The Welfare Consequences of Incoming Remote Workers for Local Residents

Hoyoung Yoo*
University of Illinois Urbana–Champaign

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Abstract

This paper studies how an influx of high-skilled remote workers impacts local residents in destination cities through remote worker relocation programs. Using the Tulsa Remote program, I provide evidence that while remote workers' arrival in shrinking areas does not influence local residents' residential or workplace locations, it has offsetting effects on local employment across different sectors. Through a spatial equilibrium model, I find that policies to attract remote workers can enhance local residents' average welfare without necessarily transferring welfare from local residents to landowners. However, this outcome relies on the availability of vacant housing, the expectation of program growth among local business and landowners, and the program funding source.

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In recent years, increasing numbers of municipalities have launched remote worker relocation programs that offer relocation subsidies to attract remote workers, hoping to boost local economic growth (Glaeser and Gottlieb, 2008; Moretti, 2010; Neumark and Simpson, 2015; Bartik, 2020). The first such program in the United States was Tulsa Remote, implemented in 2018 and funded by a nonprofit organization in Tulsa, Oklahoma. Subsequently, many other distressed regions in the United States—including West Virginia, Topeka in Kansas, Muscle Shoals in Alabama, and cities in Indiana—independently adopted similar programs in an effort to promote their economic growth. The rationales for these place-based policies often refer to agglomeration externalities (Duranton and Puga, 2004); however, economists have sometimes expressed skepticism over such policies, fearing they may cause economic inefficiencies. For example, if newly arrived remote workers from relocation programs push out local incumbents while increasing local prices, only affluent local residents, such as landowners, will stay in the area, reaping the benefits. Conversely, high-skilled remote workers may create local jobs because they arrive with jobs in hand while contributing to local spending.[1]

Noticeably, the number of remote workers has exploded in recent years (Barrero, Bloom and Davis, 2021, 2023).[2] As more workers choose to leave traditional employment hubs and settle in new cities; such spatial relocation has instigated debates about its impact on people *already* established in the destination areas.[3] With this background, it has become important to understand how remote workers impact local residents.

This paper offers the first economic insights into this question in the context of remote worker relocation programs through a spatial equilibrium model (Rosen, 1979; Roback, 1982). The model allows labor supply decisions, commuting, and elastic housing supply (Kline, 2010; Busso, Gregory and Kline, 2013; Kline and Moretti, 2014*b*). I use Tulsa Remote—the earliest and largest program of this kind—as a case study, carefully identifying the treated area to which remote workers relocated. To distinguish from the effects of COVID-19, I focus the empirical analysis on the program's effects one year after its introduction.[4]

I obtain three notable findings. First, I investigate the margins along which local residents

[1] This is in contrast to classic settings where newcomers both consume goods and compete for jobs (Card, 1990; Borjas, 2003).

[2] In the United States, the percentage of workers working primarily from home has steadily increased over the past few decades, rising from 1.18% in 2000 to 4% in 2019 and then 17.99% in 2021, according to the American Community Survey (ACS). The trend has declined from its peak during the COVID-19 pandemic, but the new steady-state level remains higher than the old one.

[3] Joseph, Talmon, "Can Affluence and Affordable Housing Coexist in Colorado's Rockies?", *New York Times*, August 26, 2023.

[4] Long-run effects are conceptually discussed in Section 4.

respond to the program in their residential and work location choices and employment-related choices. This is important because the program's inefficiency cost will depend on whether the program shock distorts local residents' choices and, if so, how. It turns out that local residents are inelastic in their residential and work location choices, which suggests strong attachment to their original choices.[5] However, they show relatively elastic responses in their sector and employment choices, shifting from tradable to nontradable sectors and transitioning from not working to working. I relate this observation to the asymmetry in the effects of incoming remote workers on local residents by industry sector due to the nontradability of produced goods. For instance, newly arrived remote workers frequent local restaurants and cafes, where the consumed goods and services are supplied within the city. The remote workers' local spending, in turn, increases labor demand in this sector. In contrast, demand for tradable goods, such as clothes and computers, is not primarily driven by the local economy, so local workers in this sector may not necessarily face a demand shift.

Second, I find no evidence of a statistically significant increase in rent prices or housing values in the treated region. This is an important observation, as changes in land values govern the welfare dynamics between local residents and landowners. I explain this finding by noting the decline in the residential vacancy rate in the treated region in response to the program's introduction (before the onset of COVID-19). Through the lens of the model, I show that population growth can fill vacancies without causing an increase in rent prices. Consequently, landowners could exploit the program's introduction by renting out vacant units to newcomers without necessarily hurting local residents.

Last, I consider the dynamic nature of the program by accounting for expectations about the program's growth among business owners and landowners. These prove important for interpreting the large treatment effects on employment in the local services and construction sectors and for the welfare analysis.

Related Literature. This paper contributes to a long strand of literature on place-based policy (Glaeser and Gottlieb, 2008; Moretti, 2010; Kline and Moretti, 2014*b*; Neumark and Simpson, 2015) by studying a policy that is rapidly gaining momentum.[6] In the context of attracting remote workers

[5] Kennan and Walker (2011) relate migration behaviors to high moving costs and Howard and Shao (2023) to persistent and spatially correlated preferences.

[6] Other place-based policies that have been the subjects of study include enterprise zones (Neumark and Kolko, 2010; Ham et al., 2011), empowerment zones (Busso, Gregory and Kline, 2013), the Tennessee Valley Authority (Kline and Moretti, 2014*a*), and opportunity zones (Coen-Pirani and Sieg, 2019; Arefeva et al., 2021; Freedman, Khanna and Neumark, 2021).

to local regions, I show that this emerging place-based policy, when implemented effectively, can benefit local residents on average. An extensive literature (Gaubert, 2018; Diamond and McQuade, 2019; Qian and Tan, 2021) examines the effects of spatial treatments on local residents and their welfare consequences in different contexts. Using the same Tulsa Remote setting, Choudhurry, Starr and Thomaz (2022) study its impact on the outcomes of participating remote workers, such as their planned next move after having relocated to Tulsa, their social involvement, and their income.[7] In contrast to these authors, I estimate the program's direct effects on local residents, which can speak to whether such programs achieve their goals. Furthermore, this paper provides the first assessment of remote worker relocation programs on local incumbents considering equilibrium effects and distributional effects.

Next, this paper adds to the work on migration by turning the spotlight on a new type of migrants: high-skilled remote workers who already have jobs outside the local economy. Tracing back to classic immigration studies (Card, 1990; Borjas, 1994, 2003; Ottaviano and Peri, 2012), research on the economic impact of newcomers on incumbents in a receiving location, especially in the labor market, has been of great interest. Compared to the characteristics of traditional economic migrants, remote workers' characteristics have different labor market implications for local residents, so this paper provides new insights. More recent studies have examined settings similar to this study's, in which newcomers consume goods but do not compete with local residents for local jobs: for example, tourism (Faber and Gaubert, 2019; Allen et al., 2020; Almagro and Dominguez-Iino, 2022), relocation of public-sector workers (Faggio and Overman, 2014; Faggio, 2019; Becker, Heblich and Sturm, 2021), refugee shocks (Borjas and Monras, 2017; Glitz et al., 2023), and relocation of retirees (Maroto et al., 2024). Adding to this strand of literature, this paper focuses on remote workers who affect local residents through a consumption shock in a nontradable sector.

Last, it relates to the growing literature on work from home (WFH). Previous studies have focused on the WFH workers' side: for example, WFH productivity (Bloom et al., 2015; Emanuel and Harrington, 2023; Liu and Su, 2022), WFH feasibility (Dingel and Neiman, 2020), WFH persistence (Barrero, Bloom and Davis, 2021, 2023; Bick et al., 2020), and the complementarity of

[7] Choudhurry, Starr and Thomaz (2022) survey four different groups: (i) Tulsa Remote members ("Tulsa Remoters"), (ii) individuals whose applications to the program were unsuccessful, (iii) individuals accepted for Tulsa Remote who ultimately did not join the program for idiosyncratic reasons ("near–Tulsa Remoters"), and (iv) individuals accepted into the program who will move to Tulsa. They find that Tulsa Remoters are likelier to stay in their cities in the next years, to actively engage in the community, and to have higher real income growth than near–Tulsa Remoters.

WFH with office work (Davis, Ghent and Gregory, 2021). In contrast, this paper studies the effects of remote workers on a different set of people: local incumbents. Another strand of the literature (Delventhal, Kwon and Parkhomenko, 2022; Brueckner, Kahn and Lin, 2023; Monte, Porcher and Rossi-Hansberg, 2023; Richard, 2024; Brueckner, 2025) investigates the implications of WFH for city structure, sometimes in interaction with state income taxes (Agrawal and Brueckner, 2025), through the lens of spatial equilibrium models. In contrast, I provide direct, causal evidence of relocated remote workers' stimulating effect on local employment and a welfare analysis.

Plan. The remainder of this paper is structured as follows. Section 1 provides institutional background on remote worker relocation programs, with a focus on the earliest and largest program, Tulsa Remote. Section 2 provides the modeling framework. Section 3 describes data and presents descriptive and reduced-form evidence on how the program affected local residents through a case study of Tulsa Remote. Section 4 provides a welfare analysis. Section 5 discusses policy considerations, and Section 6 concludes.

1 Remote Worker Relocation Programs

Since 2018, an increasing number of localities in the United States (see Figures 1a and 1b) have launched remote worker relocation programs to attract remote workers with cash incentives.[8] Most of these localities have suffered population losses (see Figure 1c) and seek to promote local economic growth by bringing in full-time remote workers, who are flexible in their location choices. While each program has its own eligibility criteria and incentives, all share the condition that participants must be remotely employed full-time and commit to residing in the city for one or two years.

Tulsa Remote.—Among remote worker relocation programs, the earliest and largest is Tulsa Remote, which was initiated in November 2018 by a nonprofit organization. To be eligible for the program, applicants have to meet five criteria: (i) full-time remote employment (including self-employment) outside of Oklahoma, (ii) at least 18 years old, (iii) eligible to work in the United States, (iv) willing to relocate to Tulsa within 6–12 months of being accepted, and (v) committed to staying in Tulsa for at least one year. Once accepted into the program, applicants receive an

[8] Other programs are discussed in the online appendix. Examples include Tulsa Remote (Tulsa, Oklahoma), Remote Shoals (Shoals, Alabama), Think Vermont (Vermont), Ascend West Virginia (Morgantown, West Virginia), and Choose Topeka (Topeka, Kansas).

incentive package consisting of a cash grant of $10,000 distributed over one year, membership to a coworking space, assistance in searching for housing, and regular community events. The six-year-old Tulsa Remote program has attracted over 3,500 remote workers to date, each bringing their remote jobs.

2 Model

I present a spatial equilibrium model that will allow me to conduct a welfare analysis of remote worker relocation programs once I have elasticity estimates in hand (Chetty, 2009). The framework is set up in the traditions of Rosen (1979) and Roback (1982) but extended to allow for richer heterogeneity, labor supply decisions, commuting, and elastic housing supply (e.g., Kline, 2010; Busso, Gregory and Kline, 2013; Kline and Moretti, 2014*b*). I also distinguish place of residence from place of work[9] and nontradable (construction and local services) from tradable sectors.

Labor Supply.— Assume a continuum of economic agents of measure one with a given skill type, high (h) or low (l). They also may live or work in neighborhoods ($\mathcal{N}$) inside ($\mathcal{N}_1$) or outside ($\mathcal{N}_0$) the area covered by relocated remote workers, i.e., $\mathcal{N} \in \{\mathcal{N}_1, \mathcal{N}_0\}$. Neighborhoods have fixed bundles of amenities consumed by residents. Commuting between neighborhoods is costly. To account for the asymmetry in remote workers' effects on local residents by industry sector, I distinguish two sectors in the economy: (i) the first sector, where the produced goods are consumed in the same location (construction sector (C) or local services sector (S)) and (ii) the second sector, where the produced goods can be consumed elsewhere (tradable sector (T)).

Agents choose which neighborhood to live in, whether to work, and (if they work) which neighborhood and sector to work in. Each agent inelastically supplies a single unit of labor. I write the utility of individual i given a skill type $e \in \{h, l\}$ living in neighborhood $j \in \{\mathcal{N}\}$ and working in

[9] A recently expanding body of literature on quantitative spatial equilibrium models distinguishes residential from workplace locations (Ahlfeldt et al., 2015; Redding and Rossi-Hansberg, 2017; Monte, Redding and Rossi-Hansberg, 2018). This distinction is rooted in the idea that a shock to one location can have spillover effects on other locations, particularly when they are connected by bilateral commuting flows. In the context of remote worker relocation programs, however, the impact of relocated remote workers does not likely propagate to other cities. Regardless, this distinction allows me to consider heterogeneity in the welfare analysis with respect to residential and working locations.

community $k \in \{\mathcal{N}\}$ and sector $e \in \{\phi, C, S, T\}$ as

$$u^e_{ijks} = w^e_{ks} - \alpha^e_p \cdot p_j - \alpha^e_r \cdot r_j - \kappa_{jk} \cdot \mathbf{1}\{s \neq \phi\} + A^e_j + \sigma^e \cdot \epsilon^e_{ijks} \tag{1}$$

$$= v^e_{jks} + \sigma^e \cdot \epsilon^e_{ijks} \tag{2}$$

where w^e_{ks} is the wage that a worker of skill type e receives by working in a work location k and in a sector s. α^e_p is the relative units of local service goods consumption, p_j is the local prices, α^e_r is the relative units of housing consumption, r_j is the local rent, κ_{jk} is the commuting cost from the residential location j to the work location k, A^e_j is the mean consumption value of local amenities in the residential location j, and the error terms ϵ^e_{ijks} represent heterogeneity in the valuation of local amenities, the value of leisure, tastes for work, and commuting costs. The error terms are independently and identically distributed across individuals i, which implies imperfectly elastic labor supply. σ^e governs the heterogeneous elasticity in skill type. v^e_{ijks} is the mean utility of each choice. I normalize the wage for nonworkers to zero ($w^e_{k\phi} = 0$) and the commuting costs for these individuals to zero ($\kappa_{jk} = 0$ if $s = \phi$).

The heterogeneity in sector choice becomes important as the change in the relative wage ratio between sectors leads to between-sector switching behavior. This is because relocated remote workers push demand for local service goods and housing but not that for tradable goods, as these can be supplied or demanded from elsewhere. On the other hand, the heterogeneity in residential and work locations will allow me to consider heterogeneity in the welfare analysis. Residents in lagging regions where remote worker relocation programs are implemented may not respond in their location decisions to the local shock if they find switching their residential locations or changing their commuting routes insufficiently desirable (Busso, Gregory and Kline, 2013; Wrede, 2013). Alternatively, this means that residents may have strong attachment to their original places (Howard and Shao, 2023).

Before moving on to labor demand, I define the average utility of agents as $V^e = E_\epsilon\left[\max_{j'k's'}\{u^e_{ij'k's'}\}\right]$. Then, the measure of agents given e in each choice of j, k, and s becomes $N^e_{jks} = \theta^e \times \frac{dV^e}{dv^e_{jks}}$ by the envelope theorem, where θ^e is the share of each skill type e.[10]

Labor Demand.—Tradable goods (Q_{kT}) are produced in each neighborhood k with a constant returns to scale technology, $Q_{kT} = F(K_{kT}, B_k\eta_{kT}) = B_k\eta_{kT}f(\chi_{kT})$, using capital ($K_{kT}$) and labor

[10] The proof can be found in Busso, Gregory and Kline (2013).

(η_{kT}) inputs, where I define the capital to effective labor ratio as $\chi_{kT} = \frac{K_{kT}}{B_k \eta_{kT}}$ and $f' > 0, f'' < 0$ hold. B_k denotes local productivity specific to the location k, such as proximity to downtown or convenient transportation. On the other hand, nontradable goods (Q_{kS}) are produced in each neighborhood k in a monopolistic competition setting. Local service firms use a constant returns to scale production technology in G such that $Q_{kS} = G(K_{kS}, B_k \eta_{kS}) = B_k \eta_{kS} g(\chi_{kS})$, where $\chi_{kS} = \frac{K_{kS}}{B_k \eta_{kS}}$ and $g' > 0, g'' < 0$ hold. They also pay a fixed operating cost C to open their businesses. Thus, local service firms have an increasing returns to scale technology after paying the fixed operating cost. This implies that greater demand for consumption in the location driven by incoming remote workers induces more firm entries, as they share the fixed operating cost with local residents (consumption externalities).

Since the supply elasticity of workers is finite (the supply curves are upward sloping), given the heterogeneity in tastes for working sectors and commuting costs, the unequal factor demands result in unequal wages across locations. In contrast, workers from different residential locations are assumed to be substitutable in production; thus, $\eta_{ks} = \sum_{j \in \mathcal{N}} \left(\eta^l_{jks} + \gamma_s \eta^h_{jks} \right)$, where γ_s denotes the returns to high-skilled relative to the returns to low-skilled labor ($\gamma_s > 1$ holds). Capital is supplied at fixed rental rate ρ to all work locations and sectors, and tradable goods are sold on an international market at price one.[11]

Tradable firms equate the value of the marginal product of each factor to its corresponding marginal cost:

$$B_k \times (f(\chi_{kT}) - \chi_{kT} \cdot f'(\chi_{kT})) = w^l_{kT} \tag{3}$$

$$\gamma_T \times B_k \times (f(\chi_{kT}) - \chi_{kT} \cdot f'(\chi_{kT})) = w^h_{kT} \tag{4}$$

$$f'(\chi_{kT}) = \rho \tag{5}$$

In contrast, local service firms can charge a mark-up $(\frac{\epsilon}{\epsilon - 1})$ on the marginal cost in their prices (p^S) because of individuals' love of variety for local service goods, where the elasticity of substitution across different local service goods is denoted as ϵ. Thus, local service firms have:

[11] These assumptions are based on the fact that neighborhoods with remote worker relocation programs are small enough for the rental rate to be taken as given and financial institutions do not have heterogeneous preferences regarding to whom they rent.

$$\frac{\epsilon-1}{\epsilon} \times p^S \times B_k \times (g(\chi_{kS}) - \chi_{kS} \cdot g'(\chi_{kS})) = w^l_{kS} \tag{6}$$

$$\gamma_S \times \frac{\epsilon-1}{\epsilon} \times p^S \times B_k \times (g(\chi_{kS}) - \chi_{kS} \cdot g'(\chi_{kS})) = w^h_{kS} \tag{7}$$

$$\frac{\epsilon-1}{\epsilon} \times p^S \times g'(\chi_{kS}) = \rho \tag{8}$$

Housing Supply.—Housing supply curves are upward sloping in each neighborhood. Each neighborhood has a continuum of landowners, who may develop housing on their plots of land in a neighborhood j at a cost continuously distributed across owners according to the monotonically increasing function Γ_j, with strictly positive support. These costs include the wages paid to the construction workers working in a neighborhood k hired by landowners. In other words, the total housing that landowners desire to provide, including that under construction, is $\hat{H}_j = \Gamma_j(cost; L_{kC})$. If landowners expect a population increase, they may be more inclined to build more housing.

Let H_j represent the total housing rented out in neighborhood j. When construction work is all completed, the owners start renting out and receive payoffs r_j minus the cost $\Gamma_j^{-1}(H_j)$.[12] Otherwise, they receive nothing. Profit maximization implies that the marginal landowner in each neighborhood breaks even on housing construction so that

$$\Gamma_j^{-1}(\hat{H}_j) = r_j \tag{9}$$

Furthermore, landowners will hire workers until their expected marginal value of labor is equal to wages. Ignoring the time difference between when workers are hired to build houses and when the houses are rented out,

$$\frac{d\hat{H}_j}{dL_{kC}} r_j = w_{kC} \tag{10}$$

The gap between $\hat{H}_j$ and H_j is equal to the sum of houses under construction and vacant houses available on the housing market. Finally, the housing market clears as follows:

$$H_j = \sum_e \sum_k \sum_s N^e_{jks} \times \alpha^e_r \tag{11}$$

Remote Worker Relocation Programs.—Remote worker relocation programs can introduce two types

[12] If landowners pay the costs upfront, which is more realistic, there might be an interest rate multiplied to $\Gamma_j^{-1}(H_j)$.

of treatments in the local economy: (i) demand shifts in nontradable goods and housing markets due to the influx of high-skilled residents (and anticipation of its continued growth) and (ii) the impact on local amenities (A_j).[13] The first channel can be seen in Equations (6), (7), and (11). While the price of tradable goods remains unaffected by demand shocks in the local economy, the prices of local services and rent may adjust in response to the demand shifts as remote workers arrive and the program expands. Therefore, more individuals are selected into working in relatively more lucrative sectors than before, and more capital is allocated to these sectors. On the other hand, if migration costs or commuting costs are high for local incumbents in these lagging regions, the local residents are likelier to adjust at the extensive margin or in their sector choices rather than in their residential or working location choices (at least, in the short run).

Next, to introduce the second channel, I formalize amenities (A_j) in a stylized way, capturing the variety of local service goods available.[14] Thus, in this case, I can write $A_j = \frac{\alpha_p^e}{\epsilon-1} M_j$, where ϵ is the elasticity of substitution across local service goods and M_j the total number of local service establishments provided in location j. For instance, a more diverse food landscape resulting from an influx of remote workers can benefit local residents by enhancing the local dining options, the benefits of which can be heterogeneous across skill types.[15]

Welfare Change.—Total social welfare in this economy is the sum of the total utility of workers and the utility of landlords, which can be written as follows:

$$W = \sum_e V^e + \sum_j \left[r_j H_j - \int_0^{H_j} \Gamma_j^{-1}(x) dx \right] \tag{12}$$

When the program is announced to relocate remote workers (R) and future cohorts ($\tilde{R}$) into a neighborhood m (and when the change is sufficiently small for the envelop theorem to hold), its

[13] Note that I assume remote workers' impacts on local productivity (B_k) is near zero, however, as they do not interact with local incumbents while working. Greenstone, Hornbeck and Moretti (2010) study agglomeration economies on the production side.

[14] This variety gain can be understood as the gains from increased choice or shorter distance to establishments (Couture, 2016).

[15] For example, Handbury (2021) finds that, in wealthier areas, firms have a larger variety of product offerings and shows high-income households value this extra access to product variety, offsetting much of the higher prices of individual products. In contrast, lower-income households care mostly about product price and less about access to more varieties. Additionally, Couture et al. (2024) show that as the rich grow richer, they demand more amenities, leading them to move downtown and leading downtown areas to increase their supply of amenities.

first-order welfare effect is (let $\hat{R} = R + \tilde{R}$):

$$\frac{d}{d\hat{R}_m}W = \sum_e \sum_j \sum_k \sum_s N^e_{jks}\Big[\frac{dw^e_{ks}}{d\hat{R}_m} - \alpha^e_p \cdot \frac{dp_j}{d\hat{R}_m} - \cancel{\alpha^e_r \cdot \frac{dr_j}{d\hat{R}_m}} + \frac{dA_j}{d\hat{R}_m}\Big]$$
$$+\cancel{\sum_j \frac{dr_j}{d\hat{R}_m}H_j} + \sum_j r_j \frac{dH_j}{d\hat{R}_m} - \frac{d\int_0^{H_j}\Gamma_j^{-1}(x)dx}{d\hat{R}_m} \tag{13}$$

For now, I assume the number of individuals who change their choices of j, k, and s is minimal. Note that the change in rent prices charged to local residents is transferred to landowners. If relocated remote workers do not push up rent prices ($\frac{dr_j}{d\hat{R}_m} \approx 0$), there will be no such transfer yet. Otherwise, Equation (13) shows that the change in welfare consists of components related to wages, local prices, amenities, housing quantities additionally rented out, and construction costs.

Figure 2 illustrates how the program's introduction affects the labor market, local service goods market, and housing market, considering both inframarginal and marginal workers. In panel (a), the introduction of remote workers causes distortions by pushing some workers to work into the local service sector, whose values of the marginal product of labor are not high enough relative to those in the tradable sector or out of the labor force yet. The same is true for the construction sector. In panel (a), this is described as the red triangle (regarding those who work in the non-tradable sector, despite their values of the marginal product of labor in these sectors not being high enough) and the blue triangle (regarding those no longer working in the tradable sector, despite having relatively high values of the marginal product of labor in these sectors). This distortion, however, does not result in a complete deadweight loss of the local economy, as the demand shift stems not only from subsidies given to remote workers (which might be a deadweight loss) but also from the incomes they bring into the neighborhood.

On the other hand, in panel (b), the entry of an increasing number of local service establishments can mitigate the deadweight loss (from a blue triangle to a red triangle) caused by the same demand shifts that distort the labor market. This, in turn, makes the local economy's welfare implications of the remote worker relocation program ambiguous. Local business incumbents held market power due to their distinctive goods, but the population increase pushes the market toward greater competition. Each firm faces a more elastic demand curve as consumers have more substitutes.

Last, panel (c) describes how vacant housing units can be filled by newly arrived remote workers without resulting in a significant rise in rent prices while the original housing supply curve, H,

becomes $\hat{H}$. Additionally, if landowners have high expectations for program growth ($\tilde{R}$), this can further boost housing supply, which, in turn, increases labor factor demand for construction workers preventively. In this case, a new housing supply curve ($\hat{H}'$), including that under new construction, will shift further upward.

2.1 Model Discussion

Relocated Remote Workers.—The model neither incorporates remote workers' location choices nor explicitly accounts for the impacts of the program on incoming remote workers. Instead, it takes the arrival of remote workers as exogenous and investigates the impacts of the program on local incumbents. The welfare effects on remote workers can be understood in two ways. First, incoming remote workers choose to relocate with the program. Therefore, by their revealed preference, relocated remote workers are unambiguously better off. Second, from the perspective of local policymakers, the welfare of incoming remote workers is not a factor of concern when the program is adopted.

Local Residents Left Behind.—My local economy model also does not prioritize the welfare effects on local residents in the cities the remote workers left. This focus is because local policymakers disregard such welfare effects on other locations.[16] Althoff et al. (2022) provide empirical evidence that local service workers left behind may suffer reduced local demand as high-skilled remote workers leave large cities. However, I note that the theoretical microfoundations of urban agglomeration economies (Duranton and Puga, 2004) imply that reallocations of remote workers from large to small cities can lead to nationwide welfare improvement. This is because the average utility with respect to an efficient city size follows a hump-shaped curve with two equilibria—small cities in the unstable equilibrium and large cities in the stable equilibrium—and relocation of remote workers from large to small cities can shift average utility up toward the peak for both types of cities.

Varieties of Local Service Goods.—The current way of modeling the varieties of goods incorporates the amenity channel in a stylized way and abstracts from amenity heterogeneity on two dimensions. The first dimension concerns different categories of local service goods, such as hair salons, restaurants, and bars.[17] The second dimension is vertical heterogeneity among local service goods,

[16] Also, these effects would be presumably even smaller.

[17] Almagro and Dominguez-Iino (2022) consider a rich set of categories of amenities, including touristic amenities, restaurants, cafe bars, food stores, nonfood stores, and nurseries, as well as local residents' demographic composition

ranging from high-end restaurants to fast-food restaurants. I make this modeling choice mainly because the sample size is not powerful enough to empirically detect heterogeneity in the effects of the program along such dimensions. The model does not differentiate these dimensions and takes them on average; but, it allows the consumption share of local service goods to differ by skill type. In this way, the model captures that the average benefits of a wider variety of goods are greater for high-skilled workers than for low-skilled workers.[18]

3 Data and Early Evidence from Tulsa Remote

3.1 Data

I use a unique dataset from Tulsa Remote with cumulative summary statistics on program participants' demographic, work, and geographic information. I complement these with ACS estimates, sourced from the National Historical Geographic Information System (NHGIS), to understand the local residents' side. Finally, I pull other datasets such as Longitudinal Employer–Household Dynamics (LEHD) Origin–Destination Employment Statistics (LODES), the Zillow observed rent index (ZORI), Federal Housing Finance Agency (FHFA) data, and United States Postal Service (USPS) vacancy data to examine labor market responses and housing market dynamics.

3.2 Descriptive Facts About Tulsa Remoters

Panel A in Table 1 presents the summary statistics of Tulsa Remoters, showing that they are mostly young and work in high-wage industry sectors. Next, Panels (a) and (b) in Figure 3 show that, compared to local incumbents in downtown Tulsa on average, Tulsa Remoters are likelier to be highly educated and high-income workers. This suggests that Tulsa Remoters potentially spend more than local downtown residents.[19] Panel (c) shows that Tulsa Remoters come mostly from bordering states or states with high living costs. The states adjacent to Oklahoma (Arkansas, Colorado, Kansas, Missouri, and Texas) show higher relative densities, likely because of lower moving costs or the convenience of returning to Oklahoma for individuals originally born in Oklahoma who

along a rich array of characteristics. This analysis leverages the dramatic growth in the spread of tourists across Amsterdam and rich amenities data.

[18] The influx of high-skilled remote workers, who align more closely with high-skilled local residents in their consumption patterns, enriches the variety of local service goods, catering more favorably to high-skilled local residents.

[19] I provide supplementary analysis in the online appendix using direct measures of consumption available from the Current Population Survey (CPS) Supplements.

moved to neighboring states.[20] States with high living costs (such as California, New York, and Texas) also demonstrate higher relative densities, implying that Tulsa Remoters benefit from lower living costs in addition to the incentive packages by moving to Tulsa.

3.3 Reduced-Form Analysis of Local Residents

Empirical Limitation.—An empirical challenge in assessing the impact of the program on local residents is the small number of incoming remote workers. To this end, I exploit the high concentration of relocated remote workers in the downtown area and focus on the impact of Tulsa Remoters on this area.[21,22] Although My empirical analysis is inherently not yet definitive, it makes an important contribution by shedding light on the program's initial effects on local residents and lays the groundwork for future research on this topic.

Empirical Strategy.—I use a simple event study framework to estimate the effects of incoming remote workers in downtown Tulsa *and* the rest of Tulsa *separately* relative to the outcomes of the other metropolitan statistical areas (MSAs) in Oklahoma (comparison group). In the event study specification, I divide the city of Tulsa into two regions—(i) downtown Tulsa and (ii) the rest of Tulsa—based on the relative density of remote workers to local residents. This ensures that the effect of incoming remote workers in the downtown area is not diluted by the rest of Tulsa, which is not yet fully covered by remote workers. The key identifying assumption is the parallel trends condition: namely, that in the absence of the adoption of Tulsa Remote, downtown Tulsa and the rest of Tulsa would have experienced changes in the outcome variable parallel to those of the remaining MSAs in Oklahoma.

To establish a set of control regions comparable to Tulsa, I restrict the sample to Oklahoma MSAs.[23] Panel B in Table 1 presents summary statistics for local residents in three regions: (i) downtown Tulsa, (ii) the rest of Tulsa, and (iii) other MSAs in Oklahoma. I note that there are more

[20] Among those born in Oklahoma, 60.3% reside in Oklahoma, and 12.0% reside in Texas, their second most popular location choice (source: ACS).

[21] Examining the effects on the entire city of Tulsa, which has not been fully covered by remote workers, could obscure the effects of Tulsa Remoters on downtown. Nonetheless, I note that the effects of the relocated remote workers presented in this section are highly localized.

[22] Figure A1a from the Tulsa Remote data shows that downtown Tulsa was the most popular destination for incoming remote workers by 2022. Anecdotally, in 2019, when the first cohort of Tulsa Remoters moved in, the program administrators encouraged them to move to downtown Tulsa for managerial purposes. As the program became more established, later cohorts began to spread across the city. Additionally, the two coworking spaces associated with the program are located downtown.

[23] The online appendix provides the map. For context, Oklahoma City is the most populous MSA in Oklahoma, followed by Tulsa and then Lawtown.

prime-age and Black people in downtown Tulsa than in other MSAs, but the levels of education and industry structures are comparable across the two groups. I also include year dummy variables to test for pretrends. If an outcome variable has systemic changes, these will show up in the preperiod estimates.

I set up the following event study design:

$$y_{c,t} = \alpha_c + \gamma_t \quad + \sum_{\substack{t=2015,\\ t\neq 2018}}^{2019} \beta_t^D \times \mathbf{1}(\text{Downtown})_c \times \mathbf{1}(\text{Year})_t + \sum_{\substack{t=2015,\\ t\neq 2018}}^{2019} \beta_t^R \times \mathbf{1}(\text{Rest})_c \times \mathbf{1}(\text{Year})_t + \epsilon_{c,t} \tag{14}$$

I include census tract fixed effects, α_c, and year fixed effects, γ_t. $\mathbf{1}(Downtown)_c$ is an indicator equal to 1 if the census tract c is in downtown Tulsa (otherwise, it is 0). Similarly, $\mathbf{1}(Rest)_c$ is an indicator equal to 1 if the census tract c is in the rest of Tulsa (otherwise, 0). I consider year-by-year pretrends by including an indicator for each year t, $\mathbf{1}(Year)_t$. Inferences for estimates are based on a census tract–clustered wild bootstrap to address the small number of treated units (Cameron, Gelbach and Miller, 2008).

Population and Income.—I conduct an event study analysis using the log of population in each census tract c and in year t (ACS 5-year estimate from $t-4$ to t) as an outcome variable.[24,25] This analysis estimates the causal effect of the program on population growth, considering potential inflows and outflows that may occur regardless of the program. I also run event study analyses on $\log(\text{income per capita})_{c,t}$, based on residential populations.[26] Figure 4 shows that downtown Tulsa experienced a 2.87% increase in population (baseline: 3,507) and a 6.44% increase in income per capita (baseline: $31,861) one year after the program while the rest of Tulsa showed no statistically significant change in either outcome. This demonstrates that the program implementation caused high-income remote workers to relocate to the downtown area in Tulsa.[27]

[24] I use the log of the population, instead of the population level, assuming linear population growth as the data pattern suggests.

[25] I also include the lag of the outcome variable, $\log(\text{pop})_{c,t-1}$, in the population analysis to control for momentum in population growth (time-varying, region-specific characteristics). A more detailed discussion appears in the online appendix.

[26] I also include the lag of the outcome variable, $\log(\text{income per capita})_{c,t-1}$.

[27] Note that this result also suggests no evidence of a displacement effect of remote workers on local residents, at least within one year. If local residents were pushed out of the downtown area by incoming remote workers, an increase in population growth in the rest of Tulsa should be observable, which is not the case.

Labor Market.—I examine the labor market activities of local residents using the LODES data, along with nonemployment data from the ACS. The main outcome variable is the log of the number of jobs in each industry sector s in each *work* census tract c and in year t.[28] Equation (14) is estimated separately for unemployment, the total number of jobs, and employment in each industry sector s. Panel A-(a) of Figure 5 demonstrates the primary causal effects of Tulsa Remote in downtown Tulsa: a slight, statistically significant reduction in nonemployment, a decline in employment in the wholesale trade and information sectors, and an increase in employment in the local services and construction sectors. However, other industry sectors experience no statistically significant changes in employment in response to the Tulsa Remote program. Moreover, Panel A-(b) of Figure 5 shows no statistically significant changes in labor market activities in the rest of Tulsa, consistent with the negligible population impact observed for this area.

Housing Market.—Panel B of Figure 5 presents the impact of Tulsa Remote's introduction on rent and housing price indices for the entire city of Tulsa, covering a longer time period.[29] Panel B-(a) shows a gradual increase in rent prices (a 0.73% rise in 2019, albeit not statistically significant), and Panel B-(b) shows negligible effects on housing prices in the city of Tulsa. In contrast, in Panels B-(c) and B-(d), downtown Tulsa experiences a decline in its vacancy rate in response to the program for the next five quarters (a 21.91% decline by 2019 on average), but the rest of Tulsa does not. Overall, this suggests that there were vacancies in the local housing market before the program and relocated remote workers started filling them without necessarily raising rent prices.[30]

3.4 Interpretation and Comparisons with Literature

Understanding Sectoral Labor Reallocation.—The findings—a reduction in nonemployment, employment increases in the local services and construction sectors, and employment declines in the wholesale trade and information sectors—point toward sectoral labor reallocation on an aggregate

[28] The outcome variable is based on the work area instead of the residence area, and thus, it does not count the jobs that remote workers come with.

[29] The ZORI and FHFA datasets do not provide geographic information at the census tract level, but they cover a longer time period.

[30] Busso, Gregory and Kline (2013) also find that population and housing rental rates remained stable in the context of empowerment zones, concluding that the subsidies generate a transfer to local workers without unintentionally providing a subsidy to absentee landlords.

scale. Coherently, the accounting exercise is calculated as follows:

$$\begin{aligned} \textit{Total Change} \quad 30 \quad &\approx \quad +1.4\% \times 2213 \quad && \textit{Nonemployment Decrease} \\ &\quad\quad -12.6\% \times 918 \quad && \textit{Wholesale Trade Decrease} \\ &\quad\quad -9.7\% \times 2291 \quad && \textit{Information Decrease} \\ &\quad\quad +7.95\% \times 3051 \quad && \textit{Local Services Increase} \\ &\quad\quad +14.3\% \times 660 \quad && \textit{Construction Increase} \end{aligned} \tag{15}$$

The total change (+30) is translated into a 0.1% change in the total number of jobs in downtown Tulsa (baseline: 30,879); this falls in the range of -0.01% and 2.5% (confidence interval reported in Panel A-(a) of Figure 5). Additionally, I examine transitions in labor market activity at the individual level using the representative sample from the CPS.[31] I confirm that such transitions occur with comparable frequency within one year. Further details are provided in the online appendix. In contrast, I find no empirical evidence of spatial labor reallocation, as there is no statistically significant effect on the number of commuters (in Appendix Figure A3) or the total number of jobs based on workplace location (in Panel A-(a) of Figure 5).

Contextualizing Treatment Effect Size.—The treatment effects reported are fairly large. To this end, I interpret my event study coefficients considering the dynamic nature of Tulsa Remote's rollout (Schmidheiny and Siegloch, 2019). For example, when local business owners decided to open their businesses, they took into account the future growth in arrivals of relocated remote workers. Therefore, I conduct the following exercise:

$$\begin{aligned} \Big(\underbrace{\$104,600}_{\text{Annual Mean Income}} + \underbrace{\$10,000}_{\text{Subsidy}} \Big) \times \underbrace{70}_{\text{Tulsa Remoters in 2019}} \times \Big(1 + \underbrace{g \times \beta}_{\text{in 2020}} + \underbrace{(g \times \beta)^2}_{\text{in 2021}} + \underbrace{(g \times \beta)^3}_{\text{in 2022}} + ... \Big) \\ \times \underbrace{0.07}_{\text{Consumption Share for Local Service Goods}} \times \underbrace{0.64}_{\text{Labor Cost Share}} \\ \approx \underbrace{3,051 \times 7.95\%}_{\text{Local Service Employment Increase}} \times \underbrace{w^S}_{\text{Annual Earning for Local Service Worker}} \end{aligned} \tag{16}$$

[31] I do not observe individuals repetitively at this granular geographic level, but the CPS has a panel structure.

where g is the annual growth rate of relocated remote workers and β is the discount rate ($\beta = 1$ means perfect foresight). Note that I take the number of Tulsa Remoters, 70, directly from the Tulsa Remote data.[32] I choose 0.07 as the consumption share of relocated remote workers for local service goods using the Consumer Expenditure Survey (CEX) Interview Survey (2019Q1).[33] The share of labor costs in total revenue for local service establishments is set to 0.64.[34] Finally, I derive Equation (16) by equalizing the labor cost share of total revenue in local service sectors collected by both the expected and realized relocated remote workers (labor costs paid by firms) to additional income given to newly hired local service workers (earned income).[35]

Next, I assume that local service business owners expect that the program will not experience further growth ($g = 100\%$) but will continue. I also impose $\beta = 0.96$.[36] With these values, I obtain the wage for local service sector workers after the program as $w^S = \$38,548$. Therefore, I calculate the labor supply elasticity of the local service sector as $7.95\%/21.06\% \approx 0.38$.[37] From the Tulsa Remote data, I note, however, that the number of Tulsa Remoters dramatically increased from 70 (in 2019) to 380 (in 2020) (in this case, $g = 543\%$). Additionally, the total number of applications to the Tulsa program in the last quarter of 2019 was 4,322, giving a very optimal view of the program expansion. Although this exercise does not provide an accurate labor supply elasticity estimate because of the uncertainty over the program growth rate (g) and possibly other factors, it shows how the Tulsa program's impact is translated into the local service sector.

I also calculate the wage change in the construction sector, taking into account the anticipated population increase in the town. This approach differs from that used in the local service sector, given the lag between the start of construction and project completion along with the seasonal

[32] Panel A-(a) of Figure 4 gives a population increase in downtown in 2019 of 101. Here, the gap between these two numbers comes from the fact that some household members (mainly spouses or partners) followed their breadwinners moving to Tulsa.

[33] On the lower end, the expenditure share for food away from home in the last quarter is 0.0541 (0.0444) for high-skilled (low-skilled) workers and, on the upper end, the expenditure share for entertainment, in addition to food away from home, is 0.1073 (0.0860) for high-skilled (low-skilled) workers.

[34] In the monopolistic competition setting, the share of labor costs in total revenue is calculated as $\frac{\epsilon-1}{\epsilon} \times \mu_S = 0.64$, where ϵ (the elasticity of substitution across local service goods) is 5.0 and μ_S (the labor share in local service sector production) is 0.8 (Valentinyi and Herrendorf, 2008). The elasticity of substitution across local service goods is set based on a range of values from 4.0 (Broda and Weinstein, 2006) to 4.8 (Oh and Seo, 2023), 8.8 (Couture, 2016), and 9.6 (Handbury and Weinstein, 2015) in different contexts. Oh and Seo (2023) estimate the elasticity of substitution across subsectors within a sector (food, retail, others); Couture (2016) estimates it between restaurants using detailed restaurant and travel data; Handbury and Weinstein (2015) estimates it for the bread product group.

[35] Note that Equation (16) does not take into account any agglomeration or general equilibrium effects that could come from local incumbents.

[36] This is based on $1/(1 + 0.04) \approx 0.9616$. The Small Business Administration 504 loan rate was approximately 4% on average in 2019.

[37] Mean annual earnings for Tulsans working in the local service industry sector was \$31,279 in 2018 (source: CPS). With the 1.8% inflation rate, this is converted to \$31,842. Thus, $(\$38,548 - \$31,842)/\$31842 \approx 21.06\%$.

cyclicity of construction work. In turn, I note that employment in the construction sector may not only rise preemptively but also exhibit volatility. Going back to Equation (10), the wage change in construction sector follows

$$\partial \log w_{kC} \approx \partial \log\Big(\frac{d\hat{H}_j}{dL_{kC}}\Big) + \partial \log r_j \tag{17}$$

Taken together, these results imply that the local services and construction sectors expanded not only because of the program implementation but also because of the high expectation that the program would continuously draw high-income remote workers. This is manifested in the continuously growing number of Tulsa Remoters presented in Panel B of Appendix Figure A1 despite the unanticipated COVID-19 shock.

Comparison with Previous Findings.—I compare the treatment effects of the program to relevant estimates from previous literature. The results from previous papers have different contexts and different time frames and thus are hard to compare directly. However, they confirm that the finding in this paper lies in the range of prior papers. In terms of labor supply elasticity, Table 7 of Curuk and Vannoorenberghe (2017) provides the national elasticity of labor to output price by two-digit NAICS industry sector. Converting their number, the elasticity of labor supply of 0.90 for NAICS code 72 (accommodation and food services) for 2005–2008, to be in response to the wage change, not the output price change, I multiply the labor share of 0.8[38] with their elasticity, and it gives 0.72, which I found comparable given the longer timeline in their setting than in mine.

Furthermore, I compare the effects of the Tulsa Remote program to the effects in the large literature on place-based policies in different contexts.[39] In general, the previously studied place-based policies are more extensive but also costlier than the Tulsa Remote Program. As a reference, the amount of subsidies provided by state and local governments in Oklahoma in a typical year is $2,190 million (Story, Fehr and Watkins, 2012),[40] and the cost of Tulsa Remote program is only

[38] This is based on Valentinyi and Herrendorf (2008).

[39] To name a few: the Tennessee Valley Authority, studied by Kline and Moretti (2014*a*), empowerment zones studied by Busso, Gregory and Kline (2013), Norwegian place-based payroll taxes studied by Ku, Schönberg and Schreiner (2020), and opportunity zones studied by Arefeva et al. (2021) and Freedman, Khanna and Neumark (2021).

[40] Some examples of such subsidies in other states include the $4 million in tax relief provided by the city of Newark to Panasonic in 2011 to move its headquarters to Newark, the $307 million in subsidies from the state of Kentucky to Ford in 2007 and 2008 in exchange for its keeping two plants in Louisville and expanding them, and the $232 million in subsidies from the state of Texas to Samsung in 2011 to locate its latest wafer fabrication facility in Austin.

approximately 0.1% of this.[41] In addition, the coverage area of the Tulsa Remote program, in contrast to other programs, is very localized, especially after only one year of the program. Busso, Gregory and Kline (2013) offer a takeaway relevant to this paper, as the empowerment zone–designated areas saw an increase in total employment (by 12 to 21%) and a rise in weekly wages inside the zone (by 8 to 13%) with no significant migration inflows to zone neighborhoods. They conclude that zone neighborhoods were not attractive enough for workers to change their residential locations despite the labor market improvements. Similarly, Ku, Schönberg and Schreiner (2020) find no worker relocation in response to the payroll tax cut in Norway but do find an employment decline that comes mainly from the extensive margin instead. In my context, I also observe no increase in arrivals of migrants other than remote workers, and the increase in local services and construction employment is sourced mainly from workers substituting away from tradable sectors and out of labor force.

Beyond the place-based policy literature, the context of this paper, a program seeking to attract remote workers, shares some traits with the context of studies on tourist shocks (Faber and Gaubert, 2019; Allen et al., 2020; Almagro and Dominguez-Iino, 2022), retiree inflows (Maroto et al., 2024), refugee inflows (Dustmann et al., 2017), and relocation of public-sector workers (Faggio and Overman, 2014; Faggio, 2019; Becker, Heblich and Sturm, 2021). These papers study the effects of each incidence, sometimes with different focuses (general equilibrium effects or heterogeneous preferences for amenities, for example). Nonetheless, they take the inflow of certain groups as demand shifters. I conceptually discuss the distinct features of a policy targeting remote workers in Section 5.

4 Welfare Analysis

In this section, I estimate the welfare effects on local residents in Tulsa with the model predictions presented in Section 2 and the reduced-form results in Section 3. In summary, there are three notable findings in Section 3. First, the event study estimates on population, commuters, and employment across sectors suggest that while local residents did not respond to the program by changing their residential or working locations after one year, they responded in their employment-related choices. Second, rent price and housing values did not statistically significantly increase

[41] The total cost of the Tulsa Remote program is calculated as $1/(1-1\times0.96)\times70\times(\$10,000(\text{stipend})+\$1{,}000$ (initial visit) + \$1,000 (coworking space membership) + \$1,000 (events and programming)). Dividing the total cost by \$2,190 million yields approximately 0.1%.

after one year of the program, while the vacancy rate went down. Last, the expectation of program growth on the part of local services business owners and landowners contributes to the fairly large estimates of the employment increases in these sectors, which is also related to wage increases in corresponding sectors. This means that business owners in local services sectors open new stores or expand in response to the demand shifts, anticipating continued relocation of future cohorts of remote workers. Additionally, landowners begin investing in new housing construction by hiring more workers with the expectation of the program growth.

With this, Panel I in Table 2 aggregates all effects across sector types to present the overall welfare effect by skill type (e), residential location (j), and working location (k) and Panel II reports the percentage change of each component, corresponding to each term in Equation (13). The impacts on wages presented in the first three rows of Panel II are derived based on the analysis in Section 3. Next, the impact on the local service goods price is computed as $\mu_S \times \Delta\%p_S$ (where μ_S of 0.8 is the labor share local service sector production) by using the model property that local service firms set their prices as a mark-up of their marginal costs and the capital price does not change.[42] Furthermore, the change in service goods amenities is reflected in the part of the price index change in local service goods. It is calculated as 8.85% based on the percentage change in total expenditure of local service goods because such increase incentivized local service firms to enter and produce differentiated goods. Finally, the changes in rent prices and housing values are negligible with the vacancy rate declined.

Going back to Panel I, if remote workers relocate to local residents' workplaces, their wages are affected, with impacts varying by sector. Conversely, if remote workers relocate to local residents' residential places, local prices and amenities are affected, with impacts varying by skill type. Otherwise, I treat the effects on wages, local prices, and amenities not relevant.[43] The summarized results are reported in columns (1)–(3). Moreover, with the convertible units (in consumption basket) in hand, I sum the effects on w, p, and A across columns (1)–(3) and report the total effects in column (4). As a result, those working downtown but living outside experience the greatest welfare improvement. This is because they benefit from wage increases without being affected by local price hikes. In contrast, those who both work and live downtown experience welfare loss (for high-skilled) or modest welfare gain (for low-skilled). I note that despite wage increases in local service and construction sectors, rising local prices negatively impact workers across all sectors,

[42] In other words, $p_k^S = \frac{\epsilon}{\epsilon-1} \cdot MC_k = \frac{\epsilon}{\epsilon-1} \cdot B_k \left(\frac{w_{kS}^l}{\mu_S}\right)^{\mu_S} \left(\frac{\rho}{1-\mu_S}\right)^{1-\mu_S}$

[43] Note that I do not account for consumption-related travel due to data limitation.

dampening the positive effects of relocated remote workers. Furthermore, these local residents would have been more negatively affected without the amenities benefit alone. Lastly, given the program's small size, most of the local residents who work and live outside are unaffected by the program.

I turn to assess the program's benefits and costs. The total benefit is estimated by summing the products of mean income and total effects, amounting to approximately $13.83 million. Because a billionaire's donation funded the program, the program is beneficial to local residents without considering its costs. In contrast, the program's total cost is calculated as $22.75 million, as noted in footnote 46. If local residents were to fund the program through taxation, it would not generate a net positive welfare gain on average, even without accounting for potential labor supply distortions. Nevertheless, if the program's future growth is not considered, the one-time cost is minimized to $0.91 million. However, in this scenario, local businesses and landowners may be less inclined to invest, which mitigates the wage effects. Moreover, the total cost could be further reduced if the local government finances expenditures by issuing bonds, for example.

5 Policy Discussion

In this section, I conceptually discuss the unique characteristics and consideration sets of remote worker relocation programs. Compared to tax credits or subsidies aimed at attracting firms, such programs have advantages in terms of feasibility and cost-effectiveness with their gradual-implementation designs. For example, when Amazon announced its plan for a second headquarters in September 2017, requesting tax breaks and other incentives from local governments, over 200 cities across Canada, Mexico, and the United States showed strong interest, proposing various incentives. The competition was fierce: After one year, a shortlist of 20 finalists was announced, and after another year, Amazon selected Arlington, Virginia, which provided $550 million for the first 25,000 jobs Amazon created. This example shows how competitive the race to attract relocating firms can be (as described, for instance, in Greenstone and Moretti, 2003), and even when such efforts succeed, they can be very costly ($22,000 per job in Virginia's case). Furthermore, when the aim is to attract a single big firm, consisting of a chunk of workers, the outcome can be all-or-nothing. In contrast, attracting individual remote workers, who can be viewed as *walking one-person establishments*, is relatively achievable and cheap ($10,000 per person in Tulsa's case). Specifically, individual economic agents attracted one at a time can be matched without excessively

large frictions, as not only are they not bundled together but they also have heterogeneous location preferences shaped by factors such as birthplace (Howard and Shao, 2023) or family composition (Venator, 2022; Anstreicher and Venator, 2024).

Moreover, the incremental design of remote worker relocation programs (in Tulsa's case, a total of six cohorts have been relocated over the last six years) allows local communities to roll out their programs over time in a flexible manner.[44] This can be cost-effective, as local communities can adjust the number of remote workers they find optimal to receive with reference to their economic circumstances. For instance, if the initial cohorts of relocated remote workers fuel city amenities, future cohorts of remote workers may find the city more appealing and be drawn more easily.[45]

Despite these positive aspects of remote worker relocation programs relative to incentive to attract firms, some might ask why the local governments do not give subsidies to local residents instead of new migrants. The benefit of bringing remote workers lies on the fact that their income is earned outside the local economy yet spent within it. According to the metrics provided by Tulsa Remote, a subsidy of $10,000 per person can extract an additional $104,600 on average per person, which can help boost the local service sector in the city. From local governments' perspective, tax revenue (from, e.g., property, sales, and income taxes) is another reason to have new people in town. When local governments introduce such programs, state governments sometimes support or, at least, approve the initiatives with the expectation of collecting state income tax from the relocated remote workers.

Nevertheless, it might be too early to conclude that remote worker relocation programs can serve as a solution for economically disadvantaged areas. Although other localities that launched their own programs following Tulsa tend to view Tulsa's case as successful, many challenges remain. Notably, the funding of the Tulsa Remote program is heavily reliant on a nonprofit organization, the George Kaiser Family Foundation.[46] The donor has generously supported the growth of the Tulsa Remote program with an almost unlimited budget, but many other localities lack such large funding pools and sometimes rely on local taxes or fundraising by local organizations to run their programs. In Tulsa's case, the extensive donor support enabled a big push, accompanied by high expectations from local business owners and land developers.[47] Without such a major boost, it may

[44] In the case of Amazon second headquarters, there was also more than one round, but remote worker relocation programs allow localities to admit remote workers in a more granular way.
[45] I note, however, that the initial cohorts of remote workers also can raise the living costs of the city.
[46] Ascend West Virginia has been also funded by a West Virginia donor, Brad D. Smith, a founder of TurboTax.
[47] In the case of the Tennessee Valley Authority, the big push came from the size of the infrastructure project, which gave rise to agglomeration effects (Kline and Moretti, 2014*a*).

be hard to create significant agglomeration economies beyond the turning point, even if the program succeeds in attracting a small number of remote workers to the area. In fact, some localities had to pause their programs because of financial hardship.[48] In addition, retaining relocated remote workers even after their committed residence period is key to maintaining the momentum of the program's success.[49]

Other considerations include the future of remote work, competition among localities to attract remote workers, and the effects of remote workers' departure on their place of origin. The question of whether remote work will continue at all (though not the focus of this paper) has proved controversial. However, the percentage of workers primarily working from home was on an increasing trend for a few decades before COVID-19 and was not negligible (at approximately 4% in 2019 based on the ACS). It is also true that more localities have set up this kind of place-based policy since COVID-19 (e.g., in Indiana). This paper addresses the first-order unanswered question: What are the impacts of incoming remote workers through the program when competition among localities is absent (as in earlier years)?[50] Finally, because relocated remote workers come from various locations, the effects on their place of origin would be negligible, in contrast to the more pronounced effects at their destinations. Moreover, if they come from areas where congestion forces are dominant, relocating location-flexible workers to areas where agglomeration forces have not yet been fully exerted could lead to welfare-enhancing results for both the sending and receiving locations *on average* while reducing inequality across locations (Duranton and Puga, 2004; Fajgelbaum and Gaubert, 2020).

6 Concluding Remarks

Over the last few decades, distressed areas in the United States and many other countries have struggled to generate economic growth because of factors including population loss, lack of investment, and geographic disadvantages. In an effort to revive these shrinking zones, policymakers have explored place-based policies. This paper contributes to previous works in this vein by investigating the welfare effects of one such policy, remote worker relocation programs. Importantly, this paper first offers direct, early empirical evidence on how the incoming remote workers affect local residents

[48] For instance, the Remote Shoals program in Alabama was temporarily paused after approximately 87 remote workers were recruited in 2019 but will resume in March 2025.

[49] In Tulsa's case, 76% of the relocated remote workers who responded to the survey reported staying in the city (source: Tulsa Remote).

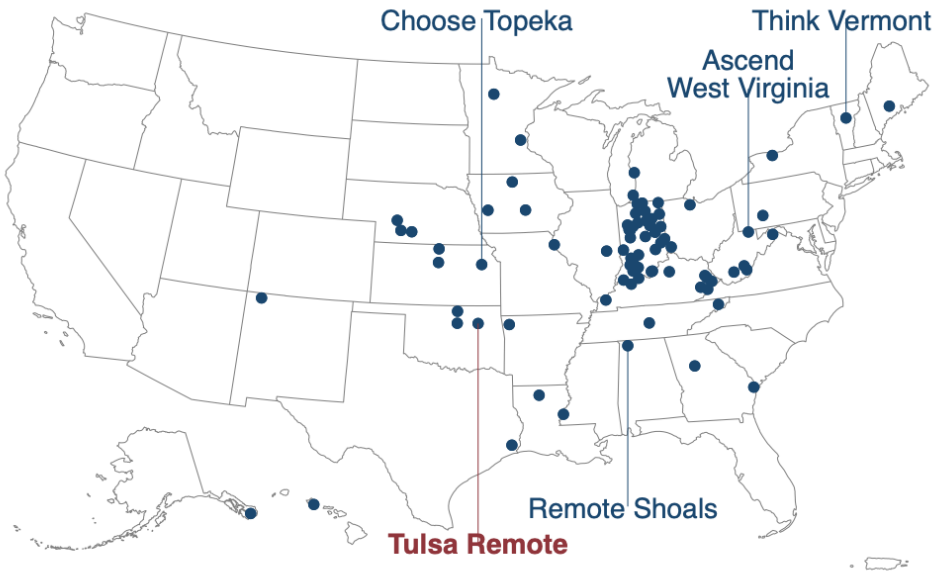
[50] Slattery (2019), Mast (2020), and Kim (2023) study competition behaviors across local governments.

in the context of Tulsa Remote. The paper also provides a modeling framework that allows me to quantify the welfare effects across heterogeneous local residents. I find that incoming remote workers have the potential to benefit local residents in destination cities. Nonetheless, it is also important to note that this result relies on vacant units being available in the areas of relocation and on high expectations of program growth among local business owners and land developers.

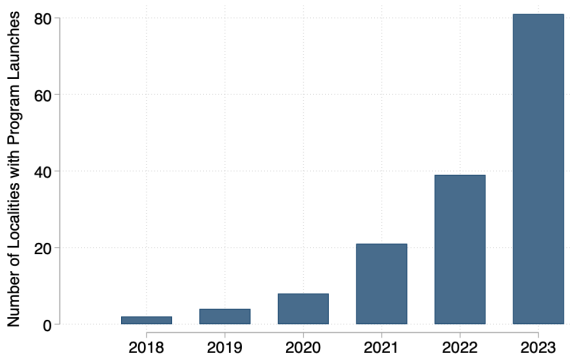
This paper cautions that policymakers seeking to attract remote workers to certain targeted areas should reflect on multiple factors: equilibrium effects, distributional effects, local economic conditions, and the public finance perspective. For example, relocated remote workers cause behavioral responses in local residents' labor supply at both the extensive and the intensive margins of sector choice. Additionally, the program increases the welfare gap between high- and low-skilled workers. Furthermore, local economic conditions, such as local industry composition and housing supply conditions, play a key role in welfare calculations. Thus, introductions of such programs in other cities should be reevaluated with their own metrics. Last, if local residents ultimately fund remote workers' relocation through taxes, this reduces the benefits they receive because of the tax burden. I anticipate that further research can provide valuable insights to shape more effective policy tools for a broader population and a wider range of regions related to the remote worker relocation programs.

Figure 1: Remote Worker Relocation Programs (as of October 2023)

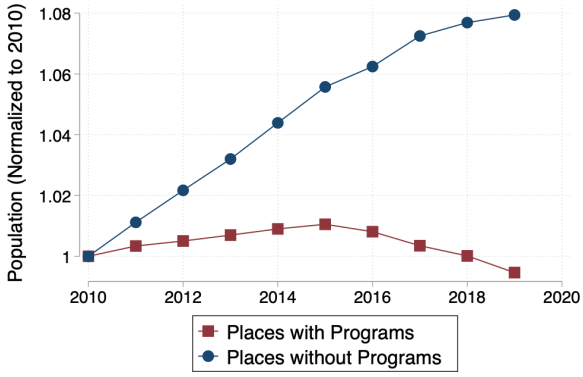
(a) Locations of Remote Worker Relocation Programs



(b) Number of Programs



(c) Population Divergence over Time

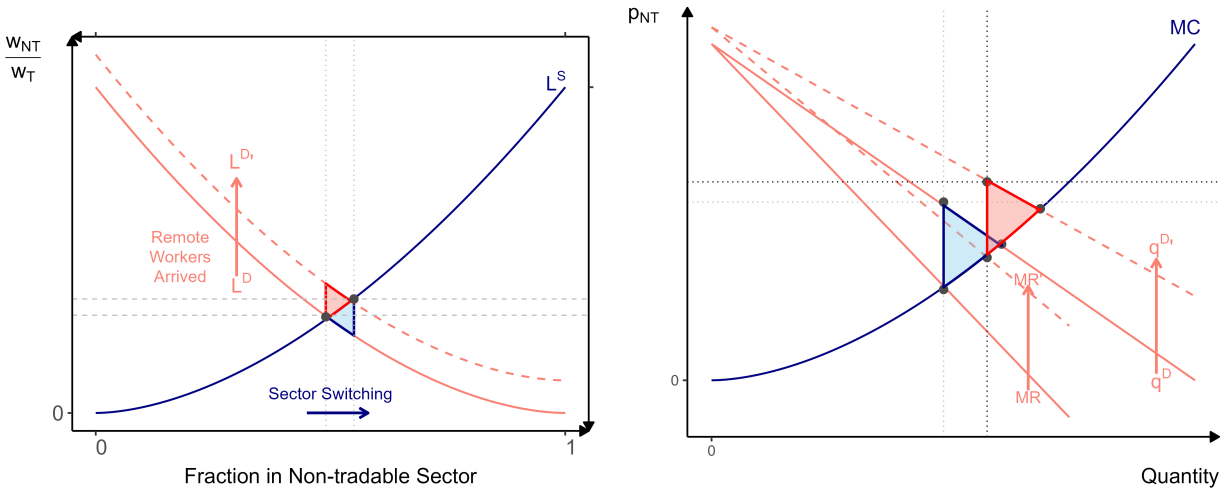


Notes: Panel (a) shows the geographic locations of localities (cities, counties, and sometimes states) that have implemented remote worker relocation programs. For details, see MakeMyMove. Panel (b) demonstrates the increasing number of such programs over the past five years. Panel (c) indicates that places with programs (in squares) experienced relative population loss, while those without programs (in circles) saw steady population growth. The sample used in panel (c) includes only the localities available in the NHGIS.

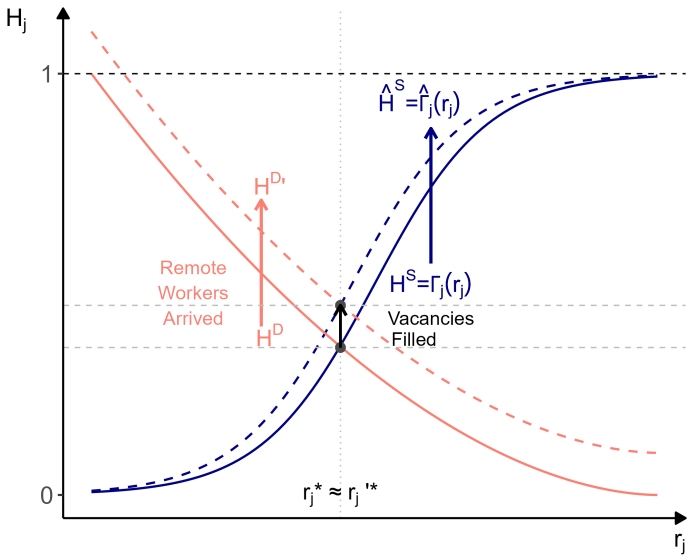
Figure 2: Illustrative Model of a Remote Worker Relocation Program

(a) Labor Market

(b) Local Service Goods Market: Each Brand



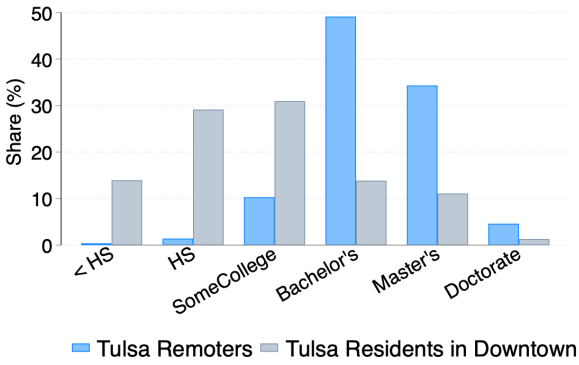
(c) Housing Market



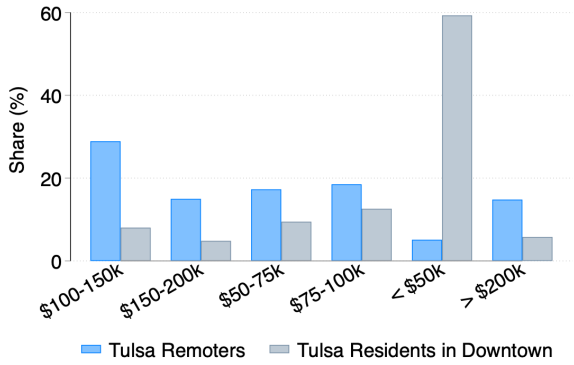
Notes: This Figure conceptually presents the impact of the program on welfare in the labor market (in panel (a)), the local service goods market for a single brand (in panel (b)), and the housing market (in panel (c)). Panel (a) describes the relative labor supply (L^S) and the labor demand in the non-tradable sector (L^D), where the relocation of remote workers shifts the labor demand curve upward. Panel (b) illustrates the deadweight loss in a monopolistic competition setting, both before and after the program (blue and red triangles). Local service establishments produce goods until the marginal cost (MC) equals the marginal revenue (MR), charging a price higher than in a competitive market. Relocated remote workers shift the demand curve upward and flatten it ($q^D \to q^{D\prime}$) . As more establishments enter, the market moves toward greater competition. Panel (c) graphically illustrates the case where the rent price does not increase significantly, as vacancies are filled, despite relocated remote workers shifting the housing demand curve upward ($H^D \to H^{D\prime}$). As vacancies are filled, the housing supply curve, which includes only the rented units, shifts upward ($H^S \to H^{S\prime} \approx \hat{H}^S$). Note that shift of each curve is not precisely quantified, but illustrates comparative statics.

Figure 3: Descriptive Characteristics of Tulsa Remoters

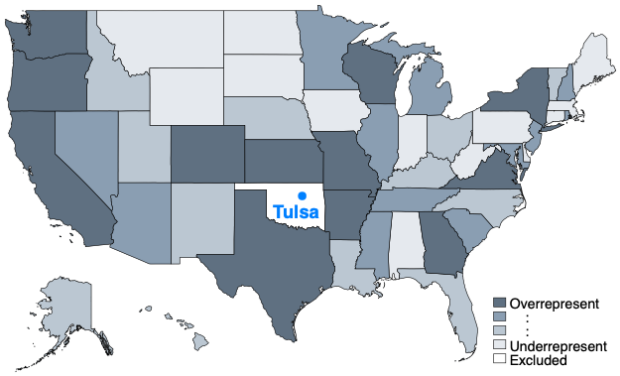
(a) Education Distribution



(b) Income Distribution



(c) Relative Density of Tulsa Remoters' Origin State to Remote Worker Population



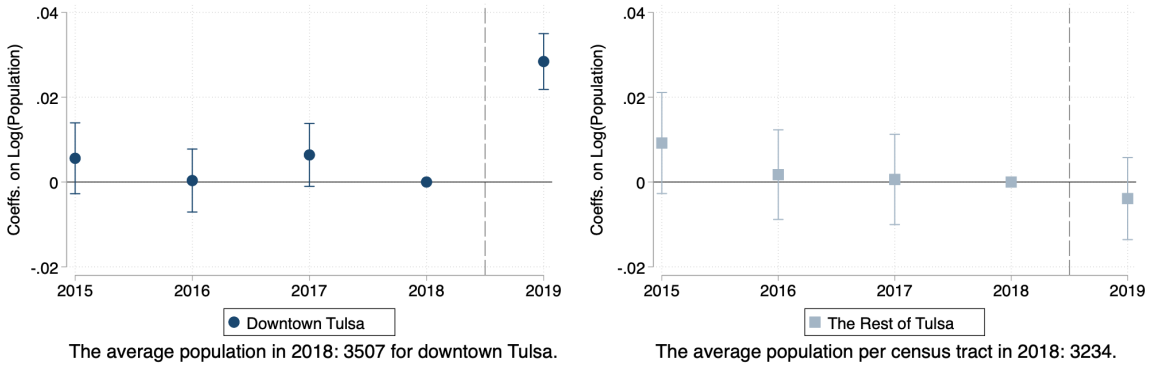
Notes: Panels (a) and (b) show the education and income distribution of Tulsa Remoters and local incumbents in downtown Tulsa. The distribution of Tulsa Remoters is from the Tulsa Remote data, and the distribution of local incumbents in Tulsa is from the ACS. Panel (c) presents a measure of the representativeness of Tulsa Remoters' origins by comparing two sets of metrics: the percentage of Tulsa Remoters from each state (source: Tulsa Remote data) and the percentage of remote workers from each state (source: ACS). Therefore, states marked as "overrepresent" (or "underrepresent") indicate that they have a higher (or lower) share of remote workers relocated to Tulsa. The number of observations in the Tulsa Remote data is 1,139 (as of July 2022).

Figure 4: Downtown Tulsa as Tulsa Remoters' Destination in 2019

A. Population

(a) Downtown Tulsa

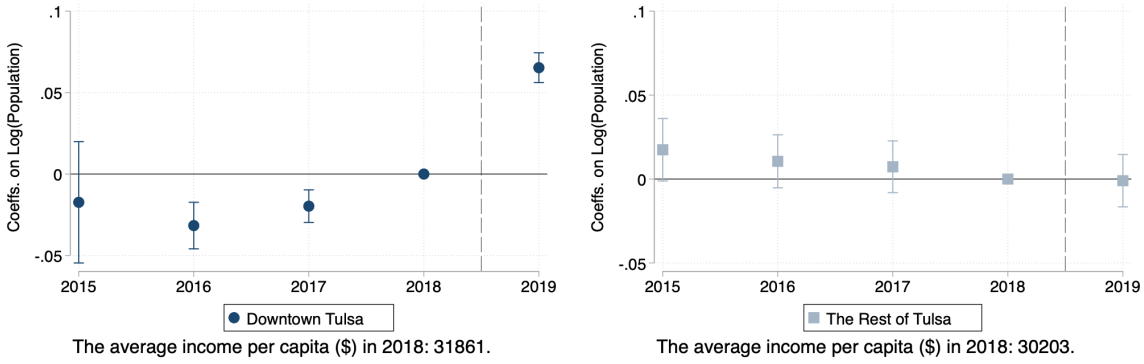
(b) Rest of Tulsa



B. Income Per Capita

(a) Downtown Tulsa

(b) Rest of Tulsa



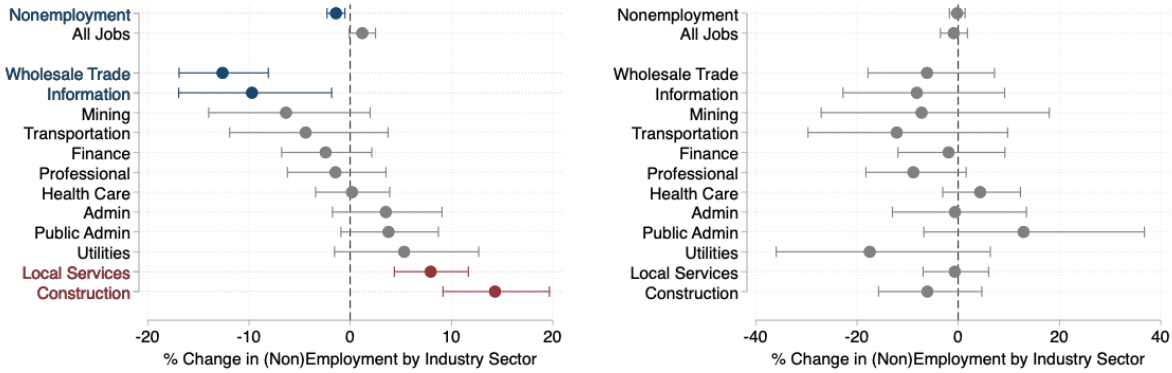
Notes: Panels A-(a) and A-(b) plot the coefficients $\hat{\beta}_t^D$ and $\hat{\beta}_t^R$, respectively, from Equation (14) with lagged outcomes. The 95% confidence intervals are based on a census tract–clustered wild bootstrap with 9,999 replications and a six-point weight distribution (Webb, 2013). Panels B-(a) and B-(b) plot the corresponding coefficients for income per capita as the outcome variable. The data source is ACS 5-year estimates, covering the periods 2011–2015 to 2015–2019.

Figure 5: Labor and Housing Market Effects of Tulsa Remote Program Introduction

A. Labor Market: Sectoral Labor Reallocation (in 2019)

(a) Downtown Tulsa

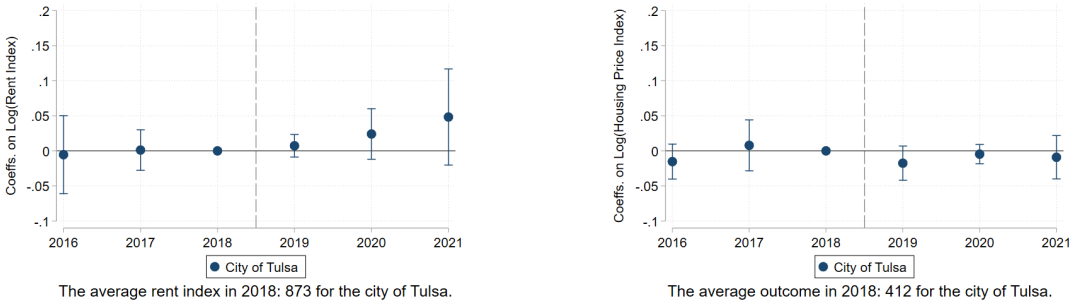
(b) Rest of Tulsa



B. Residential Housing Market: Rent Price, Housing Price, and Vacancy Rate

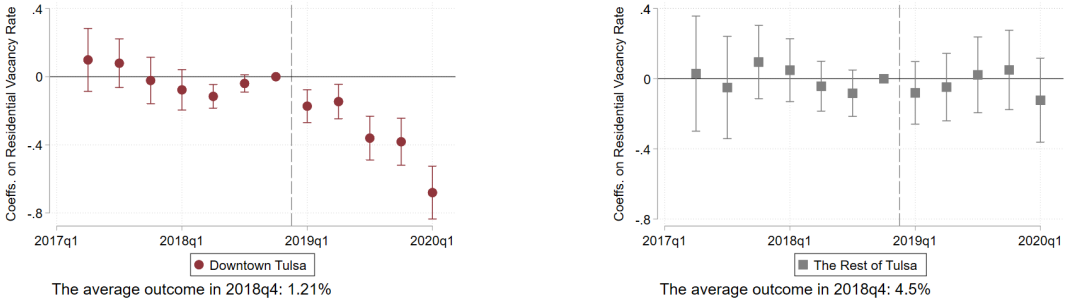
(a) Rent Price Index

(b) Housing Price Index



(c) Vacancy Rate in Downtown Tulsa

(d) Vacancy Rate in Rest of Tulsa



Notes: Panel A presents the estimates $\hat{\beta}^{D}_{2019}$ (in panel A-(a)) and the estimates $\hat{\beta}^{R}_{2019}$ (in panel A-(b)) from Equation (14) for nonemployment and the number of jobs by industry sector in percentage change terms. Industry sectors are classified by two-digit NAICS code, including only those with employment shares exceeding 2%. The 95% confidence intervals are based on a census tract–clustered wild bootstrap with 9,999 replications and a six-point weight distribution (Webb, 2013). The data source is LODES Workplace Area Characteristics (WAC) (U.S. Census Bureau, 2019). Panels B-(a) and B-(b) present year-by-year estimates of the rent price index (source: ZORI) and the housing price index (source: FHFA), interacting with the city of Tulsa (because of data availability). The 95% confidence intervals are based on a ZIP code–clustered wild bootstrap. Panels B-(c) and B-(d) present quarter-by-quarter estimates for downtown Tulsa (in panel B-(c)) and for the rest of Tulsa (in panel B-(d)) for the residential vacancy rate (source: USPS). The 95% confidence intervals are based on a census tract–clustered wild bootstrap.

Table 1: Baseline Summary Statistics of Tulsa Remoters and Local Residents

A. Summary Statistics of Tulsa Remoters

Demographics	
Age	38
Male	0.517
% White, non-Hispanic	0.834
% Black, non-Hispanic	0.054
% Hispanic	0.028
Working Information	
% Professional, scientific, and technical services	0.311
% Information	0.144
% Education services	0.118
Annual Income ($2019)	104,600

B. Summary Statistics of Local Residents by Exposure to Tulsa Remoters

	Downtown	Rest of Tulsa	Other MSAs in OK
Race/Ethnicity			
% White, non-Hispanic	0.65	0.64	0.74
% Black, non-Hispanic	0.19	0.15	0.08
% Hispanic	0.10	0.16	0.10
Age			
% Ages $\leq$24	0.19	0.35	0.35
% Ages 25-44	0.48	0.27	0.27
% Ages 45-64	0.27	0.24	0.25
% Ages $\geq$65	0.06	0.13	0.13
Education			
% Some College	0.42	0.40	0.39
Industry			
% Sevices	0.17	0.24	0.21
Population	3440	377446	2159128

Notes: ACS = American Community Survey and MSA = Metropolitan Statistical Area. Panel A shows the across-tract means for various population characteristics weighted by each tract's census population. Panel B displays the average number of jobs at the census tract level in each geographic region over the pre-intervention years from 2015 to 2018. Local Service: NAICS 72 and 81; Construction: NAICS 23; Wholesale Trade: NAICS 42; and Manufacturing: NAICS 31–33.

Table 2: Welfare Analysis by 2019

I. Total Impact of the Program	Total Headcounts (in 2019)	Mean Income (2018 data but in \$2019)	(1) Effects on w	(2) Effects on p	(3) Effects on A	(4) Total Effects
A. High-Skilled Local Residents						
Working and living downtown	1,710	32,716	0.83	–1.18	0.15	-0.19
Working downtown but living outside	16,229	32,716	1.60	–	–	1.60
Working and living outside	126,009	31,061	–	–	–	0
B. Low-Skilled Local Residents						
Working and living downtown	1,658	32,181	0.83	–0.84	0.11	0.10
Working downtown but living outside	10,460	32,181	1.60	–	–	1.60
Working and living outside	198,500	30,553	–	–	–	0
C. Landlords	25,174	470,630	–	–	–	0
II. Average Impact of the Program in Downtown	**OLS/Implied Impact**	**Computed Method**				
Wage in construction sector	8.52%	Back-of-the-envelope				
Wage in local services sector	21.06%	Back-of-the-envelope				
Wage in tradable sector	0%	Model assumption				
Local service goods price	–16.85%	Back-of-the-envelope				
Local service goods amenities	8.85%	Back-of-the-envelope				
log(rent)	Not significant	Event Study				
log (housing value)	Not significant	Event Study				
Vacancy rate	–21.91%	Event Study				

Notes: Panel I presents the effects on wages (w), local prices (p), and local service goods amenities (A) by skill type (e), residential location (j), and working location (k). Panel II presents the percentage change of each component, corresponding to each term in Equation (13) based on event study analysis and back-of-the-envelope calculations. In Panel I, total headcounts are reported using population data by residential location from NHGIS and commuting linkage information from LODES OD. The share of landlords in Tulsa is assumed to be 7.1% (source: Internal Revenue Service). The values of mean income are reported using the per capita income from NHGIS (2018) but converted into \$2019 by multiplying the inflation rate of 1.8%. The relative income share of high-skilled to low-skilled local residents from the CPS (2018) is used. In column (1), the effects on w are computed by considering the heterogeneous effects across working sectors with the corresponding employment weights. The values in column (2) are derived by multiplying the consumption share of local service goods (0.7 for high-skilled and 0.5 for low-skilled, as explained in the footnote 32) with the effects on local service goods prices. The effects on amenities in column (3) are also reweighted by using the consumption share by skill type and $\frac{1}{\epsilon-1}$. The total effects in column (4) are the sum across columns (1)–(3). The total effect for landlords is set to zero, as the additional rental revenue approximately offsets the total labor cost.

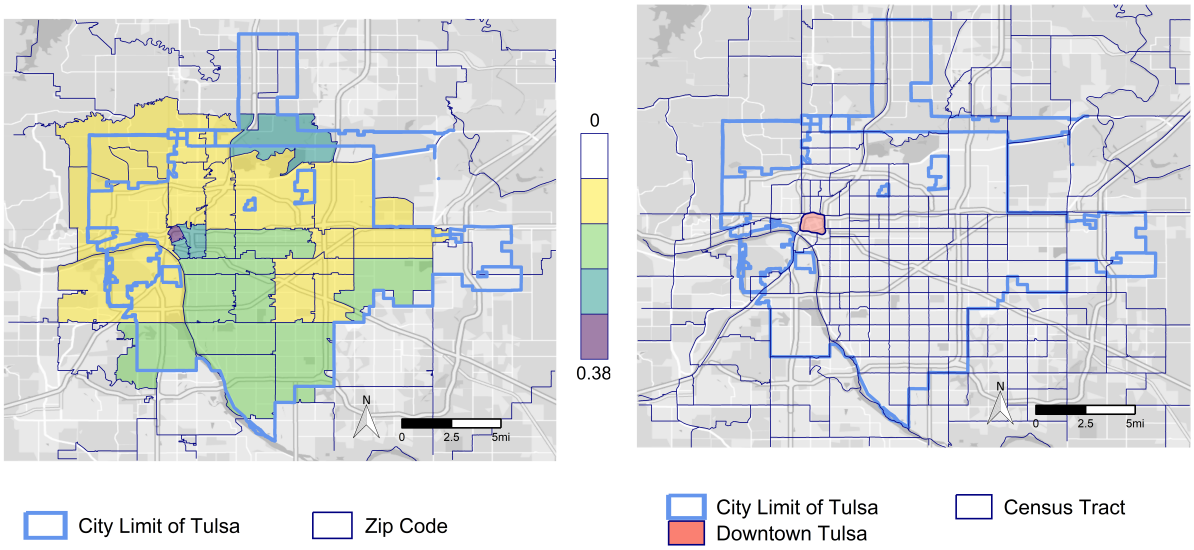
A Appendix Figures

Figure A1: Details About Tulsa Remote Program

A. Relative Density of Tulsa Remoters and Central Business District in Tulsa

(a) Tulsa by Zip Code

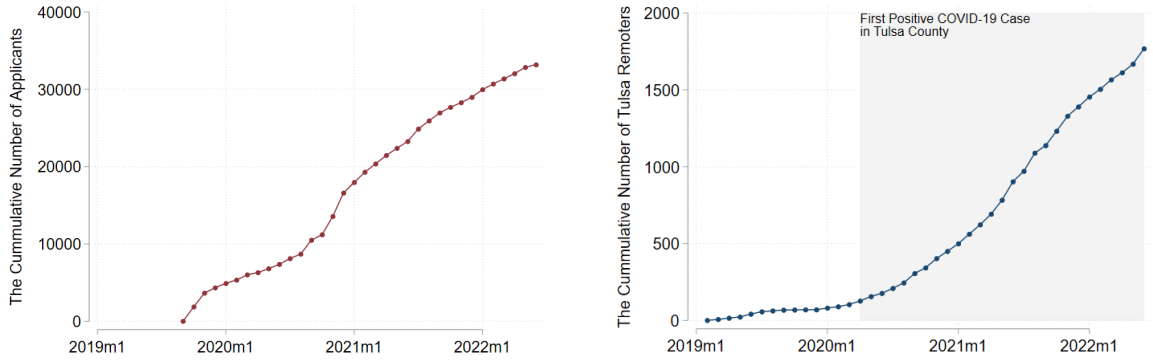
(b) Tulsa by Census Tract



B. Number of Tulsa Remote Applicants and Tulsa Remoters

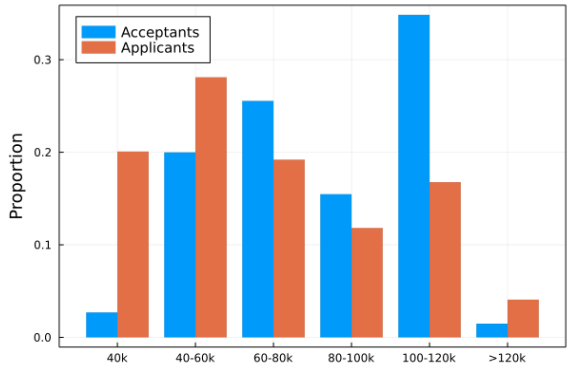
(a) Cumulative Number of Applicants

(b) Cumulative Number of Tulsa Remoters

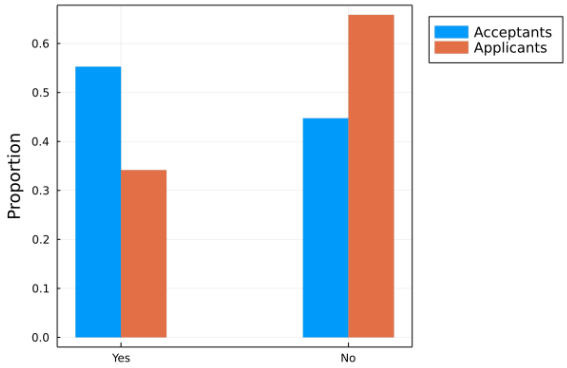


C. Program Selection: Income and Local Attachment

(a) Income Distribution



(b) Friends/Family in Tulsa?



Notes: Panel A-(a) presents the relative density of Tulsa Remoters to local residents (out of 1) by zip code (as of July 2022). Panel A-(b) shows the geographic division of Tulsa by census tract, the geographic unit of the outcome variable. The highlighted area in panel A-(b) corresponds exactly to downtown Tulsa. Panel B-(a) shows the cumulative number of program applicants, and Panel B-(b) shows the cumulative number of Tulsa Remoters. The number of applicants before September 2019 is not available. Panel C-(a) shows the income distribution of applicants accepted into the Tulsa Remote program and that of applicants overall. Panel C-(b) shows the proportion of accepted applicants and all applicants who answered "yes/no" to the question "Do you have friends/family in Tulsa?" (source: Tulsa Remote).

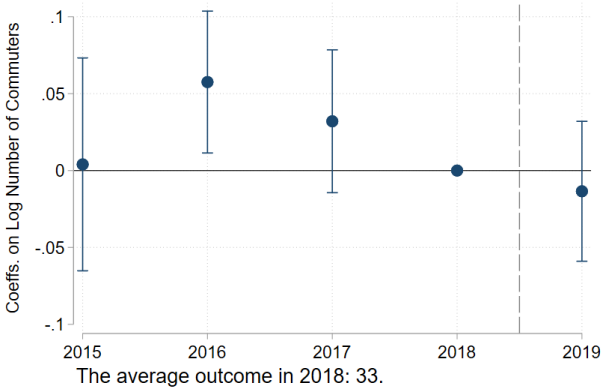
B Absence of Empirical Evidence on Spatial Reallocation

To test for spatial reallocation in response to the influx of remote workers, I run the following regression using LODES data:

$$log(commuters)_{o,d,t} = \omega_o + \delta_d + \gamma_t + \sum_{\substack{t=2015,\\ t\neq 2018}}^{2019} \beta_t^D \times \mathbf{1}(\text{Downtown})_d \times \mathbf{1}(\text{Year})_t + \epsilon_{o,d,t} \tag{18}$$

where ω_o is the origin (census tract) fixed effect, δ_d is the destination (census tract) fixed effect, and γ_t is the year fixed effect. The outcome variable is the log of the number of commuters in residence place o and workplace d in year t. The inference is based on census tract–clustered robust standard errors.

Figure A3: Absence of Empirical Evidence on Spatial Reallocation



Notes: The figure reports the $\hat{\beta}_t^D$ coefficients from Equation (18). The data are from LODES.

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