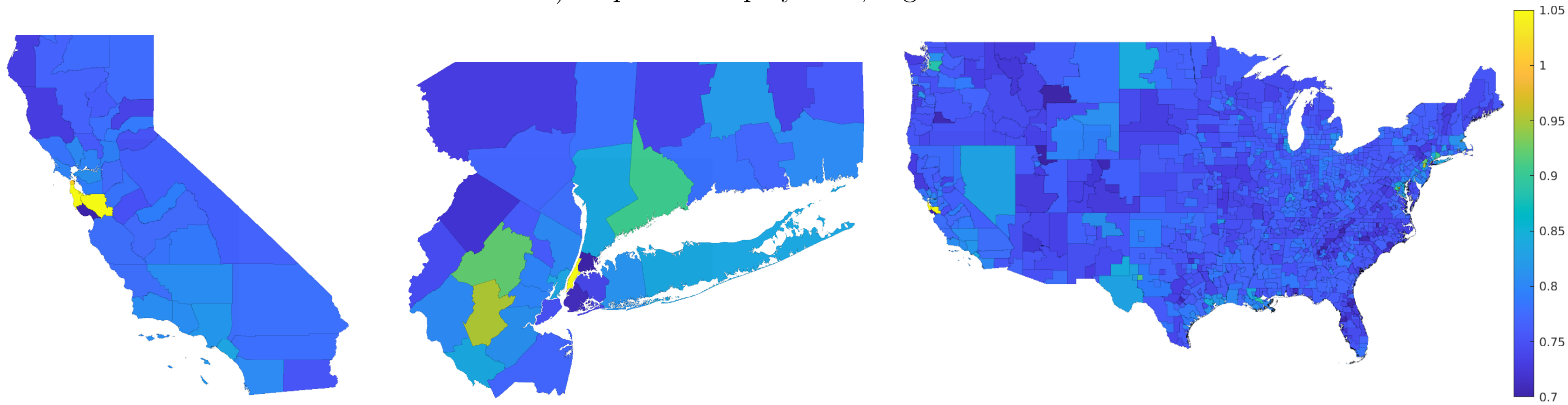


Notes: See below.

c) In-person employment, low-skill

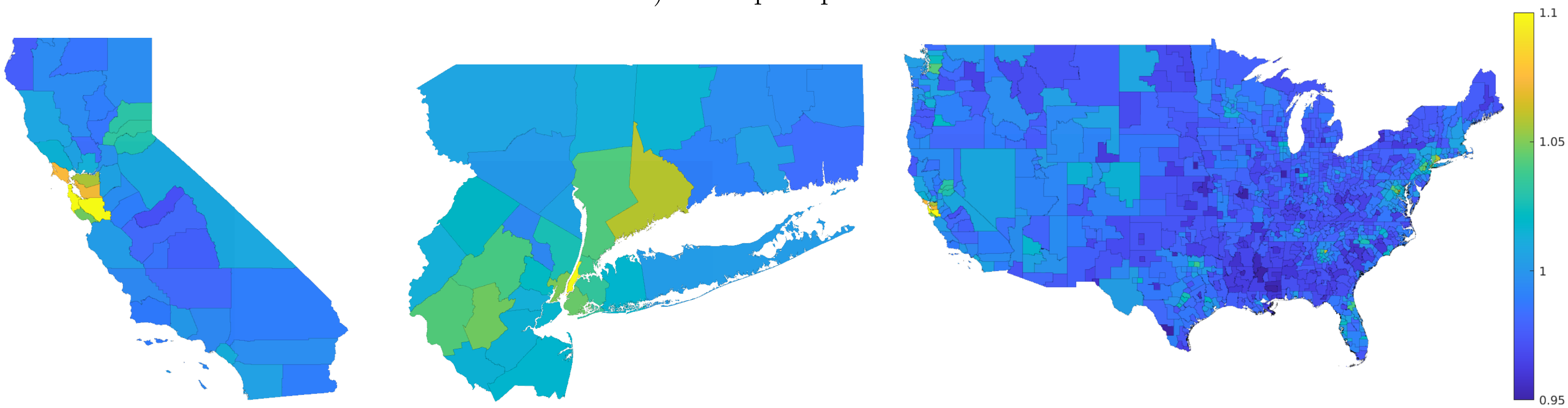


d) In-person employment, high-skill



Notes: See below.

e) Floorspace prices



Notes: Growth rates of local endogenous variables relative to 2019 levels as predicted by the model after imposing the WFH shift. All parameters are as in Table 1, except for $\rho^1 = 2.5, \rho^2 = 2$. Left panel focuses on California, central panel on New York City, and right panel shows all 48 contiguous states. The spatial units are the 2010 Workplace PUMAs as defined by the US Census Bureau.