The Welfare Consequences of Incoming Remote Workers on Local Residents

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Abstract

This paper explores the impact of an influx of high-skilled remote workers on local residents in destination cities. Dozens of U.S. municipalities have recently implemented Remote Worker Relocation Programs that provide cash incentives to remote workers who relocate to their city. Using Tulsa Remote as a case study—the largest and the earliest such program funded by a non-profit organization—and employing an event study design, I find that the program was effective in attracting remote workers but had offsetting effects on local employment across sectors. The local service sector saw growth, while the wholesale trade sector experienced a decline likely due to local residents' sector switching behavior. To assess the overall and distributional effects of this kind of policy, I build and estimate a structural equilibrium model that takes into account workers' sector choices with a nonemployment option. The program slightly improves the average welfare of local residents primarily due to higher wages and a greater variety of local goods. This compensates for increased rents and prices for local goods. However, nonemployed and low-skilled renters in the tradable sector are adversely affected. Finally, when a Remote Worker Relocation Program is financed by local taxes, the average net benefit of the program is substantially reduced depending on the retention of remote workers.

JEL Classification: J21, J61, R12, R13, R50
Keywords: Remote Worker Relocation Programs, Tulsa Remote, Local Residents, Welfare, Tax

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1 Introduction

In recent years, the number of remote workers has exploded.[1] One major implication of this fact is the potential for geographic reallocation: workers can choose to leave traditional employment hubs and settle in new cities. This spatial relocation instigates debates about its impact on those who are already established in these areas.[2] In contrast to classic settings where newcomers both consume goods and take jobs (Card, 1990; Borjas, 2003), high-skilled remote workers arrive with jobs in hand and contribute to local spending without competing for local jobs. Although local job seekers face minimal competition from remote workers for local employment, a new group of people can drive up local prices (Mondragon and Wieland, 2022). Importantly, an increasing number of municipalities have launched "Remote Worker Relocation Programs" that offer relocation subsidies to attract remote workers. This paper investigates the economic consequences on local residents of an influx of remote workers induced by such policy by using reduced-form analysis and developing a comprehensive, yet intuitive and transparent local economy model.

This paper has two primary objectives. The first is to assess the aggregate and distributional impacts of incoming remote workers on local residents. Motivated by asymmetric effects of incoming remote workers on local residents by industry sector both conceptually and empirically, the model distinguishes between the local service sector and the tradable sector, along with nonemployment. For instance, newly arrived remote workers will frequent local restaurants and cafes, and such goods and services are supplied within the city. In contrast, demand for tradable goods, such as clothes and computers, is not mainly driven by the local economy, so local workers in this sector may not necessarily benefit. The second objective of the paper is to examine the implications of how the program is financed. For example, if it is tax-financed, then the gains from having more high-skilled workers must be weighed against the tax cost of attracting them. Therefore, incorporating this aspect ensures an in-depth program evaluation.

I provide direct empirical evidence on the impact of newly arrived remote workers on local residents by using a case study of Tulsa Remote—the largest and earliest Remote Worker Relocation Program in the United States funded by a non-profit organization. I use unique Tulsa Remote data and a wide range of datasets to study various outcomes on local residents' side such as local employment across sectors, the number of establishments, consumption patterns, rents, and housing prices. The empirical strategy exploits the geographic distribution of remote workers who are incentivized to relocate by the program. In particular, it capitalizes on the initial concentration of remote workers in downtown in the

[1] In the United States, the percentage of workers primarily working from home has steadily increased over the past few decades, with a remarkable surge in recent years, rising from 1.18% in 2000 to 17.99% in 2021 (ACS) (see Appendix Figure A1). Barrero, Bloom and Davis (2021, 2023) provide the survey evidence that full days worked at home account for 28 percent of paid workdays among Americans 20–64 years old as of mid-2023, which is about four times the 2019 rate and ten times the rate in the mid-1990s.

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

first cohort, designed by program administrators.[3] Consequently, I compare the area within Tulsa that receives remote workers to other areas without them outside of Tulsa before and after the start of Tulsa Remote. The empirical strategy of separating downtown from the rest of Tulsa as a treated region based on remote workers' concentration 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. On the other hand, this empirical strategy is not threatened by possible confounding factors in the context of Remote Worker Relocation Programs. In other words, Tulsa does not show fundamental differences in urban city dynamics between downtown and the periphery areas, unlike major cities in the United States, such as Seattle, Boston, and New York City. The key identifying assumption is that the localities with remote workers would have experienced the same evolution in outcomes as other localities without them outside of Tulsa if remote workers had not arrived. I demonstrate that this assumption holds credibly throughout the pre-program period. I also conduct a battery of robustness checks varying the control group, which shows that effects in downtown Tulsa were not driven by a choice of control group.

Using the event study design, I show that the Tulsa Remote program attracted remote workers who would not have relocated otherwise, resulting in a 2.87% increase in the downtown population after one year of the program based on the American Community Survey (ACS). The increased population size matches the number of relocated remote workers observed in the Tulsa Remote program's data. By using the ACS, I also observe a 6.44% increase in income in this area after remote workers are relocated, whose income is approximately two to three times that of local incumbents. However, there was no evidence of geographic displacement effect on local residents—the total population and local employment in Tulsa beyond the downtown area remained unchanged. Instead, I find the evidence of sectoral labor reallocation. The local service sector experienced a 7.95% increase in employment (*direct* effect) likely due to remote workers' substantive local spending, which is translated into 2.36 local service job creations per remote worker. On the other hand, the employment in the tradable sector fell (*indirect* effect), where the main action comes from the wholesale trade sector. Nonemployment slightly declined. I conclude that these findings are based on the sector switching behavior of workers from the tradable to the local service sector, likely in response to the change in relative wages, and a shift from nonemployment to employment. I also find that the number of local service establishments increased, which contributes to enrich the varieties of local service goods offered to local residents. Additionally, I find the heterogeneous effects on local employment by each sector within each earning group—jobs with lower earnings demonstrated a more pronounced employment response in both the local service and wholesale trade sectors. Lastly, I detect the data evidence of high housing supply elasticity in Tulsa (Saiz, 2010).

Next, I develop a static, local economy model to quantify the equilibrium and distributional impacts of this kind of policy more generally and conduct counterfactual experiments. The model incorporates rich

[3] Program administrators provide housing information primarily in the downtown area to the first cohort of remote workers to lessen non-compliance. For example, one could be accepted into the program but may not necessarily reside in Tulsa.

heterogeneity among local residents in skill type, working sector, and land ownership. A local worker given a skill type choose between the local service sector and the tradable sector, in addition to nonemployment. This distinction is important because the effects of incoming remote workers on local residents vary based on local residents' working sector due to the non-tradability of produced goods in each sector. For example, the increased consumption demand for local service goods driven by remote workers is propagated into heightened labor demand in the same sector in the local economy because local service firms seek to exploit their potential profits by producing more using more labor input. On the contrary, the increased consumption demand for tradable goods by remote workers does not necessarily translate into increased labor demand in the tradable sector in the local economy. This is because tradable goods produced outside the local economy can be shipped to compensate the increased consumption demand in the local economy. Another key component of the model is the monopolistic competition setting for local service firms (Dixit and Stiglitz, 1977; Krugman, 1980). Each differentiated local service good is produced by each local service firm. As a greater number of consumers owing to newly arrived remote workers share the fixed entry cost that each firm pays, the growing number of local service firms contributes to an enhanced variety of these goods, as evidenced in the event study analysis (agglomeration economics, Duranton and Puga (2004)). As a result, a richer variety of local service goods benefits not only incoming remote workers but also local incumbents. Lastly, immobile local landowners receive land income from local workers and firms and use it to consume goods. Newly arrived remote workers increase the land demand in the local economy. In summary, the model consists of the goods market for local service and tradable sectors, the labor markets for local service and tradable sectors, and the land market. With this framework, I examine both the direct and indirect channels through which newly arrived remote workers impact local incumbents in the local economy.

I estimate the model using indirect inference (Gourieroux, Monfort and Renault, 1993). In other words, I use the auxiliary parameters estimated in the reduced-form analysis to discipline the model parameters. In the model, I generate two local economy equilibria under two regimes: the baseline equilibrium and the post-equilibrium under the program regime. I simulate a policy shock by adding the increase in consumption demand for local service goods, tradable goods, and land, driven by remote workers who do not participate in the local labor market. By comparing the model results of two equilibria, I derive the model moments and match them with the auxiliary parameters. For instance, the elasticity of labor supply substitution parameter is identified by the labor demand shock in the local service sector and is disciplined by the causal estimate of the local service employment increase. The model results are tightly connected to the reduced form results both qualitatively and quantitatively.

The estimated model and counterfactual simulations deliver three major takeaways on (1) the aggregated welfare impact of incoming remote workers on local incumbents, (2) its distributional impact on heterogeneous local residents, and (3) the public finance perspectives of such programs.

First, despite subsidizing newcomers, not local residents directly, the program in Tulsa improves the average welfare of local residents by 1.28%, measured by the consumption equivalence relative to nominal income. This is primarily due to higher wages stemming from the increased local consumption by remote workers and greater varieties of local goods, offsetting increased rents and prices for local goods. Such benefit hinges on the fact that newcomers bring the income they earn by working remotely elsewhere but spend within the local economy.

Second, the program generates heterogeneous impacts on local residents. High-skilled local service workers benefit the most aside from landowners, while nonemployed workers and low-skilled renters working in the tradable sector experience a slight welfare loss negatively affected by higher rents and prices for local service goods. This results in an increase in the welfare gap between high-skilled and low-skilled workers although the income gap between the two was not salient. Noticeably, the modeling framework suggests that such differential impacts will depend on local economic conditions including industry composition and housing supply elasticity.

Finally, I evaluate counterfactual scenarios of a Remote Worker Relocation Program that is financed by tax, in contrast to the case of Tulsa Remote, which is funded by a non-profit organization. This analysis can be particularly useful for cities considering implementing a similar program without donor funding available, which is the case in most instances. To conduct this analysis, I impose an income tax, collected from both local residents and newly arrived remote workers, to fund the subsidies provided to remote workers.

I find that the benefits brought by remote workers to local residents can still outweigh the costs borne by local residents, such as increased rents, higher local goods prices, and importantly taxes. However, the program's benefit is substantially reduced when local residents contribute to financing it. Local residents who pay taxes to subsidize remote workers have lower disposable income compared to the case without taxes. Additionally, this leads to reduced consumption by local residents and lower income for local service workers as a general equilibrium effect. However, this depends on the retention rate of remote workers because the additional tax revenue collected from remote workers can compensate for the interest payment incurred from the local government's borrowing to pay the subsidy.

Related Literature. Although the increased prevalence of remote work opportunities provides geographic flexibility to many individuals, there is a severe dearth of investigation into their economic effects on local incumbents in their new destinations. This paper offers insights into how the influx of remote workers impacts the local economy, filling a significant knowledge gap.

This paper engages the literature on three major fronts. First, it pushes the burgeoning literature surrounding work from home (hereafter WFH). The previous focus has been on the WFH workers' side: for example, WFH productivity (Bloom et al., 2015; Emanuel and Harrington, 2023; Choudhury, Foroughi and Larson, 2021; 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 WFH to office work (Davis, Ghent and Gregory, 2021). In contrast, this paper studies the effects of remote workers on a different set of people: the local residents. Another strand of literature (Delventhal and Parkhomenko, 2020; Delventhal, Kwon and Parkhomenko, 2022; Brueckner, Kahn and Lin, 2023) speaks to the implications of WFH on city structure through the lens of a spatial equilibrium model, sometimes with the interaction with state income taxes (Agrawal and Brueckner, 2022). This paper provides direct, causal evidence on the relocated remote workers' stimulating effect on local employment. One paper related to this study is Althoff et al. (2022). Using the outflow of remote workers from cities during COVID-19, the authors find empirical evidence of local service workers' dependence on the local spending of remote workers. Compared to Althoff et al. (2022), this paper builds and estimates a structural equilibrium model and analyzes the welfare effects on local residents with richer heterogeneity using the inflow of remote workers instead of the outflow.

Second, this paper adds to the work on migration by turning the spotlight on a new type of migrant: high-skilled remote workers who already secured jobs outside the local economy. Dating back to classic immigration studies (Card, 1990; Borjas, 1994, 2003; Ottaviano and Peri, 2012), the economic impact of newcomers on natives in a receiving location has been of great interest, especially in the labor market. Compared to immigrants, the nature of remote workers gives different implications for local residents in the labor market, so this paper provides new insight. Relatively more recent studies provide a similar setting to this study where newcomers consume goods but do not compete with local residents for local jobs, including the variation in tourists (Faber and Gaubert, 2019; Allen et al., 2020; Almagro and Dominguez-Iino, 2022), the relocation of public sector workers (Faggio and Overman, 2014; Faggio, 2019; Becker, Heblich and Sturm, 2021), and the influx of retirees (Serow, 2003). Adding to this strand of literature, this paper focuses on remote workers who affect local residents through a consumption shock without directly disturbing the labor supply channel.

Lastly, this paper contributes to the place-based policy literature (Glaeser and Gottlieb, 2008; Moretti, 2010; Kline and Moretti, 2014*b*; Neumark and Simpson, 2015) by studying a policy rapidly gaining momentum.[4] In the context of attracting remote workers to local regions, I show that this emerging place-based policy can benefit local residents on average when implemented effectively. Pertinently, 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 setting as I do, Choudhurry, Starr and Thomaz (2022) study the impact of the Tulsa Remote program on the outcomes of participating remote workers: their next moving plan after relocating to

[4] Other place-based policies studied are: Enterprise Zone (Neumark and Kolko, 2010; Ham et al., 2011), Empowerment Zone (Busso, Gregory and Kline, 2013), Tennessee Valley Authority (Kline and Moretti, 2014*a*), and Opportunity Zone (Coen-Pirani and Sieg, 2019; Arefeva et al., 2021).

Tulsa, social involvement, and income.[5] However, they do not provide the effects of the program on local residents, which is the fundamental motive of the programs. This paper first provides a comprehensive assessment of Remote Worker Relocation Programs on local incumbents considering equilibrium effects, distributional effects, a public finance perspective, and local economic conditions.

Organization. The remainder of this paper is structured as follows. Section 2 provides the institutional background of Remote Worker Relocation Programs overall, with a focus on the benchmark program, Tulsa Remote.[6] Section 3 outlines the data and Section 4 presents the descriptive and reduced-form evidence on how remote workers affect local residents. Section 5 explains the structural local economy model and Section 6 describes the estimation. Section 7 conducts the welfare analysis and Section 8 explores the welfare impacts of a Remote Worker Relocation Program under alternative scenarios including when it is subsidized by local taxes. Section 9 concludes.

2 Institutional Background

2.1 Overview

Since 2018, 81 localities in the United States (see Figure 1a) have launched Remote Worker Relocation Programs (hereafter, RWRPs). The first four among these programs are: Tulsa Remote (in Tulsa, Oklahoma), Think Vermont (in Vermont), Ascend West Virginia (in Morgantown, West Virginia), and Go Topeka (in Topeka, Kansas). Both the number of RWRPs and the size of each program have been increasing. It is also noticeable that a large number of RWRPs are concentrated in Indiana, which is attributed to a statewide movement by a state government. Each program has its own eligibility criteria and incentives, but all require full-time remote employment on a daily basis and a commitment to reside in the city for a period of one to two years. Once remote workers are accepted into the program and move to the city, they receive a full incentive package, including cash grants ($3,000-$19,000), gift cards, free access to coworking spaces, and local community events. The funding for these programs comes from local governments or non-profit organizations. I provide a census of RWRPs in the United States (as of September 2022) with details of each program in Appendix A.2.[7] This unique, hand-collected data demonstrates that Tulsa Remote is a feasible case study among other programs.

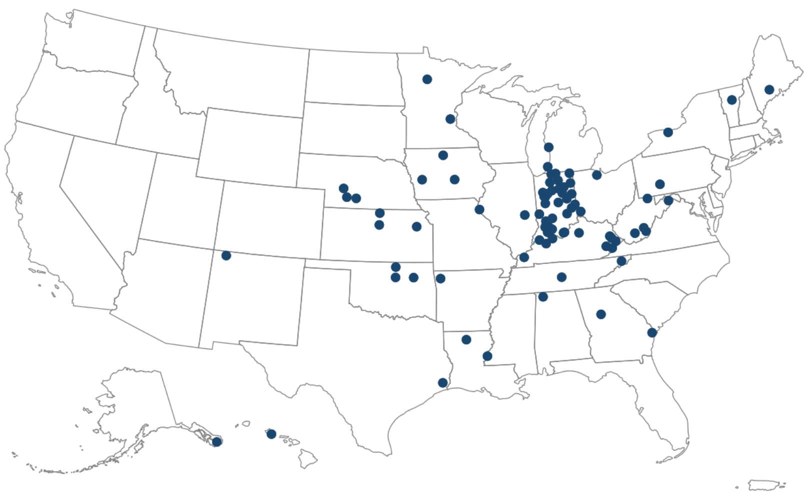
[5] Choudhurry, Starr and Thomaz (2022) conduct a survey of four different groups: (i) Tulsa Remote members ("Tulsa Remoters"), (ii) individuals whose application to the program was not successful, (iii) individuals who were accepted into the Tulsa Remote program but did not join the program for idiosyncratic reasons ("near-Tulsa Remoters"), and (iv) individuals who were accepted into the program and will move to Tulsa. They find Tulsa Remoters are more likely to stay in their cities in the next years, actively engage in the community, and have higher real income growth relative to near-Tulsa Remoters.

[6] Other programs are explained in Appendix A.2.

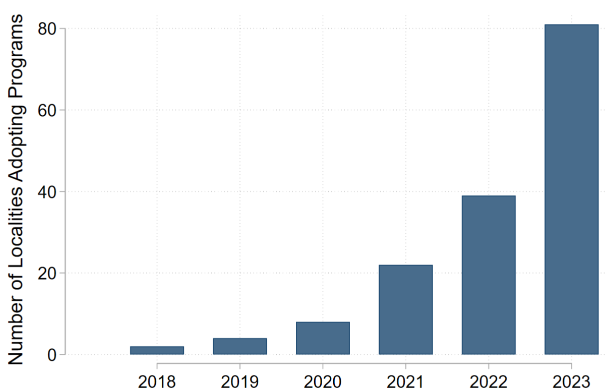
[7] The main reference is MakeMyMove, an application platform where remote workers can browse relocation offers and design their own plans. I supplement this information with program reports, websites, local news, and sometimes interviews with the program administrators. The substantive details of each program are reported such as the start year, number of applicants, number of remote workers who have relocated, incentives offered, funding source, and eligibility requirements.

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

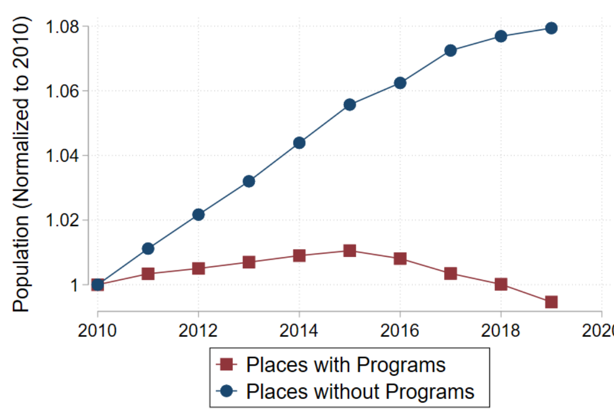
(a) Map of Remote Worker Relocation Programs



(b) The Cumulative Number of Programs Over Time



(c) Depopulation in Localities with Programs



Notes: Panel (a) shows the geographic locations of localities (cities, counties, or sometimes states) that have implemented Remote Worker Relocation Programs. For more details such as the number of relocated remote workers per program so far, see Appendix Table A.2. Panel (b) demonstrates the increasing number of Remote Worker Relocation Programs over the past five years. Panel (c) indicates that places with programs (in squares) experienced population loss, while those without programs (in circles) saw steady population growth. The sample used in panel (c) only includes the localities available in the National Historical Geographic Information System (NHGIS). Due to this data limitation, there are 549 places included in the sample, in addition to two states (Vermont and West Virginia). Places with programs include nine cities (Fayetteville in Arkansas, Springdale in Arkansas, Savannah in Georgia, Honolulu in Hawaii, Bloomington city in Indiana, Topeka in Kansas, Rochester in New York, Tulsa in Oklahoma, and Beaumont in Texas) and two states (Vermont and West Virginia).

2.2 Tulsa Remote

Although Tulsa Remote was initiated in 2018, its origin traces back to the late 1990s when the George Kaiser Family Foundation (GKFF) was established. The mission of this foundation is to disrupt the "intergenerational cycle of poverty in Tulsa." However, the foundation faced problems associated with: (i) the absence of enough job opportunities for talented workers to move to Tulsa and (ii) a lack of a strong workforce. With these challenges as a backdrop, the GKFF began to consider a different type of workers—-those who could work from anywhere and bring their jobs with them when they moved to Tulsa. The executive director of Tulsa Remote in their program report (Tulsa Remote, LLC, 2023b) says:

> *"We thought one way to advance our economy would be to focus on attracting remote workers—employees who can work from anywhere, given a laptop and a Wi-Fi connection. In this way, we hoped to build a more inclusive and resilient local economy."*

Timing and Size. Tulsa Remote was launched in November 2018, which is the first among RWRPs before the widespread popularity of remote work due to COVID-19. This timing is particularly advantageous in my empirical setting, as it predates the boom in remote work and avoids endogeneity concerns.[8] This differs from many other RWRPs, which not only started after the emergence of COVID-19[9] but also do not currently have enough post-periods to track the program's effects. Tulsa Remote also has the largest number of participating remote workers (more than 2,500 as of 2023 and about 100 as of 2019), hereafter Tulsa Remoters, among RWRPs.[10]

Funding Source. Tulsa Remote was initiated by the GKFF, not the local government. In November 2018, with approval from the City of Tulsa, GKFF announced the launch of Tulsa Remote (see Appendix Figure A2a) with funding coming from the Kaiser-Francis Oil company. Such direct cash transfer allows me to simplify the model estimation later without solving the government's problem.[11,12]

Eligibility Criteria and Benefits. To be eligible for the program, applicants must meet four criteria: (i) full-time remote employment (including self-employment) *outside* of Oklahoma,[13] (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. Tulsa Remote allows multiple ap-

[8] When the program was implemented, the program founder did not expect COVID-19 or the boom in remote work.

[9] More than 90% of programs were adopted after COVID-19. Separating COVID-19 effect from the program effect is empirically challenging as not much variation is left after COVID-19 is considered, meaning the COVID shock was too devastating.

[10] The second largest program is Think Vermont, which has drawn about 500 remote workers so far.

[11] I set up the government's problem in counterfactual analysis (see Section 8).

[12] In April 2021, Oklahoma state government passed the legislation (House Bill 3887) that it reimburses a large part of the incentive.

[13] As the program only accepts applicants who reside outside of Oklahoma, I employ other Metropolitan Statistical Areas (MSAs) within Oklahoma as a control group in my empirical analysis in Section 4.2. This enables a comparison of the impact of remote workers on the local residents in Tulsa, where the program is active, with other MSAs in Oklahoma where the program is inactive.

plications per household, meaning that couples within the same family can be accepted together.[14] Once accepted into the program, applicants receive an incentive package consisting of a cash grant of $10,000 distributed over one year, membership to a coworking space,[15] assistance in searching for housing, and regular community events. The program is designed to foster community engagement among remote workers and local residents through monthly dinners and regular events.

Selection Process. As the program has been oversubscribed beyond expectations (see panels (a) and (b) in Appendix Figure A3 for the number of applicants and that of Tulsa Remoters), the Tulsa Remote team selects applicants by reviewing each application. First, reviewers check if an applicant meets all the eligibility criteria. For instance, full-time remote employment should be verified. Next, video interviews are conducted with each applicant who passes the first stage. Lastly, an in-person visit is scheduled, especially if the finalist has no previous experience in Tulsa. In this selection process, it appears that two criteria play the most significant role: (i) income and (ii) assimilation and attachment to Tulsa. As shown in panels (c) and (d) in Appendix Figure A3, those who are accepted are more likely to be high-income individuals and have friends or family in Tulsa, compared to the applicants. Tulsa Remote also states on its website (Tulsa Remote, LLC, 2023a):

> *"The ideal candidate is a fully-employed individual with the flexibility to work anywhere, who does not currently reside in Oklahoma or work for a company based in Oklahoma and is looking for a community to call home. While the program has only a one-year commitment, the ideal candidate is open to calling Tulsa their home long-term."*

The five-year-old Tulsa Remote program has attracted over 2,500 remote workers to date, each bringing their own remote jobs.[16]

3 Data

This section provides an overview of the data. The data are gathered from various public and confidential sources, including Tulsa Remote. Section 3.1 explains the data used to understand the characteristics of *Tulsa Remoters* and *remote workers* in general. Section 3.2 illustrates the data used to examine the effect

[14] This feature does not hold for every program. For example, Choose Topeka considers only one application per household.

[15] Coworking space is an arrangement in which workers from different companies share an office space. Appendix Figure A4 provides photographs of the facilities available for Tulsa Remoters at two coworking spaces located downtown.

[16] In terms of remote workers shutting down the labor supply channel, there can be two counter-intuitive scenarios: (i) family members of relocated remote workers take local jobs and (ii) remote workers themselves also can take local jobs in the long run. Data facts and institutional background can reassure the first scenario. The number of household members is on average 1.5 for Tulsa Remote participants. Also, the Tulsa Remote program allows multiple applications within the same household (which is not the case for all Remote Worker Relocation Programs). Indeed, there are couples who have both been accepted by the program in Tulsa. Furthermore, a spouse remains nonemployed when there is a high-earning breadwinner in the household. Regarding the second scenario, this does not happen in my analysis because Tulsa Remoters' committed period is one year, and my empirical analysis covers only one year of the post-period.

of Tulsa Remoters on *local residents*. I mainly describe unique datasets in this section but leave further details on other publicly available datasets in Appendix B.

3.1 Data on Remote Workers

I describe the characteristics of Tulsa Remoters by using Tulsa Remote data.[17] This unique dataset includes cumulative summary statistics of demographic, working, and geographic information of program applicants and participants in three snapshots (July 2020, July 2021, and July 2022). The summary statistics of Tulsa Remote participants are presented in Table 1 (as of July 2022), showing that the majority of participants work in high-paying industries such as professional, scientific, and technical services and information. Furthermore, Tulsa Remote data includes the geographic distribution of participants' origin states and their residential locations in Tulsa.[18]

Table 1: Summary Statistics of Tulsa Remoters

A. Demographic Information	
Age	38
Male	0.517
White, non-Hispanic	0.834
Black, non-Hispanic	0.054
Hispanic	0.028
B. Working Information	
Professional, scientific, and technical services	0.311
Information	0.144
Education services	0.118

Notes: The number of observations is 1,769 (July 2022).

Moreover, I supplement the Tulsa Remote data with census tract-level, 5-year American Community Survey (ACS) estimates downloaded from the National Historical Geographic Information System (NHGIS). The ACS provides rich demographic, working, and geographic information with a large sample size of individuals.[19] I also use the Current Population Survey (CPS) Food Security Supplement and Work Schedules Supplement to examine the food spending patterns of remote workers compared to non-remote workers, which motivates the consumption channel of remote workers.

[17] Tulsa Remote data is acquired from program administrators under a Data Transfer and Use Agreement (DTUA). A research team at Harvard Business School, in partnership with the Economic Innovation Group (Daniel, Kennedy and Kenan, 2021), also conducted an additional survey in July 2021.

[18] I note that Tulsa Remote data has been available since 2020, although the post-period used in my analysis is 2019 (after one year of the program's implementation in 2018). Nevertheless, Tulsa Remote data (2020-2022) shows a stable and consistent descriptive pattern of remote workers over three years with a growing size.

[19] The ACS asks about the means of transportation used on the most recent day of work, which includes the option of "worked at home," and I use this variable to categorize remote workers.

3.2 Data on Local Residents

I pull multiple datasets to analyze how various outcomes respond to the inflow of remote workers. This set of data includes LEHD Origin-Destination Employment Statistics for *employment*, SafeGraph for *consumption*, Your-economy Time Series (YTS) for *establishment activity*, and the Federal Housing Finance Agency (FHFA) Housing Price Index (HPI) for *housing prices*. The comprehensive use of multiple data sources ensures that the model is closely tied to empirical results. Detailed information on each dataset can be found in Appendix B.

4 Descriptive and Reduced-Form Analyses: Remote Workers and Local Residents

This section serves two purposes. First, it motivates the mechanisms through which remote workers can affect local residents by describing the economic characteristics of remote workers. Second, it prepares the model estimation by presenting causal estimates of the impact of incoming remote workers on various outcomes, which will discipline the model parameters. To this end, this section consists of two parts: (i) a descriptive analysis of *remote workers*, and (ii) a reduced-form analysis to estimate the effects of newly arrived remote workers on *local residents*.

4.1 Descriptive Analysis of Remote Workers

I present descriptive analyses of remote workers, with a focus on Tulsa Remoters, mainly to demonstrate the consumption channel through which remote workers affect local residents.

Fact #1: Tulsa Remoters are high-skilled and high-income workers. Panels (a) and (b) in Figure 2 show that Tulsa Remoters are typically highly educated and high-income workers, compared to local incumbents in Tulsa on average. This suggests that each Tulsa Remoter can potentially spend more than the average local resident does.

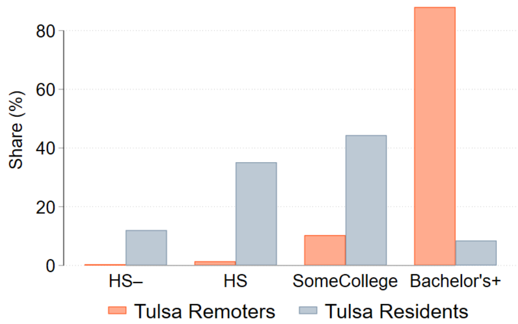
Fact #2: Tulsa Remoters mostly come from bordering states or high living cost states. Panel (c) in Figure 2 presents the relative density of Tulsa Remoters' previous residence to remote workers by state. It shows that Tulsa Remoters are more likely to come from neighboring states of Oklahoma or from states with a high cost of living, after conditioning on the density of remote workers. This stylized fact yields two takeaways. First, the states adjacent to Oklahoma—namely Arkansas, Colorado, Kansas, Missouri, and Texas— exhibit higher relative densities, likely due to lower moving costs (Kennan and Walker, 2010) or the convenience of returning to Oklahoma for individuals who were originally born in Oklahoma but had moved to neighboring states.[20] Second, states characterized by high living costs, such

[20] 60.3% of those who were born in Oklahoma reside in Oklahoma and 12.0% of them reside in Texas as the second most

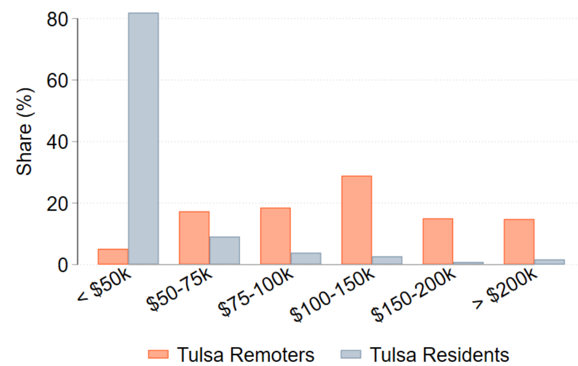
as California, New York, and Texas, demonstrate higher relative densities. This implies that Tulsa Remoters benefit from lower living costs in addition to incentive packages offered by the Tulsa Remote program.

Figure 2: Tulsa Remoters: Education, Income, and Origin

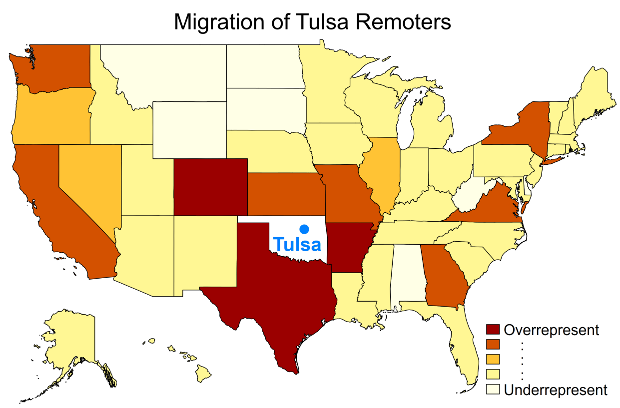
(a) Education Distribution



(b) Income Distribution



(c) The Relative Density of Tulsa Remoters' Origin State



Notes: Panel (a) and panel (b) show the education and income distribution of Tulsa Remoters and local incumbents in Tulsa. The distribution of Tulsa Remoters is from Tulsa Remote, and the distribution of local incumbents in Tulsa is from 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 (using Tulsa Remote data) and the percentage of remote workers in each state (using ACS). Therefore, states marked as 'overrepresent' (or 'underrepresent') indicate that they have a higher (or lower) share of remote workers relocated to Tulsa. The sample is 1,139 Tulsa Remoters (as of July 2022).

Fact #3: Remote workers spend more on food than non-remote workers do, particularly at restaurants rather than grocery stores. To understand remote workers' consumption patterns, I use CPS Supplements and run the following regression:

popular destination (source: ACS).

$$y_i = \alpha + \beta \times \mathbf{1}(\text{Remote Work})_i + \gamma \mathbf{X}_i + \varepsilon_i \tag{1}$$

where $\mathbf{1}$(Remote Work) denotes an indicator of an individual i being a remote worker and $\mathbf{X}_i$ is a set of demographic and working characteristics, such as the number of household members and whether located in a metropolitan area. The outcome variables used in each column in Table 2 are: (1) an indicator of ever eating out in the past week (*extensive* margin), (2) the log of the total amount ($) spent on food at restaurants and cafeterias in the past week (*intensive* margin), (3) the log of the total amount ($) spent on food at grocery stores or supermarkets in the past week, and (4) the log of the usual weekly amount ($) spent on food per week. Table 2 shows that remote workers dine out more frequently (by 8 percentage points) and spend more (by about 47 percent) at restaurants in the past week than non-remote workers do. The disparity between the two groups is more pronounced in restaurant spending compared to spending at supermarkets or grocery stores.

Table 2: The Food Consumption Patterns of Remote Workers

	Restaurants or Cafeterias		Market/Grocery	Total Food
	Ever Eat Out (1)	Amount (2)	(3)	(4)
$\mathbf{1}$(Remote Work)	0.079	0.389	0.074	0.100
	(0.009)	(0.039)	(0.016)	(0.014)
Mean	0.776	2.754	4.308	4.617
R-squared	0.105	0.154	0.144	0.180
Observations	21,947	21,947	19,752	21,860

Notes: The $\hat{\beta}$ coefficients in Equation (1) are reported and household clustered robust standard errors are in parenthesis. The covariates $\mathbf{X}_i$ include the total number of households, dummies for metropolitan status, age, age^2, sex, race, ethnicity, education, employment status, marital status, and occupation. Details about what variables are used can be found in Appendix C.1.

This stylized fact contrasts the differential impact of remote workers on local residents concerning food expenditure types: dining out versus grocery shopping. First, food at restaurants are non-tradable goods, given that culinary dishes are consumed where they are finally produced. In contrast, groceries such as canned foods, cereal, sodas, and snacks can be easily transported from distant locations. Second, foods at restaurants are often deemed *luxury goods* in comparison to groceries. Restaurants typically charge customers for cooking and serving in addition to the cost of the food ingredients itself, while purchasing groceries and cooking at home saves consumers money. Consequently, remote workers as young urban professionals can substantially increase the demand for restaurant workers (Couture and Handbury, 2020). In summary, if remote workers are more inclined to dine out, their consumption behavior contributes to increasing the demand for labor in the restaurant sector more than it does in the retail sector.

4.2 Reduced-Form Analysis of Local Residents

Empirical Challenge. The inherent empirical challenge in capturing the effect of the program on local residents lies in the small number of incoming remote workers (small treatment size). To this end, I exploit the unequal residential distribution of relocated remote workers (variation in treatment intensity).[21] Specifically, Figure 3a shows that Tulsa Remoters are concentrated in the downtown area.[22] Thus, downtown Tulsa is more exposed to remote workers who bring new cash to town.

Empirical Strategy. I use an event study framework to estimate the effects of incoming remote workers in downtown Tulsa *and* in the rest of Tulsa *separately* compared to the other Metropolitan Statistical Areas (MSAs) in the state of 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, motivated by 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 parallel trends: in the absence of Tulsa Remote, downtown Tulsa and the rest of Tulsa would experience a change of the outcome variable that moves in parallel with the remaining MSAs in Oklahoma. The net effect excluding the time trend effect estimated by using the comparison group gives the treatment effect of Tulsa Remote on downtown Tulsa and on the rest of Tulsa.

To establish a set of control regions that are comparable to Tulsa, I restrict the sample to Metropolitan Statistical Areas (MSAs) in Oklahoma (see Appendix Figure C2). By doing so, the comparison group has a population density similar to Tulsa. For example, Oklahoma City is the most populated MSA in Oklahoma, Lawton is the third, and Tulsa is the second. Panel A in Table 3 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 prime-age populations and Blacks in downtown Tulsa compared to other MSAs, but the level of education and the industry structure are comparable across the two groups. I also include year dummy variables to test for pre-trends. If an outcome variable has systemic changes, these will be shown in the estimates for the pre-periods.

[21] Similarly, in the context of the education market in Chile, Neilson (2013) studies how voucher policy affects school quality by considering the “policy exposure," which is measured as the share of policy-eligible students.

[22] Figure 3a is based on July 2022, while the post-period in my analysis is 2019. However, snapshots from July 2020, July 2021, and July 2022 show the consistent pattern that downtown Tulsa has been the most popular destination for incoming remote workers. As anecdotal evidence, in 2019, when the first cohort of Tulsa Remoters moved in, the program administrators encouraged them to move to downtown Tulsa for managerial purpose. As the program became more established, later cohorts began to spread out across the city, as manifested in Figure C4. Additionally, I note that the two coworking spaces are located downtown.

Table 3: Baseline Summary Statistics of Local Residents by Exposure to Remote Workers

A. ACS: Census Tract Level 5-year Estimates (2015-2018)

	Downtown	The Rest of Tulsa	Other MSAs in Oklahoma
Race/Ethnicity			
% White	0.65	0.64	0.74
% Black	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			
% Manufacturing	0.03	0.05	0.04
% Sevices	0.17	0.24	0.21
Population	3440	377446	2159128

B. LODES (WAC): Employment Composition by Sectors at Work Census Tract Level (2015-2018)

	Downtown	The Rest of Tulsa	Other MSAs in Oklahoma
Construction (NAICS 23)	0.02	0.05	0.09
	(0.00)	(0.06)	(0.11)
Local Services (NAICS 72, 81)	0.09	0.16	0.14
	(0.01)	(0.13)	(0.13)
Manufacturing (NAICS 31-33)	0.01	0.07	0.07
	(0.00)	(0.13)	(0.12)
Wholesale Trade (NAICS 42)	0.03	0.05	0.04
	(0.00)	(0.08)	(0.05)
# of Observations	4	468	2288

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.

Finally, I set up the following event study equation:

$$\begin{aligned} y_{c,t} = \alpha_c + \gamma_t \quad &+ \sum_{\substack{t=2015,\\ t\neq 2018}}^{2019} \beta_t^D \times \mathbf{1}(\text{Downtown})_c \times \mathbf{1}(\text{Year})_t \\ &+ \sum_{\substack{t=2015,\\ t\neq 2018}}^{2019} \beta_t^R \times \mathbf{1}(\text{Rest})_c \times \mathbf{1}(\text{Year})_t + \varepsilon_{c,t} \end{aligned} \tag{2}$$

I include the census tract fixed effect, α_c, and the year fixed effect, 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 is all based on census tract clustered wild bootstrap to address the small number of treated units (Cameron, Gelbach and Miller, 2008).

Population. I conduct an event study analysis by using the log of the population in each census tract c and in year t (ACS 5-year estimate from $t-4$ to t) as an outcome variable.[23] This aims to estimate the causal effect of the program on population growth while considering potential inflows and outflows that may occur regardless of the program. Additionally, I include the lag of the outcome variable, $\log(\text{pop})_{c,t-1}$, in population analysis to control any momentum in population growth (time-varying, region-specific characteristics). I provide a more detailed discussion in Appendix Figure C3.

I plot the coefficients of interest (corresponding to $\hat{\beta}_t^D$ and $\hat{\beta}_t^R$ in Equation (2)) in Figure 3c and Figure 3d respectively. Figure 3c shows that the population in downtown Tulsa experiences a 2.87% growth after one year of the program. The effect size is translated to a net increase of 101 individuals,[24] which is exactly matched with the number of Tulsa Remoters (reported in Appendix Figure A3b). On the other hand, Figure 3d shows that the area within the city limit of Tulsa but outside of downtown does not experience any statistically significant effect on population growth. This finding is consistent with the descriptive fact that the first cohort of incoming remote workers was mostly induced to downtown. 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 the population growth in the rest of Tulsa could have been observed.

Appendix Figure C4 shows longer post-periods (2019-2021) based on the availability of ACS data although I note that COVID-19 possibly pushes down the program effects. In 2021 after the peak of the COVID-19 outbreak, both downtown Tulsa and the rest of Tulsa experience population growth. This confirms the growing scale of the program and the spread of remote workers throughout the city in the following years.[25]

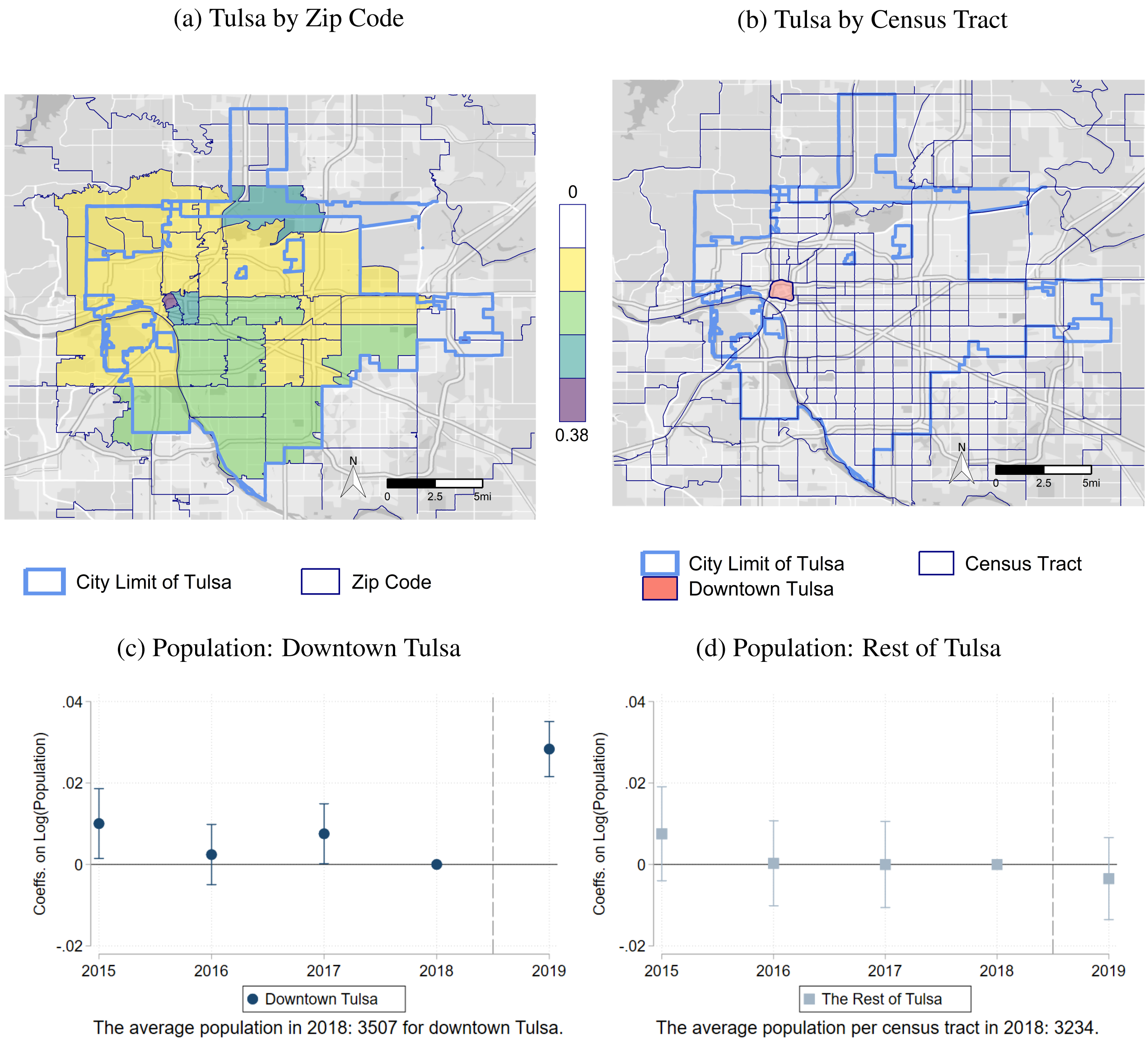
Income Per Capita and Non-employment. I also run event study analyses on $\log(\text{income per capita})_{c,t}$ and $\log(\text{nonemployment})_{c,t}$ which are based on residential populations, and plot the event study estimates in Appendix Figure C5. Downtown Tulsa experiences an increase in income per capita by 6.44% after

[23] I use the log of the population, not the population level, as the outcome variable under the assumption that population growth is linear.

[24] The effect size of 2.87% is calculated as $(e^{0.0283}-1)\times 100 \approx 2.87\%$. The net increase of population is 3507 (baseline) $\times 0.0287$ (point estimate) ≈ 101.

[25] Including a lagged variable with multiple post-periods can absorb the program effects though, which indicates that the program effects could have been larger than what is plotted. However, including a lagged variable plays a role in eliminating pre-trends.

Figure 3: Relative Density of Tulsa Remoters, Central Business District (CBD) in Tulsa, and Population Growth in Tulsa



Notes: Panel (a) presents the relative density of Tulsa Remoters to local residents by zip code (as of July 2022). Panel (b) shows the geographic division of Tulsa by census tract, which is the geographic unit of the outcome variable. The highlighted area in panel (b) corresponds exactly to downtown Tulsa. Panels (c) and (d) plot the coefficients $\hat{\beta}_t^D$ and $\hat{\beta}_t^R$ respectively in Equation (2). The 95% confidence intervals are based on census tract-clustered wild bootstrap with 9,999 replications and a six-point weight distribution (Webb, 2013). The data source is ACS 5-year estimates.

one year of the program, while the rest of Tulsa does not experience any effect in income per capita. This supports that high-income remote workers indeed move to the downtown area, induced by the program. On the other hand, downtown Tulsa experiences a decline in the number of nonemployed including both out of the labor force and unemployed workers by 1.16%.[26,27]

Employment. Next, I examine the employment of local residents using the LODES. The 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. The outcome variable is based on the work area instead of the residence area. Therefore, it does not count the jobs that remote workers come with but their jobs are counted based on their employment locations outside the city. The Equation (2) is run for each industry sector s separately: (i) local service sector, (ii) construction, (iii) wholesale trade, and (iv) manufacturing. The comprehensive results are reported in Table C2. However, the primary causal effects of Tulsa Remote are materialized in the local service and wholesale trade sectors.

Figure 4a shows that Tulsa Remote leads to a 7.95% increase in employment in the local service sector in downtown area with the confidence interval ranging from 4.36% to 11.67% with the counterfactual baseline 2991.[28] The local service sector includes accommodation and food services (NAICS 72) and other services (NAICS 81). Similar to the negligible population effect, the rest of Tulsa does not show a statistically significant local employment effect. On the other hand, the wholesale trade sector in downtown Tulsa experiences a decline of 12.6% in the number of jobs (counterfactual mean: 928).[29] However, there are no noticeable statistically significant changes in employment across other industry sectors in response to the Tulsa Remote program (see Appendix Figure C7). Therefore, I classify the industry sectors into two: the local service sector and the remaining tradable sector.[30]

Causal Interpretation. To bolster a causal interpretation of my estimates, I conduct a battery of robustness checks of the main result: the increase in employment in the local service sector. These checks involve varying the control group: (i) downtown areas in Oklahoma, (ii) the rest of Tulsa, (iii) MSAs in neighboring states, (iv) downtown areas in the United States, and (v) the cities that implemented the program after Tulsa Remote, as well as adding covariates. The results of these checks are summarized in Appendix Figure C8 and show that the main finding is robust across a different set of analyses. Furthermore, I employ a synthetic control method (Abadie, Diamond and Hainmueller, 2010) in an effort to

[26] As I include the counts of nonemployment, not the fraction of nonemployment, the decline in nonemployment is driven by local incumbents, not by the incoming remote workers.

[27] Regarding the hike of the event study estimate $\hat{\beta}^D_{t=2016}$, the author concludes that it is due to the protest in response to the Killing of Terence Crutcher. In an effort to find a better control group, I conduct a synthetic control method in Appendix Figure C6. The result supports the decline in nonemployment.

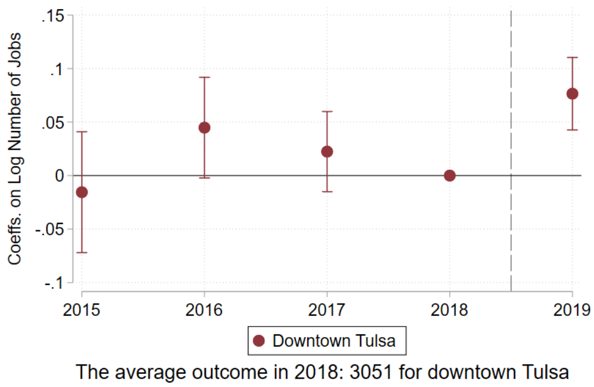
[28] The effect size of 7.95% is calculated as $(e^{0.0765}-1)\times 100 \approx 7.95\%$. I subsequently obtain 2.36 as a local job multiplier by dividing the employment increase in the local service sector by the population increase. This means that one new worker (a high-skilled remote worker) generates 2.36 local service jobs. For comparison, Moretti (2010) finds a local job multiplier of 2.52 in response to skilled tradable jobs and of 1.04 in response to unskilled tradable jobs. For a comprehensive comparison to previous literature, see Appendix Table C3.

[29] This is calculated as $(e^{0.1348}-1)\times 100 \approx 12.6\%$

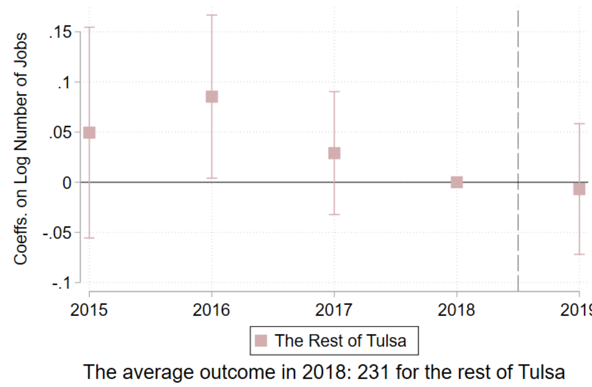
[30] The bulk of tradable sector activity in response to the program stems from the wholesale trade sector in my analysis. This can be understood by the fact that the employment fraction in wholesale trade sector is about three times that of manufacturing sector (see Table 3).

Figure 4: Event Study Analysis: Effect of Tulsa Remote on Number of Jobs in Each Industry Sector

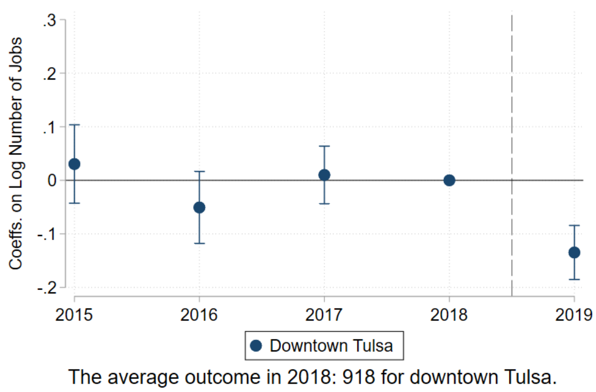
(a) Local Service Sector: Downtown Tulsa ($\hat{\beta}^D$)



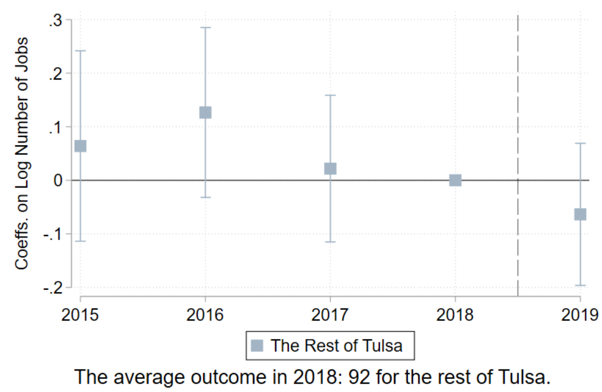
(b) Local Service Sector: Rest of Tulsa ($\hat{\beta}^R$)



(c) Wholesale Trade Sector: Downtown Tulsa ($\hat{\beta}^D$)



(d) Wholesale Trade Sector: Rest of Tulsa ($\hat{\beta}^R$)



Notes: Panel (a) and (b) respectively present $\hat{\beta}_t^D$ estimates (in circles) and $\hat{\beta}_t^R$ estimates (in squares) in Equation (2) for the services sector. Panel (c) and (d) respectively present $\hat{\beta}_t^D$ estimates (in circles) and $\hat{\beta}_t^R$ estimates (in squares) respectively for the wholesale trade sector. The 95% confidence intervals are based on census tract-clustered wild bootstrap with 9,999 replications and a six-point weight distribution (Webb, 2013). The data source is LODES WAC (U.S. Census Bureau, 2019). Zero outcomes, which comprise less than 5%, are excluded.

find the most comparable group in a longer horizon as well as to deal with the single treated unit (see Appendix Figure C9). Lastly, to be fully transparent, I provide the raw data plots of the outcome variables in Appendix Figure C10, which shows a clear increase in local service employment in downtown Tulsa in 2019.

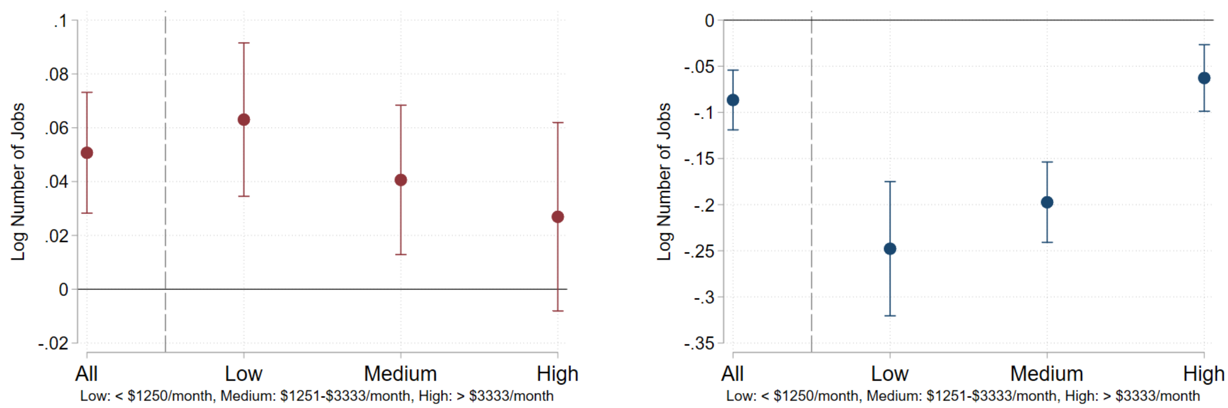
Heterogeneity in Employment. I also examine the employment effects in downtown area across three different earning groups: low, medium, and high[31] by using the same event study framework that has been conducted. Figure 5 summarizes event study estimates (β_{2019}^D), normalized by the standard deviations of

[31] Specifically, less than \$1,250/month (for the low-earning group), \$1,251-3,333/month (for the medium-earning group), and more than \$3333/month (for the high-earning group), which is classified by the Census.

the relevant outcome variables (see Appendix Table C4 for the complete results). The results demonstrate that the increase in the number of jobs in the local service sector is greatest for lowest-earning jobs. Symmetrically, a decrease in the number of jobs in the wholesale trade sector is most pronounced in the lowest-earning jobs. This differential employment response in each earning group is incorporated as the skill heterogeneity in the model.

Figure 5: Event Study Analysis: Heterogeneous Effect of Tulsa Remote on Number of Jobs by Earnings

(a) Local Service Sector (b) Tradable Sector: Wholesale Trade



Notes: The figures present the normalized $\hat{\beta}^D_{t=2019}$s by the standard deviation of the outcome variable in each earning groups (low, medium, and high) and two industry sectors: local service (NAICS 72 and NAICS 81) in panel (a) and wholesale trade (NAICS 42) in panel (b). Note that the point estimate labeled as 'All' on the x-axis in each panel corresponds to the point estimate $\hat{\beta}_{t=2019}$ in each panel in Figure 4. The 95% confidence intervals are based on census tract-clustered wild bootstrap with 9,999 replications and a six-point weight distribution (Webb, 2013). The full estimates are reported in Appendix Table C4.

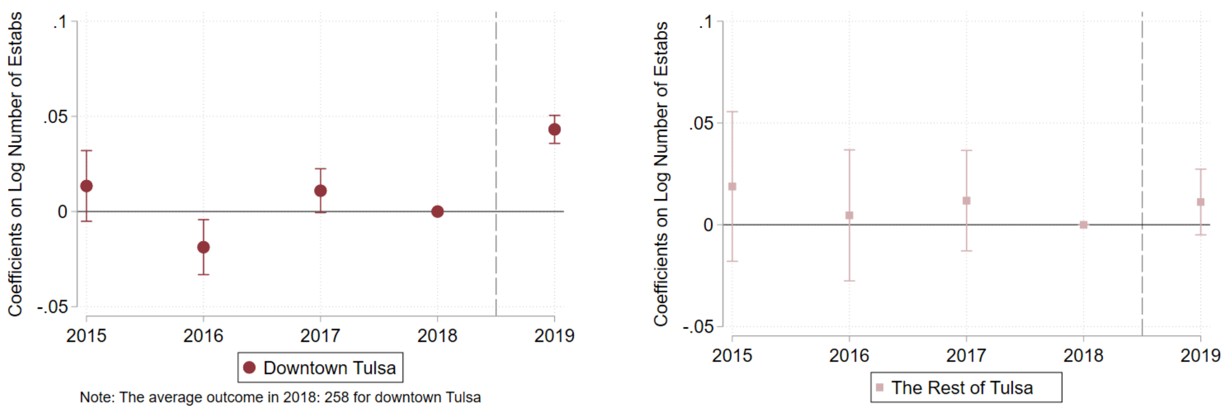
Varieties of Goods. One important channel through which remote workers can benefit local residents is by enriching the variety of local service goods.[32] Increased consumption induced by remote workers incentivizes more establishments to enter the market—this phenomenon is commonly referred to as the agglomeration effect through sharing (Duranton and Puga, 2004). To test this hypothesis in data, I run an event study regression using the total number of establishments in the local service sector from the YTS as the outcome variable (as in Equation (2)). Figure 6 illustrates that downtown experiences an increase in the total number of establishments by 4.38% with the baseline 258. Each establishment serves as a proxy for a unique variety of goods. For instance, Shake Shack produces distinct hamburgers compared to In-N-Out. In cases where establishments of the same brand enter, the variety gain can be understood as an advantage of proximity. I provide direct evidence of variety gain for both local residents and remote

[32] According to Tulsa Remote, LLC (2023b), the 1,852 remote members living in Tulsa (as of 2022) are contributing to the city's cultural and recreational attractions, including live music, fine restaurants, and extensive public parks. For more insights on the impact of newcomers on local attractions with a richer heterogeneity in the context of tourists, see Almagro and Dominguez-Iino (2022).

workers in Appendix C.7.

Figure 6: Event Study Analysis: Effect of Tulsa Remote on Number of Establishments in Local Service Sector

(a) Downtown (b) Rest of Tulsa



Notes: Panel (a) and (b) respectively present $\hat{\beta}_t^D$ estimates and $\hat{\beta}_t^R$ estimates in Equation 2. The 95% confidence intervals are based on census tract-clustered wild bootstrap with 9,999 replications and a six-point weight distribution (Webb, 2013). The data source is the YTS.

Additional Analyses. To understand other equilibrium outcomes, I also examine consumer visits and housing prices (see Appendix C.8 for details). Both the total number of visits and visitors increase in downtown Tulsa. However, I do not detect any statistically significant effect on housing prices in downtown Tulsa relative to other MSAs in Oklahoma after one year of the program. I conclude that this is attributable to the high housing supply elasticity in Tulsa (Saiz (2010) estimates it as 3.35).[33]

I also examine transitions in labor market activity at the individual level using the panel structure in the CPS. The collective findings regarding the increase in employment in the local service sector and the decrease in employment in the wholesale trade sector, along with the reduction in non-employment, point towards labor reallocation on an aggregate scale. However, I do not observe individuals repetitively at this granular geographic level. Instead, I confirm that such transitions occur reasonably frequently within one year. Further details are provided in Appendix Table C5.

Summary of Findings. All things considered, the local service sector expands as high-income remote workers contribute to spending on local goods in the city. This leads to sectoral labor reallocation, with a shift from the tradable sector to the local service sector in addition to a transition from nonemployment. This is evidenced by the increase in local service employment and the growth of establishments in the

[33] This phenomenon is not uncommon. For example, Busso, Gregory and Kline (2013) find that Empowerment Zones raised local employment, but population and rental rates of housing remained stable, suggesting that the targeted neighborhoods had some slack in the local housing market.

local service sector, but with the decline in employment in the wholesale trade sector (90% of the local service employment increase) and the reduction in unemployment (10% of the local service employment increase). On the other hand, I do not find any empirical evidence on spatial reallocation. There is no statistically significant change in either the total number of commuters to downtown or the total number of jobs in the city of Tulsa (see panels (a) and (b) in Appendix Figure C15 for the details).

5 A Local Economy Model of Goods Market, Labor Market, and Land Market

To understand the mechanisms by which the influx of remote workers affects local residents beyond the reduced-form results, to quantify the welfare effects, and to evaluate policy counterfactuals, I develop a local economy model. I generate two equilibria (the baseline equilibrium and the post-equilibrium under the program regime) and then compare the two.

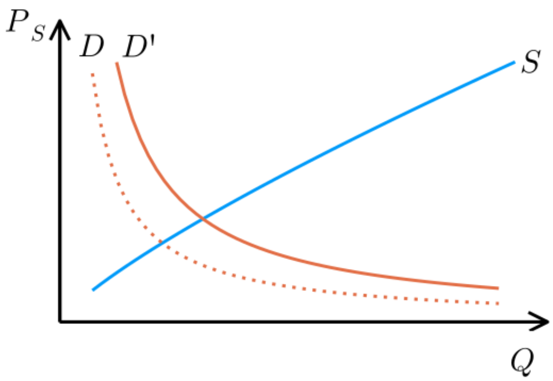
Model Intuition. I illustrate how the model operates using Figure 7, emphasizing the economic aspects of incoming remote workers: they are *not* employed within the local economy but still consume goods in the local economy. Therefore, remote workers themselves do not directly shift the local labor supply, even though they move in and work, in contrast to classic settings (Card, 1990; Borjas, 1994). This leads to heterogeneous impacts on local residents across different industry sectors. Newly arrived remote workers increase demand for local service goods ($D \to D'$ in panel (a)), increasing labor demand in the same sector ($D \to D'$ in panel (c))—i.e., *the direct effect*. However, the increased consumption of tradable goods by remote workers (in panel (b)) does not lead to increased labor demand in the tradable sector because the price remains constant, being determined outside of the local economy. Instead, the increased labor demand in the local service sector induces workers in the tradable sector to switch their industry sector, shifting the labor supply curve to the left ($S \to S'$ in panel (d) and subsequently $S \to S'$ in panel (c) due to the change in relative wage)—i.e., *the indirect effect*. The land demand curve also shifts to the right ($D \to D'$ in panel (e)), raising the land price along the supply curve.

Key Parameters. The model is mainly governed by, but not limited to, three sets of parameters. The first set includes parameters that produce the elasticity of labor supply in the extensive margin (between nonemployed and employed) and in the intensive margin (between the local service sector and tradable sector), which correspond to the slope of the labor supply curve in panel (c) in Figure 7. These parameters (later introduced as σ, ρ_h, and ρ_l) together determine how workers are reallocated following an increase in labor demand in the local service sector.

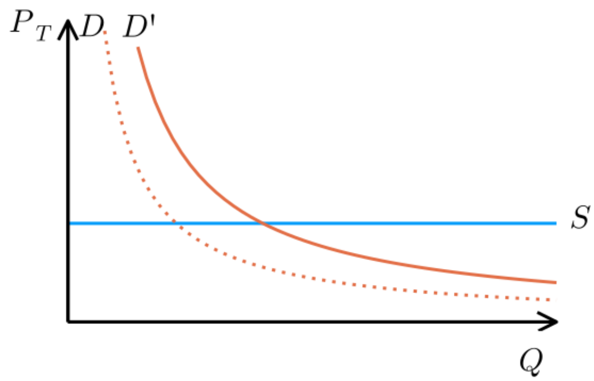
The second is the elasticity of the labor demand in the tradable sector, which can be found in panel (d) in Figure 7 and later introduced as θ_T. This parameter is crucial due to the labor supply substitution

Figure 7: Illustration of A Local Economy Model: Goods Market, Labor Market, and Land Market

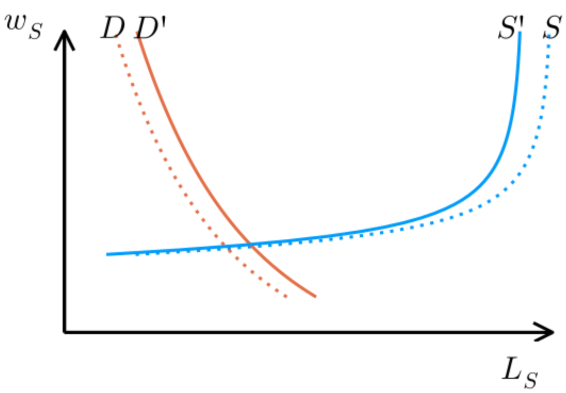
(a) Local Service Goods Market



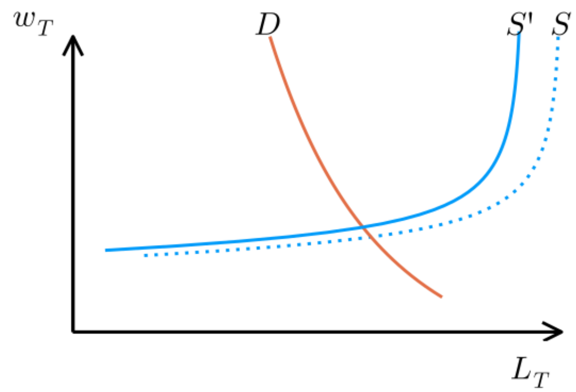
(b) Tradable Goods Market



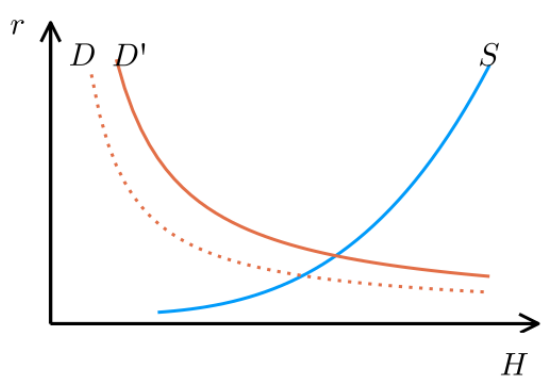
(c) Local Service Labor Market



(d) Tradable Labor Market



(e) Land Market



Notes: The five panels illustrate five local markets for local service goods in panel (a), tradable goods in panel (b), labor in the local service sector in panel (c), labor in the tradable sector in panel (d), and land in panel (e). The price of tradable goods is determined externally, indicated by the horizontal line in panel (b). The dashed lines indicate previous demand or supply curves without the program. The graphs are quantitatively computed to closely follow the model equations presented later. However, these graphs abstract from skill heterogeneity and the monopolistic competition setting in the local service goods market to convey the intuition in a simple way.

behavior of workers switching from the tradable sector to the local service sector. In other words, depending on the elasticity of the labor demand of tradable firms, the extent to which wages increase for the remaining tradable workers is determined; for example, if the labor demand of tradable firms is perfectly elastic, there would be no wage change in the spirit of factor price equalization (Samuelson, 1948). On the other hand, if the city mainly produces intermediate tradable goods, instead of final tradable goods, this can imply a downward-sloping labor demand curve (Rossi-Hansberg, Sarte and Schwartzman, 2019).

The final set is the elasticity of housing supply (later notated as γ), as it governs the extent to which housing prices increase as a result of the increase in housing demand driven by remote workers.

I now detail each component of the model, beginning with the workers (the first set of local residents),[34] local service firms and tradable firms, and immobile landlords (the second set of local residents).

5.1 Local Residents: Workers

Labor Supply. Worker i of a given skill type $e \in \{h, \ell\}$ (high or low) in a city chooses a working sector $k \in \{\phi, S, T\}$ (nonemployment, local service sector, or tradable sector).[35] The worker i's problem is:

$$\max_{k\in\{\phi,S,T\}} U_{i,e,k} = \max_{k\in\{\phi,S,T\}} \Big\{ \overbrace{V_{e,k=\phi} + \xi_{i,e,k=\phi}}^{\text{Nonemployment}(\phi)}, \overbrace{\overbrace{V_{e,k=S} + \xi_{i,e,k=S}}^{\text{Service sector}(S)}, \overbrace{V_{e,k=T} + \xi_{i,e,k=T}}^{\text{Tradable sector}(T)}}^{\text{Employment}(W)} \Big\} \tag{3}$$

where $V_{e,k}$ is the utility observed from consumption, and $\xi_{i,e,k}$ represents the unobserved taste of each choice between nonemployment ($k = \phi$), working in the local service sector ($k = S$), and working in the tradable sector ($k = T$). Specifically, the distribution of $\xi_{i,e,k}$ has a nested logit structure (McFadden, 1978; Berry, 1994; Cardell, 1997), characterized as follows:

$$\xi_{i,e,k} = log\mu_{e,k} + \sigma \cdot (\zeta_{i,j(k)} + (1-\rho_e) \cdot \varepsilon_{i,j,k}) \tag{4}$$

where $\varepsilon_{i,j,k}$ is drawn from a Type 1 Extreme Value distribution.[36,37] Then, $\xi_{i,e,k}$ is correlated across the working sectors ($k \in \{S, T\}$) in the same group $j = W$, where the correlation is indicated by $0 \leq \rho_e < 1$.[38] As $(1-\rho_e)$ goes to one, the within-group correlation of idiosyncratic shocks goes to zero, and as $(1-\rho_e)$

[34] In the model, all workers are renters who do not own land but spend a certain portion of their income on housing. In the data, workers make payments for rent or mortgage fees.

[35] In the model, the distinction between the local service sector and the tradable sector is based on the non-tradability of produced goods. Non-tradable, local service goods are all consumed in the local economy where they are produced. Tradable goods can be shipped around. In the data, the local service sector corresponds to two-digit NAICS codes 72 (Accommodation and Food Services) and 81 (Other Services), while the tradable sector includes the rest.

[36] The cumulative density function of $\varepsilon_{i,j,k}$ is $Pr(\varepsilon_{i,j,k} \leq t) = e^{-e^t}$.

[37] Furthermore, $\zeta_{i,j(k)} + (1-\rho_e) \cdot \varepsilon_{i,j,k}$ follows a Type 1 Extreme Value distribution with the unique distribution of $\zeta_{i,j(k)}$.

[38] To be precise, the statistic $1-\rho_e$ is a measure of correlation, but the correlation is more complex than $1-\rho_e$ (Train, 2009).

approaches zero, the within-group correlation goes to one. The group $j=\phi$ is reserved for unemployment (outside option). Next, $log\mu_{e,k}$ is the mean shifter of the relative taste of working in the sector k to nonemployment, which is common across individuals within a skill type e.[39] I allow a different value of $log\mu_{e,k}$ across skill types to explain skill sorting patterns in the data.[40] Lastly, σ governs the elasticity of labor supply, especially in the extensive margin. The closed-form solutions for the shares of skill type e in the local service sector ($L^{supply}_{e,S}$), in the tradable sector ($L^{supply}_{e,T}$), and for not working ($L_{e,\phi}$) are expressed in Appendix D.1.

Conditional on working, workers are more likely to take local service jobs as the relative wage ($\frac{w_{e,S}}{w_{e,T}}$) or taste ($\frac{\mu_{e,S}}{\mu_{e,T}}$) of local service jobs to tradable jobs (of skill type e) on average increases. More workers are willing to take local service jobs if the variation of the idiosyncratic shocks (σ or $1-\rho_e$) is higher (more outliers).[41]

Consumption. A worker i of a skill type e who is working in a sector k consumes land (Q^H_{ek}), local service goods (Q^S_{ek}), and all the (other) tradable goods (Q^T_{ek}) while receiving a skill and sector-specific wage (w_{ek}) and paying the proportional tax (τ).[42] Thus, the after-tax income becomes $I_{ek}=(1-\tau\cdot\mathbf{1}\{\text{working}\}_k)w_{ek}$. If an individual does not work, he receives the unemployment benefit ($w_{e,k=\phi}$) and does not pay the income tax. The indirect utility of consumption (V_{ek}) is given by:

$$
\begin{aligned}
V_{ek}(I_{ek},r,P_S,\bar{P}_T) \quad &\equiv \quad \max_{Q^H_{ek},Q^S_{ek},Q^T_{ek}} \alpha^H_e\cdot logQ^H_{ek}+\alpha^S_e\cdot logQ^S_{ek}+(1-\alpha^H_e-\alpha^S_e)\cdot logQ^T_{ek} && (5)\\
&\qquad \text{s.t.} \quad r\cdot Q^H_{ek}+P_S\cdot Q^S_{ek}+\bar{P}_T\cdot Q^T_{ek}=(1-\tau\cdot\mathbf{1}\{\text{working}\}_k)w_{ek}=I_{ek} && (6)\\
&= \quad log\left(\frac{I_{ek}}{(r)^{\alpha^H_e}\cdot(P_S)^{\alpha^S_e}\cdot(\bar{P}_T)^{1-\alpha^H_e-\alpha^S_e}}\right)+Const. && (7)
\end{aligned}
$$

The price for land (r) and the price index for local service goods (P_S) are determined within the city. In contrast, the price for tradable goods ($\bar{P}_T$) is fixed, because the city is small enough to take it as given. Additionally, α^H_e represents the share of income spent on land, α^S_e on local service goods, and $(1-\alpha^H_e-\alpha^S_e)$ on tradable goods. The consumption shares are heterogeneous in skill type.[43]

[39] The value of $log\mu_{e,k=\phi}$ is normalized to zero.

[40] For example, 4.52% of the high-skilled workers work in the local service sector, while 7.32% of the low-skilled workers work in the local service sector. On the other hand, 63.44% of the highly skilled workers work in the tradable sector, but 40.43% of the low-skilled workers work in the tradable sector. Appendix Table C5 provides the details.

[41] As $L^{supply}_{e,T}>L^{supply}_{e,S}$ $(i.e., \mu_{e,T}w_{e,T}>\mu_{e,S}w_{e,S})$ holds in data, local service jobs are less desirable on average, considering both wage and non-wage amenity (taste) together.

[42] In the baseline equilibrium, I put $\tau=0$.

[43] It might be a strong assumption that individuals, given the same skill type, consume housing, local service goods, and tradable goods with the same shares. However, I argue that the effects of remote workers on local residents are primarily heterogeneous in terms of skill dimension due to their consumption patterns, with the other dimensions (such as age and gender) of secondary interest.

Local Service Goods Consumption. Workers have a constant elasticity of substitution (CES) preference for local service goods, which are a continuum of differentiated local goods (Dixit and Stiglitz, 1977):

$$Q_{ek}^{S} = \left(\int_{0}^{M_S} \left(q_{ek}(\omega)\right)^{\frac{\varepsilon-1}{\varepsilon}} d\omega \right)^{\frac{\varepsilon}{\varepsilon-1}} \quad \text{where} \quad \varepsilon > 1 \tag{8}$$

where $q_{ek}(\omega)$ is the amount of local service goods of a variety ω, M_S is the measure of varieties available, and ε is the elasticity of substitution. Given the share of consumption on local service goods (α_e^S), a worker of a skill type e in a sector k solves a constrained maximization problem.[44] The demand for local service goods of a variety ω is given by:

$$q_{ek}(\omega) = \left(\frac{p(\omega)}{P_S}\right)^{-\varepsilon} \times \frac{\alpha_e^S \cdot I_{ek}}{P_S} \text{ where } P_S \equiv \left(\int_{0}^{M_S} p(\omega)^{1-\varepsilon} d\omega \right)^{\frac{1}{1-\varepsilon}}, \; p(\omega) = p_S \text{ for } \forall \omega \tag{9}$$

where P_S is the price index for a bundle of local service goods. I assume that local service firms in the city share the same technology. Thus, local service firms are symmetric, setting the price at the same level (p_S), and thus $P_S = \left(M_S \cdot p_S^{1-\varepsilon}\right)^{\frac{1}{1-\varepsilon}}$ holds. Furthermore, a bundle of local service goods consumption in Equation (8) is expressed as:

$$Q_{ek}^{S} = \frac{\alpha_e^S \cdot I_{ek}}{P_S} = \frac{\alpha_e^S \cdot I_{ek}}{M_S^{\frac{1}{1-\varepsilon}} \cdot p_S} \tag{10}$$

Plugging $P_S = \left(M_S \cdot p_S^{1-\varepsilon}\right)^{\frac{1}{1-\varepsilon}}$ into Equation (7) gives the indirect utility of consumption as:

$$V_{ek}(I_{ek}, r, M_S, p_S, \bar{P}_T) = log\left(\frac{I_{ek}}{(r)^{\alpha_e^H} \cdot (M_S^{\frac{1}{1-\varepsilon}} \cdot p_S)^{\alpha_e^S} \cdot (\bar{P}_T)^{1-\alpha_e^H-\alpha_e^S}} \right) + Const. \tag{11}$$

More importantly, Equation (11) shows that a worker is better off with more varieties, and this tendency is strengthened when the elasticity of substitution is lower. This variety gain can be understood as the gains from increased choice or shorter distance to establishments (Couture, 2016), as I provide details in Appendix Figure C12. For example, if a small town does not have any Ethiopian restaurants, having an Ethiopian option benefits local incumbents.

5.2 Firms

There are two types of firms: local service firms and tradable firms. Local service firms produce a variety of goods that are consumed within a city, while a representative firm in the tradable sector produces tradable goods that are consumed across cities.

[44] See Appendix D.1 for details.

Local Service Firm. A measure M_S of symmetric local service firms, indexed by ω, each produces goods of variety ω using human capital input and land input. Under monopolistic competition, firms maximize their profits by choosing how much to produce, given the Marshallian demand function they face, as shown in Equation (9). The firm's problem is given by:

$$\pi_S(\omega) = \max_{p_S(\omega), y_S(\omega), \eta_S(\omega), h_S(\omega)} p_S(\omega) \cdot y_S(\omega) - \lambda_S \cdot \eta_S(\omega) - r \cdot h_S(\omega) - F \tag{12}$$

Here, λ_S is a human capital rental rate for one efficiency unit of labor in local service firms; $\eta_S(\omega)$ is the total human capital input; r is the land price; $h_S(\omega)$ is the land input; and F is a fixed operating cost.[45] The firm's production technology is given by:

$$y_S(\omega) = A_S \cdot \eta_S(\omega)^{\theta_S} h_S(\omega)^{1-\theta_S} \tag{13}$$

$$\text{where } \eta_S(\omega) \equiv l_{\ell S}(\omega) + \tau^S \cdot l_{hS}(\omega) \tag{14}$$

where A_S is a common total factor productivity for local service firms in the city. $l_{\ell S}(\omega)$ is the human capital input of low-skilled workers; $l_{hS}(\omega)$ is the human capital input of high-skilled workers; and τ^S is the relative efficiency labor of high-skilled workers in the production of local service goods compared to low-skilled workers ($\tau^S > 1$). Consequently, low-skilled workers receive $w_{\ell,S} = \lambda_S$ and high-skilled workers receive $w_{h,S} = \tau^S \cdot \lambda_S$. Note that high-skilled workers and low-skilled workers are perfectly substitutable with each other, with different levels of productivity and corresponding wages.

From the profit maximization condition, the price is a mark-up of the marginal cost:

$$p_S(\omega) = \left(\frac{\varepsilon}{\varepsilon - 1}\right) \cdot MC_S \tag{15}$$

where the marginal cost (which is also the unit cost) is given by (see Appendix D.2 for the derivations):

$$MC_S = \frac{1}{A_S} \cdot \left(\frac{\lambda_S}{\theta_S}\right)^{\theta_S} \cdot \left(\frac{r}{1-\theta_S}\right)^{1-\theta_S} \tag{16}$$

Local service firms have a certain degree of market power to set the price, resulting from consumers' preferences for differentiated goods. The lower the elasticity of substitution is, the higher the price that local service sector firms can set. Also, I assume that all local service sector firms in the city share the same total factor productivity (A_S), and they set the same price. The heterogeneity of local service firms within the local economy is characterized by the specialty of goods they produce indexed by ω.

[45] Note that local service firms have increasing returns to scale technology, as the average fixed operating costs decline as more output is produced. Therefore, no single firm wants to produce one more variety of goods. Similarly, no single variety is produced by more than one firm because consumers prefer to consume differentiated goods.

Under competitive labor and land markets, each firm's profit maximization condition gives:

$$\lambda_S \cdot \eta_S = \theta_S \cdot MC_S \cdot y_S \tag{17}$$
$$r \cdot h_S = (1-\theta_S) \cdot MC_S \cdot y_S \tag{18}$$

In other words, θ_S and $(1-\theta_S)$ are shares of the variable costs that are spent on labor and land (see Appendix D.2 for details).

Tradable Firm. Under perfect competition, a tradable firm produces tradable goods using local human capital input and land input. A tradable firm maximizes the profit given by:

$$\pi_T = \max_{Y_T, \eta_T, H_T} \bar{P}_T \cdot Y_T - \lambda_T \cdot \eta_T - r \cdot H_T \tag{19}$$

where $\bar{P}_T$ is the price of tradable goods, which is given. Y_T is the output of tradable goods, λ_T is a human capital rental rate for one unit of efficiency labor, η_T is the total human capital input, r is the land price, and H_T is the land input. The firm's production technology is:

$$Y_T = A_T \cdot \eta_T^{\theta_T} \cdot H_T^{1-\theta_T} \tag{20}$$
$$\text{where } \eta_T \equiv L_{\ell T} + \tau^T \cdot L_{hT} \tag{21}$$

where A_T is the total factor productivity for producing tradable goods. The human capital input (η_T) is from both low-skilled workers ($L_{\ell T}$) and high-skilled workers (L_{hT}) with a relative efficiency of labor of high-skilled workers to low-skilled workers ($\tau^T > 1$). Low-skilled workers receive $w_{\ell,T} = \lambda_T$, and high-skilled workers receive $w_{h,T} = \tau^T \cdot \lambda_T$ according to their human capital. High-skilled workers and low-skilled workers are perfect substitutes, with different levels of productivity and wages.

The firm's profit maximization problem gives:

$$\eta_T^d(\lambda_T; H_T) = \left(\frac{\bar{P}_T A_T \theta_T}{\lambda_T}\right)^{\frac{1}{1-\theta_T}} H_T \tag{22}$$

which implies a downward-sloping labor demand curve where the elasticity of labor demand is $-\frac{1}{1-\theta_T}$. Under competitive labor and land markets, the firms' profit maximization implies:

$$\lambda_T \cdot \eta_T = \theta_T \bar{P}_T Y_T \tag{23}$$
$$r \cdot H_T = (1-\theta_T) \bar{P}_T Y_T \tag{24}$$

Equations (23) and (24) show that θ_T share of revenue is spent on labor and $(1-\theta_T)$ share of revenue on land. Note that factor markets are cleared within the local economy, but the tradable goods market is not cleared within the local economy. Tradable goods can be imported to satisfy the excess demand in the city or exported to absorb the excess supply of the city.

Although the local economy model alone does not clear the tradable goods market, it is worth noting that the local economy cannot function as an autarky as long as local residents demand tradable goods from the outside. The local economy also needs to produce tradable goods to trade.

5.3 Local Residents: Immobile Landlords

The model assumes that the land in the local economy is owned by immobile landlords (Redding and Rossi-Hansberg, 2017; Monte, Redding and Rossi-Hansberg, 2018), who consume their land income locally. Specifically, landlords of each skill type e consume both local service goods and tradable goods with the renormalized consumption shares of $\frac{\alpha_e^S}{\alpha_e^S+\alpha_e^T}$ and $\frac{\alpha_e^T}{\alpha_e^S+\alpha_e^T}$ respectively, which implies homethetic preferences. Therefore, the indirect utility of a landlord (whose income is $I^{landlord}$) is given by:

$$V_e^{landlord}(I_e^{landlord}, P_S, \bar{P}_T) \equiv \max_{Q_e^S, Q_e^T} \left(\frac{\alpha_e^S}{\alpha_e^S+\alpha_e^T}\right) \cdot log Q_e^S + \left(\frac{\alpha_e^T}{\alpha_e^S+\alpha_e^T}\right) \cdot log Q_e^T \tag{25}$$

$$\text{s.t.} \quad P_S \cdot Q_e^S + \bar{P}_T \cdot Q_e^T = I_e^{landlord} \tag{26}$$

$$= log\left(\frac{I_e^{landlord}}{(P_S)^{\frac{\alpha_e^S}{\alpha_e^S+\alpha_e^T}} \cdot (\bar{P}_T)^{\frac{\alpha_e^T}{\alpha_e^S+\alpha_e^T}}}\right) + Const. \tag{27}$$

The aggregated land income is collected from workers, local service firms, and tradable firms. There is no price difference between residential and commercial floor space due to a no-arbitrage condition.

The developed land is supplied with an elasticity of land supply. The supply of land (H) in the location depends on the endogenous price of land (r) as well as the exogenous geographic characteristics of the location ($\bar{H}$):

$$H = \bar{H} \cdot r^{\gamma} \tag{28}$$

where $\gamma > 0$ is the land supply elasticity. If $\gamma = 0$, the land is perfectly inelastically supplied and if $\gamma \to \infty$, the land is perfectly elastically supplied.

5.4 Baseline Equilibrium

Armed with solutions to the local residents' problems (in Section 5.1 and Section 5.3) and firms' problems (in Section 5.2), equilibrium objects are achieved through market clearing conditions. This is a small, open, local economy model; thus, the price of tradable goods is taken as given. In contrast, the labor market is cleared in the local economy as I assume there are no commuters.[46] Before I fully describe the

[46] This is reasonable, considering the empirical fact that cities that have adopted Remote Worker Relocation Programs do not have a large number of commuters because these cities are isolated without many residential areas around. For example, the average one-way commute time is approximately 17.86 minutes for Tulsa residents but 25.63 minutes for all workers in

equilibrium, I show how the measure of differentiated goods is determined.

Proposition 1. *Measure of Differentiated Goods*
Under monopolistic competition, the measure of differentiated local service goods is determined by the free entry condition, which equates profits (revenue - factor costs) to fixed operating costs (see the proof in Appendix D.2).

$$M_S = \frac{\sum_e \alpha_e^S \cdot \bar{I}_e^{workers} + \sum_e \left(\pi_e^{landlord} \cdot \frac{\alpha_e^S}{\alpha_e^S + \alpha_e^T}\right) \cdot \bar{I}^{landlords}}{\varepsilon \cdot F} \tag{29}$$

where $\bar{I}_e^{workers}$ denotes the total income of workers in skill type e ($\bar{I}_e^{workers} = \sum_k I_{ek} \cdot L_{ek}$) and $\bar{I}^{landlords}$ denotes the total income of landlords ($\bar{I}^{landlords} = r \cdot H$). The total land supply in the city is H.

Equation (29) shows the relationship between the abundance of local service goods and the income spent on local service goods by local residents and landlords.[47] Furthermore, the measure of local service goods increases as the elasticity of substitution decreases. Intuitively, more firms are incentivized to enter the market if they can charge a higher markup, because consumers have a stronger preference for diverse goods. Lastly, the measure of local service goods increases when the fixed operating cost is lower. With a lower barrier, more firms are induced to enter the market.

The equilibrium condition is summarized below.

Definition 1. *Baseline Equilibrium*
Given taste parameters $(\sigma, \rho_e, \mu_{e,k})$, elasticity of substitution across local goods (ε), productivity (A_S, A_T), fixed operating costs (F), land supply $(\bar{H})$, and the total measure of workers 1, the equilibrium consists of prices $\{p_S, r, w_{e,k}\}$ and quantities $\{Q_S, H, L_{e,k}\}$. The equilibrium objects satisfy the following conditions:

1. *The labor supply in each sector satisfies Equations (45a), (45b) and (45c).*

2. *Local residents solve the utility maximization problem that determines the consumption demands of land, local service goods, and tradable goods (Equations (5), (6), (25), and (26)).*

3. *Local service firms solve the profit maximization problem which determines the price, the amount of production, the total human capital input, and land input (Equations (12) and (15)).*

4. *The measure of varieties for local service goods (M_S) is determined by the zero profit condition as shown in Equation (29).*

5. *Given the total income of workers and immobile landlords ($\bar{I}^{workers} = \sum_e \sum_k I_{ek} \cdot L_{ek}$ and $\bar{I}^{landlords} = r \cdot H$), the revenue of local service firms is equal to the expenditure on local service goods consumed*

the United States (source: 2011 ACS). Therefore, the program's effect on commuters is not the margin of interest.

[47] Note that they have a linear relationship. However, when the varieties of goods enter the utility function, it is in a concave way.

by workers and landlords. Thus, $p^*(\omega)$ solves

$$\int_0^{M_S} p(\omega)y(\omega)d\omega = \underbrace{\sum_e \alpha_e^S \cdot \bar{I}_e^{workers}}_{Workers} + \underbrace{\sum_e \frac{\alpha_e^S}{\alpha_e^S+\alpha_e^T} \cdot \left(\pi_e^{landlords} \cdot \bar{I}^{landlords}\right)}_{Landlords} \tag{30}$$

where $\pi_e^{landlords}$ is the distributed share of the total land income to landlord type e, which is given.

6. *The land market is cleared by equating the land supply to the land demand:*

$$H = \bar{H} \cdot r^\gamma = \underbrace{\sum_e \sum_k Q_{ek}^H \cdot L_{ek}}_{Workers} + \underbrace{M_S \cdot h_S}_{Local\ service\ firms} + \underbrace{H_T}_{Tradable\ firm} \tag{31}$$

7. *In addition to the land market clearing condition, the income of the landlords is equal to the sum of the consumption of the land paid by local workers, and the land costs paid by local service firms and tradable firms:*

$$r \cdot H = \underbrace{\sum_e \alpha_e^H \cdot \bar{I}_e^{workers}}_{Workers} + \underbrace{M_S \cdot (1-\theta_S)p_S y_S}_{Local\ service\ firms} + \underbrace{(1-\theta_T)\bar{P}_T Y_T}_{Tradable\ firms} \tag{32}$$

5.5 After Remote Worker Relocation Program

I now describe the post-equilibrium conditions where newly arrived remote workers consume in the city but do not supply labor within the city. The total subsidy amount given to remote workers is funded by a non-profit organization (through donations).

Definition 2. *Post-equilibrium*

1. *Relocated remote workers consume land, local service goods, and tradable goods by solving their utility maximization problem, similar to high-skilled local residents (the consumption shares are α_h^H, α_h^S, and α_h^T). The difference is that the income of remote workers is sourced from outside the local economy.*

2. *The demand for local service goods increases as relocated remote workers consume local goods. The Equation (30) now becomes:*

$$\int_0^{M_S} p(\omega)y(\omega)d\omega = \underbrace{\sum_e \alpha_e^S \cdot \bar{I}_e^{workers}}_{Workers} + \underbrace{\sum_e \frac{\alpha_e^S}{\alpha_e^S+\alpha_e^T} \cdot \left(\pi_e^{landlords} \cdot \bar{I}^{landlords}\right)}_{Landlords} + \underbrace{\alpha_h^S \cdot \bar{I}^{remote}}_{Remote\ workers} \tag{30'}$$

where $\bar{I}^{remote} (= \bar{w}_R \cdot L_R)$ is the total income of remote workers. The relative share of remote workers to local residents is denoted by L_R and their average income is $\bar{w}_R$.

3. *The increased demand for local service goods in Equation (30') leads to an increase in labor demand in the local service sector as shown in Equation (17).*

4. *The increased demand for local service goods also induces more local service firms to enter the market as described below:*

$$M_S = \frac{\sum_e \alpha_e^S \cdot \bar{I}_e^{workers} + \sum_e \left(\pi_e^{landowner} \cdot \frac{\alpha_e^S}{\alpha_e^S + \alpha_e^T}\right) \cdot \bar{I}^{landlords} + \alpha_h^S \cdot \bar{I}^{remote}}{\varepsilon \cdot F} \tag{29'}$$

   This illustrates how incoming remote workers can benefit local residents by sharing fixed operating costs. More population in the city boosting demand for local service goods induces more local service firms to open their businesses, competing for profits until existing firms' profits drop to zero. Consequently, a wider variety of local service goods is provided in the local economy.

5. *As the relative wage between three sectors (local service sector, tradable sector, and not working) in the post equilibrium changes (for example, $\frac{w_{e,S}^{post}}{w_{e,T}^{post}} > \frac{w_{e,S}}{w_{e,T}}$), the labor supplies are reallocated following Equations (45a), (45b), and (45c) with the post-equilibrium wages. The sector-switching behavior continues until the marginal worker becomes indifferent. For example, a marginal worker in the tradable industry sector is indifferent between staying in the tradable sector and leaving for the local service sector.*

6. *The demand for land increases as relocated remote workers also consume land. Equation (31) becomes*

$$H = \bar{H} \cdot r^{\gamma} = \underbrace{\sum_e \sum_k Q_{ek}^H \cdot L_{ek}}_{Workers} + \underbrace{M_S \cdot h_S}_{Local\ service\ firms} + \underbrace{H_T}_{Tradable\ firm} + \underbrace{Q_{remote}^H \cdot L_R}_{Remote\ workers} \tag{31'}$$

7. *Along with the land market clearing condition, the income of landlords is the sum of the land consumption paid for by local workers and remote workers, and the land costs paid by local service firms and tradable firms:*

$$r \cdot H = \underbrace{\sum_e \alpha_e^H \cdot \bar{I}_e^{workers}}_{Workers} + \underbrace{M_S \cdot (1-\theta_S) p_S y_S}_{Local\ service\ firms} + \underbrace{(1-\theta_T)\bar{P}_T Y_T}_{Tradable\ firms} + \underbrace{\alpha^H \cdot \bar{I}^{remote}}_{Remote\ workers} \tag{32'}$$

5.6 Model Discussion

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 considers the arrival of remote workers as exogenous and investigates the impacts of the program on the local incumbents' side. The welfare effects on remote workers can be understood with two institutional facts. First, from the perspective of local policymakers, the welfare of incoming remote workers is not a factor of concern when implementing the program. Second, incoming remote workers choose to relocate with the program. Therefore, it is straightforward that relocated remote workers benefit according to their revealed preference.

Local Residents Left Behind. The local economy model presented also does not prioritize studying the welfare effects of local residents in other cities from which remote workers have departed. The current literature (Althoff et al., 2022) provides empirical evidence that local service workers left behind may suffer from a declined local demand as high-skilled remote workers leave big cities. This suggests that the national welfare effects of this kind of policy can be mitigated. However, the theoretical micro-foundations of urban agglomeration economies (Duranton and Puga, 2004) imply that reallocating remote workers from large to small cities can lead to nationwide welfare improvement. This is because the 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.[48] Although exploring this avenue will be interesting, this set of people is less relevant in the context of RWRPs due to the programs' small size and relatively short histories so far.[49]

Varieties of Goods. The current way of modeling the varieties of goods incorporates the amenity channel in a stylized way and abstracts away from amenity heterogeneities in two dimensions. The first dimension concerns different categories of local service goods, such as hair salons, restaurants, and bars.[50] The second dimension is vertical heterogeneity among local service goods, ranging from high-end restaurants to fast-food restaurants. This modeling choice is mainly because the sample size has not been powerful enough to empirically investigate such heterogeneities in the effects of the program. The model does not differentiate these dimensions and takes them on average; instead, it allows for a different consumption share of local service goods by skill type. In this way, the model, at the very least, captures that the benefits of a wider variety of goods are greater for high-skilled workers than for low-skilled workers on average. 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.

Commuting. A recently expanding body of literature on quantitative spatial equilibrium models distinguishes between residential and workplace locations (Ahlfeldt et al., 2015; Redding and Rossi-Hansberg, 2017). This distinction is rooted in the idea that a shock to one location can have spillover effects on other

[48] For more details, refer to Figure 1 in Duranton and Puga (2004).

[49] For example, Kline and Moretti (2014*a*) study the effects of the Tenessee Valley Authority (TVA) program on both local and national economies. The TVA context is more pertinent to study the aggregate impact because of its extensive scale (described as the "big push" development strategy) and long-term analysis period (1970–2000).

[50] Almagro and Dominguez-Iino (2022) consider rich amenities, including touristic amenities, restaurants, cafe bars, food stores, non-food stores, and nurseries, as well as the rich demographic compositions of local residents. This analysis leverages the dramatic growth in tourists spread across Amsterdam, as well as rich amenities data.

locations, particularly when these locations are connected by bilateral commuting flows (Monte, Redding and Rossi-Hansberg, 2018). However, in the spirit of RWRPs, the cities to which my model is applied are isolated with small populations. As a result, commuting is not an important margin to consider when assessing the program's effects.[51,52]

6 Estimation Procedure and Results

I discuss the estimation preparation, identification, estimation process, and estimation results. The key estimation strategy is indirect inference (Gourieroux, Monfort and Renault, 1993). I use the causal estimates presented in Section 4 to uncover the model parameters.

6.1 Matching Model to Data

Table 4 summarizes the data used in estimation. Panel A reports the population share and average income by skill type (low and high), employment sector (local service sector, tradable sector, and nonemployment), and land ownership[53] in the city of Tulsa. The most recent year for which the city identifier for Tulsa is available in the ACS is 2011.[54] 'High-skilled' individuals are classified as having some college education, while 'low-skilled' individuals are classified as at most high school graduates. Row-wise, 'nonemployed' refers to individuals who reported not being employed (either unemployed or not in the labor force) and are renters.[55] 'Local service' comprises workers in industry sectors with NACIS codes 72 (Accommodation and Food Services) and 81 (Other Services), while 'tradable' includes workers in all remaining sectors. Finally, 'landowners' are individuals who own a house that is free and clear of a mortgage, or are individuals who own a house with a mortgage and are not working.[56] The sample in the ACS data is restricted to those who are over 18 years old and reside in the city of Tulsa. This process leaves me with 2,531 individuals.

[51] Indeed, I do not find any statistically or economically significant effects on the number of commuters into downtown Tulsa in the event study framework using LODES data.

[52] The migration margin is also not relevant in this context because there is no discernible change in Tulsa's population after accounting for the influx of remote workers.

[53] To match the model concept to the data, I use the variables 'OWNERSHP,' and 'MORTGAGE' in the ACS. Then, I categorize landowners as follows: (i) those who own the housing unit without mortgages, or (ii) those who own the housing unit and do not work. In this way, individuals who work and have mortgages or other lending arrangements despite owning the housing unit are classified as workers, not landowners. These individuals allocate a significant amount of their income to pay mortgage loans.

[54] The variable 'CITY' in the ACS defines the city of residence for households located in identifiable cities.

[55] For reference, the maximum amount of unemployment benefits in Oklahoma is $539 per week with a maximum duration of 26 weeks, resulting in a total of $14,014 per year. It is worth noting that the average incomes for the non-employed reported in Table 4 are below this maximum.

[56] In the welfare analysis part in Section 7, I include the version where wealth increase is accrued to mortgage payers who are working (in this case, homeowners).

Table 4: Data Moments and Event Study Estimates Used in Structural Estimation to Match the Model

A. Before Program (Source: 2011 1-year ACS)

	I. Share (%)			II. Income ($2011)		
	High-skilled	Low-skilled	Total	High-skilled	Low-skilled	Mean
Nonemployed	5.38	8.70	14.07	13879	9794	11503
				(13364)	(11301)	(12276)
Local Service	4.21	4.62	8.84	29414	17183	23250
				(30145)	(19359)	(25952)
Tradable	28.62	19.08	47.70	52613	28211	42885
				(58738)	(27017)	(50071)
Landowners	14.40	14.99	29.39	64787	20658	45907
				(83657)	(17387)	(67821)
	52.61	47.39	100.00	50816	24577	
				(60782)	(24799)	

B. After Program (Source: Tulsa Remote, ACS, and LODES, and YTS)

Description	Model Concept	Value	Source
Population increase	L_R	2.87%	Tulsa Remote, ACS
		[2.18%, 3.57%]	
Mean wage of Tulsa Remoters ($2019)	w_R	104,600	Tulsa Remote
Subsidy for Tulsa Remoters ($2019)	$Subsidy$	10,000	Tulsa Remote
Event study estimate (non-employment)	$\%\Delta L_\phi$	–1.16%	ACS
		[–2.18%, –0.12%]	
Event study estimate (local service employment, high)	$\%\Delta L_{h,S}$	3.52%	LODES
		[–1.04%, 7.97%]	
Event study estimate (local service employment, low)	$\%\Delta L_{l,S}$	8.28%	LODES
		[4.34%, 11.58%]	
Event study estimate (local service establishments)	$\%\Delta M_S$	4.38%	YTS
		[3.62%, 5.15%]	

Notes: Panel A summarizes the population share (the total population is normalized to 1) and the average income of each type, which are used to match the baseline equilibrium in the model. The data source is the 2011 1-year ACS, and the values are weighted using 'PERWT'. The standard deviations are reported in parentheses. Panel B summarizes some data moments (source: Tulsa Remote) and the event study estimates (source: ACS, LODES, and YTS), that help discipline the post-equilibrium objects. The 95% confidence intervals based on census tract-clustered wild bootstrap, are reported in brackets. Wages are all normalized to be 27839 ($2011) = 1 in the estimation process, i.e., $w_{\ell,T} = 1$. Three event study estimates ($\%\Delta L_\phi, \%\Delta L_{h,S}, \%\Delta L_{l,S}$) are used as targeted moments in indirect inference.

The second data set I use is Tulsa Remote data. It informs the size of the increase in consumption demand driven by incoming remote workers in the post-equilibrium. Specifically, I use two sets of information: (i) the number of Tulsa Remoters over time, along with their residential distribution, and (ii) their average income. By supplementing Tulsa Remote data with 5-year ACS estimates, I measure the influx of remote workers into downtown Tulsa as a 2.87% increase in population relative to the total number of incumbent residents in the downtown area. Next, the income of Tulsa Remoters on average is reported to be \$104,600 (in 2019 dollars), and the subsidy that Tulsa Remoters receive is \$10,000. Therefore, I calculate the total income added to the city by remote workers as $L_R \times (w_R + Subsidy) = 0.0287 \times (\$104,600 + \$10,000)$, with the total population in the city normalized to 1.

Finally, I use four auxiliary models that give four causal estimates (reported in panel B of Table 4). The first one estimates the percentage decrease in nonemployment. The next two models concern the percentage increase in employment within the local service sector, separately for high-skilled and low-skilled workers. Finally, I report the percentage increase in the number of local service establishments.

Translation of Downtown Effects to City Effects. The local economy model uses a city as a geographic unit, but the event study estimates are relevant to downtown Tulsa. Because the spatial unit of the treatment during the study period (2019) is not sufficiently large, I inevitably assume that the rest of Tulsa would have experienced the same effects if they were subjected to the same treatment size in the model estimation. With this assumption, I linearly extrapolate the treatment size and effects estimated in downtown Tulsa to the entire city.

Time Period. The post-equilibrium model describes long-run outcomes with prices and quantities fully adjusted, while the data moments in panel B of Table 4 show program effects after one year. To relieve the timeframe tension between the model and the data, I do not impose the zero-profit condition on tradable firms when solving the model in the post-regime.[57] Along the transition path, tradable firms will exit as they experience negative profits.[58]

6.2 Estimation Procedure

Externally Set Parameters. Panel A of Table 5 lists the externally set parameters, which are either not the primary focus of the model or less identifiable within the empirical setting of this paper. The values are validated by using the existing literature and publicly available data. For example, the expenditure shares for housing ($\alpha_h^H = 0.2$ and $\alpha_l^H = 0.33$) are taken from Davis, Ghent and Gregory (2021), who use the 2019 American Housing Survey. This is also in line with other literature, such as Davis and Ortalo-Magné (2011) and Ahlfeldt et al. (2015), who have 0.25 on average.

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

[57] However, I impose the zero-profit condition on local service firms given the empirical finding that the number of local service establishments increases after the program, satisfying the zero profit condition. This asymmetry can be understood by a different nature of local service firms from tradable firms; for example, mom-and-pop local service stores are arguably more flexible in entry and exit decisions without binding to headquarters' decisions.

[58] Here is recent anecdotal evidence that warehouses (tradable firms) are replaced by restaurants in downtown Tulsa: Molla, Rani, "Tulsa will pay you to live there. And you'll love it.," *Vox*, 12 June, 2023.

Weinstein, 2015).[59] Oh and Seo (2023) estimate the elasticity of substitution across *subsectors* within a sector (food, retail, others); Couture (2016) estimates the elasticity of substitution between *restaurants* using detailed restaurant and travel data;[60] Handbury and Weinstein (2015) estimates it as 9.6 for the *bread* product group. Given that local service goods encompass not only restaurants but also bars, hair salons, and cafes in this paper, I set $\varepsilon = 5.0$.

The labor shares in the Cobb-Douglas production output for the local service sector and the tradable sector are benchmarked using Valentinyi and Herrendorf (2008) in general. To be specific, I set $\theta_S = 0.8$ following Ahlfeldt et al. (2015). Although I do not model the capital market (i.e. there is no capital input in firms' production) as in Ahlfeldt et al. (2015), the operating fixed cost that local service firms pay can be understood as the capital cost. Taking this into account, the share of total revenue allocated to labor cost becomes $\frac{\varepsilon-1}{\varepsilon} \times \theta_S = 0.8 \times 0.8 = 0.64$, which aligns with the central number in the literature (e.g., Davis, Ghent and Gregory (2021)). I put $\theta_T = 0.67 \approx \frac{2}{3}$.

Jointly Estimated Parameters with Identification. Panel B of Table 5 summarizes 11 jointly estimated parameters using indirect inference. This is the just-identified case with 11 data moments summarized in Appendix Table E1. While they are all jointly estimated, the conceptual identification argument for each parameter with the most useful moment is as follows.

The scale parameter (σ) partially represents the elasticity of labor supply in the extensive margin, and this is informed by the non-employment decline after the program implementation ($\%\Delta L_\phi$). Each correlation parameter (ρ_h, ρ_l) governs the elasticity of labor supply substitution in the intensive margin between the local service sector and the tradable sector for each skill type. They are identified by the employment increase within the local service sector among high-skilled and low-skilled workers, respectively ($\%\Delta L_{h,S}$ and $\%\Delta L_{l,S}$).

The location parameters ($\mu_{h,S}, \mu_{l,S}, \mu_{h,T}, \mu_{l,T}$) represent the average taste for working in the local service sector and the tradable sector relative to nonemployment in each skill type. They are identified using the relative income ($\frac{w_{h,S}}{w_{h,\phi}}, \frac{w_{h,T}}{w_{h,\phi}}, \frac{w_{l,S}}{w_{l,\phi}}, \frac{w_{l,T}}{w_{l,\phi}}$) in conjunction with the employment shares ($\frac{L_{h,S}}{L_h}, \frac{L_{h,T}}{L_h}, \frac{L_{l,S}}{L_l}, \frac{L_{l,T}}{L_l}$).

The consumption share of local service goods for each skill type (α_h^S, α_l^S) is informed by the share of local service workers ($L_{h,S}, L_{l,S}$) along with their wages. Intuitively, the amount of local service goods consumed balances out the amount produced within this economy.

Human capital rental rates (τ^S, τ^T) are determined by the relative wage of high-skilled workers to

[59] In the trade literature, 4.0 is a commonly used elasticity of substitution, but local service goods are likely to have a different elasticity compared to internationally traded goods.

[60] Couture (2016) shows that the estimated elasticity of substitution generates much extra travel beyond the closest restaurant and substantial welfare gains.

low-skilled workers ($\frac{w_{h,S}}{w_{l,S}}, \frac{w_{h,T}}{w_{l,T}}$) in each sector.

Other Parameters. Some remaining parameters are readily estimated through model inversion (see panel C of Table 5). Without estimating the total factor productivities of local service firms and tradable firms separately, I estimate the ratio of these productivities along with the ratio of the price of local service goods to the price of tradable goods ($\frac{A_T \bar{P}_T}{A_S p_S}$) to be able to invert the efficiency wage in the tradable sector in the internal model estimation. Next, I use the total number of establishments (M_S) to estimate the fixed cost of local service firms (F). I allow the separate fixed operating cost of local service firms in the post-equilibrium (F_{post}) and this is identified by the increase in the total number of establishments in response to the influx of remote workers ($\%\Delta M_S$). This can be understood as each establishment needing to be equipped with more capital to serve more customers.[61] Lastly, I employ the housing supply elasticity (γ) provided by Saiz (2010) to estimate the land price (r_{post}) in the post-equilibrium. Given the increase in land demand driven by incoming remote workers, the housing supply elasticity dictates the extent to which land price increases in the post-equilibrium.

Estimation Process. I describe the estimation process step by step:

1. Given a set of potential parameters, I generate the baseline equilibrium, $\{L_{ek}, w_{ek}, p_S, M_S, H, r\}$.
2. I then generate the post-equilibrium $\{L'_{ek}, w'_{ek}, p'_S, M'_S, H', r'\}$ by adding demand for local service goods and land from remote workers.
   a. In the post-equilibrium, $w_{h,\phi}$ and $w_{l,\phi}$ do not change in response to the program shock.
   b. The amount of land used by tradable firms remains constant in the post-equilibrium.
3. By comparing the baseline equilibrium and the post-equilibrium, I calculate $\%\Delta L_\phi$, $\%\Delta L_{h,S}$, $\%\Delta L_{l,S}$, and $\%\Delta M_S$.
4. Finally, I iterate this inner loop process (steps 1-3) until I find a set of jointly estimated parameters where the model moments precisely match the data moments.[62,63]

Further details of the estimation process are described in Appendix E.1.

6.3 Estimation Results

Panel B of Table 5 presents the results of the estimation. To better interpret estimates, I convert them to the elasticities of labor supply in Table 6. The extensive margin column reports the elasticity of the *total*

[61] Imposing the same fixed cost in the post-equilibrium will increase the welfare benefits of local residents as an increase in the number of establishments will be greater.

[62] All data moments are exactly matched at least until the fifth decimal point. The total error sum is 2.03E-10 with a gradient of 6.39E-25 at the reported estimates.

[63] Computationally, I conduct a grid search to obtain sensible initial values and then use the Optim package in Julia with the Nelder-Mead algorithm for all of them to find the global minimum.

Table 5: Model Parameterization

Parameter	Description	Value	Evaluated by
	A. Externally Set Parameters		
I. Workers			
α_h^H	Consumption share for housing (high)	0.20	Davis, Ghent and Gregory (2021)
α_l^H	Consumption share for housing (low)	0.33	Davis, Ghent and Gregory (2021)
ε	Elasticity of substitution across local service goods	5.0	Oh and Seo (2023), Couture (2016), Handbury and Weinstein (2015)
II. Firms			
θ_S	Labor share in production (local service sector)	0.80	Valentinyi and Herrendorf (2008)
θ_T	Labor share in production (tradable sector)	0.67	Valentinyi and Herrendorf (2008)
	B. Jointly Estimated		
I. Workers			
σ	Variation of taste shock (scale parameter)	0.2259	$\%\Delta L_\phi$
		(0.2859)	
ρ_h	Correlation of taste shock across sectors (high)	0.0772	$\%\Delta L_{h,S}$
		(0.1596)	
ρ_l	Correlation of taste shock across sectors (low)	0.6323	$\%\Delta L_{l,S}$
		(0.1744)	
$\mu_{h,S}$	Mean taste of working in local service (high)	0.4628	$w_{h,S}/w_{h,\phi}$
		(0.0005)	
$\mu_{l,S}$	Mean taste of working in local service (low)	0.6241	$w_{l,S}/w_{l,\phi}$
		(0.0003)	
$\mu_{h,T}$	Mean taste of working in tradable (high)	0.3858	$w_{h,T}/w_{h,\phi}$
		(0.0002)	
$\mu_{l,T}$	Mean taste of working in tradable (low)	0.4277	$w_{l,T}/w_{l,\phi}$
		(0.0002)	
α_h^S	Consumption share for local service goods (high)	0.0705	$L_{h,S}$
		(0.0001)	
α_l^S	Consumption share for tradable goods (low)	0.0570	$L_{l,S}$
		(0.0001)	
II. Firms			
τ_S	Human capital rental rate in local service sector	1.7118	$w_{h,S}/w_{l,S}$
		(0.0003)	
τ_T	Human capital rental rate in tradable sector	1.8650	$w_{h,T}/w_{l,T}$
		(0.0005)	
	C. Others		
$(A_T\bar{P}_T)/(A_S p_S)$	Total factor productivity ratio × price ratio	1.2392	$w_{l,T}$
F	Operating fixed cost (baseline)	9.09E-06	M_S
F_{post}	Operating fixed cost (post)	9.27E-06	$\%\Delta M_S$
rent	Rent price	0.2803	ACS
$\text{rent}_{post}/\text{rent}$	Rent ratio	1.0084	Saiz (2010)

Notes: In panel A, the expenditure shares for housing (α_h^H, α_l^H) are taken from Davis, Ghent and Gregory (2021), who use the 2019 American Housing Survey. The labor shares in production for the local service sector and the tradable sector are taken from Valentinyi and Herrendorf (2008). In panel B, standard errors are reported in parentheses. The first three standard errors are based on bootstrap with 500 replications. The next eight standard errors are calculated using the standard sandwich formula with the numerically derived gradient. In panel C, rent (r) reports the annual rent on average (to be specific, calculated as monthly rent (the variable 'RENT' in ACS) $\times 12$ months on average using the weight, 'PERWT') with the normalized rent price (to $w_{\ell,T} = 1$).

relative labor supply with respect to the relative wage of *each* industry sector to not working, when all else equal. In other words, it is given by:

$$\frac{\partial log\left(\frac{L_{e,W}}{L_{e,\phi}}\right)}{\partial log\left(\frac{w_{e,k}}{w_{e,\phi}}\right)} = \frac{1}{\sigma} \times \frac{\left(w_{e,k}\mu_{e,k}\right)^{\frac{1}{\sigma(1-\rho_e)}}}{\left(w_{e,S}\mu_{e,S}\right)^{\frac{1}{\sigma(1-\rho_e)}} + \left(w_{e,T}\mu_{e,T}\right)^{\frac{1}{\sigma(1-\rho_e)}}} \quad \text{for } k \in \{S,T\} \tag{33}$$

The intensive margin column presents the elasticity of labor supply substitution between two sectors, which is given by:

$$\frac{\partial log\left(\frac{L_{e,S}}{L_{e,T}}\right)}{\partial log\left(\frac{w_{e,S}}{w_{e,T}}\right)} = \frac{1}{\sigma(1-\rho_e)} \tag{34}$$

The extensive margin elasticities reported in Table 6 differ from traditional labor supply elasticity (i.e., $\frac{\partial logL}{\partial logw}$) because they are derived using closed-form solutions within the nested logit structure imposed in the model. For example, a 1% increase in the relative wage of working in the local service sector corresponds to a 2.12% (2.20%) increase in the *relative* labor supply to not working for high-skilled (low-skilled) workers. On the other hand, a 1% increase in the relative wage of working in the tradable sector corresponds to a 2.31% (2.22%) increase in the *relative* labor supply to not working for high-skilled (low-skilled) workers. High-skilled workers are slightly more elastic to the wage increase in the tradable sector, but are slightly less elastic to the wage increase in the local service sector, compared to low-skilled workers.

The intensive margin elasticities of relative labor supply in response to relative wages are respectively 4.80 and 12.04 for high-skilled workers and low-skilled workers, respectively. This means that a 1% increase in the relative wage in the local service sector to the tradable sector corresponds to a 4.80% (12.04%) increase in the relative labor supply of the local service sector compared to the tradable sector for high-skilled (low-skilled) workers. Intuitively, the stronger correlation between working in the local service sector and working in the tradable sector for low-skilled workers compared to high-skilled workers results in the higher intensive margin elasticity for low-skilled workers.

Next, the location parameters ($\mu_{S,h}, \mu_{S,l}, \mu_{T,h}, \mu_{T,l}$) are all below 1, which indicates that both high-skilled and low-skilled workers prefer not working over working on average. Moreover, working in the local service sector is more attractive than working in the tradable sector for low-skilled workers ($\mu_{S,l} > \mu_{T,l}$), but not as much as for high-skilled workers on average.

Lastly, the consumption shares for local service goods (α_h^S, α_l^S) are estimated to be 0.0705 and 0.0570 for high-skilled and low-skilled workers, respectively. Using the Consumer Expenditure Survey (CEX) Interview Survey (2019Q1), I confirm that these estimates fall within reasonable ranges. On the lower end, the expenditure shares for food away from home in the last quarter are 0.0541 and 0.0444 for high-skilled and low-skilled workers, respectively. On the upper end, the expenditure shares for entertainment, in addition to food away from home, are 0.1073 and 0.0860 for high-skilled and low-skilled workers.

Table 6: Elasticity of Labor Supply

	Extensive Margin		Intensive Margin
	Local Service	Tradable	
High-skilled	2.12	2.31	4.80
Low-skilled	2.20	2.22	12.04

Notes: Table reports the elasticities of labor supply in both extensive and intensive margins. The derivations are in Appendix E.2. These estimates are slightly at the upper end of the range of estimates found in the previous literature (see details in Appendix Table E2).

7 Welfare Analysis

In this section, I use model estimates to examine the welfare effects of incoming remote workers on local incumbents. I partition local residents into twelve types defined by (i) skill type, (ii) working sector with and without the program, and (iii) land ownership, classified as follows:

- Among high-skilled residents (panel A in Table 7a): (a) always nonemployed workers, (b) newly employed workers, (c) always local service workers, (d) switchers, (e) always tradable workers, and (f) landowners who do not work;

- Among low-skilled residents (panel B in Table 7a): (a) always nonemployed workers, (b) newly employed workers, (c) always local service workers, (d) switchers, (e) always tradable workers, and (f) landowners who do not work

Always nonemployed workers ($\phi \to \phi$) are defined as those who always remain nonemployed regardless of the program implementation. Newly employed workers ($\phi \to W$) are those who are employed either in the local service sector or in the tradable sector with the program, but were not previously employed. Always local service workers ($S \to S$) are those who always work in the local service sector. Switchers ($T \to S$) are those who transition from the tradable sector to the local service sector. Lastly, always tradable workers ($T \to T$) are defined as those who work in the tradable sector in both regimes.[64] Among landowners, there are high-skilled and low-skilled individuals; the skill heterogeneity among landowners leads to different distributions of land income and different consumption patterns (preference). The share of each type is reported in columns (1)s of Table 7a.

[64] Alternatively, I can notate this using the standard treatment language (Imbens and Angrist, 1994; Heckman, Lochner and Taber, 1999). For example, if I use a pair notation (y_0, y_1), then nonemployed are expressed as (ϕ, ϕ), newly employed are (ϕ, W), and always local service workers are (S, S).

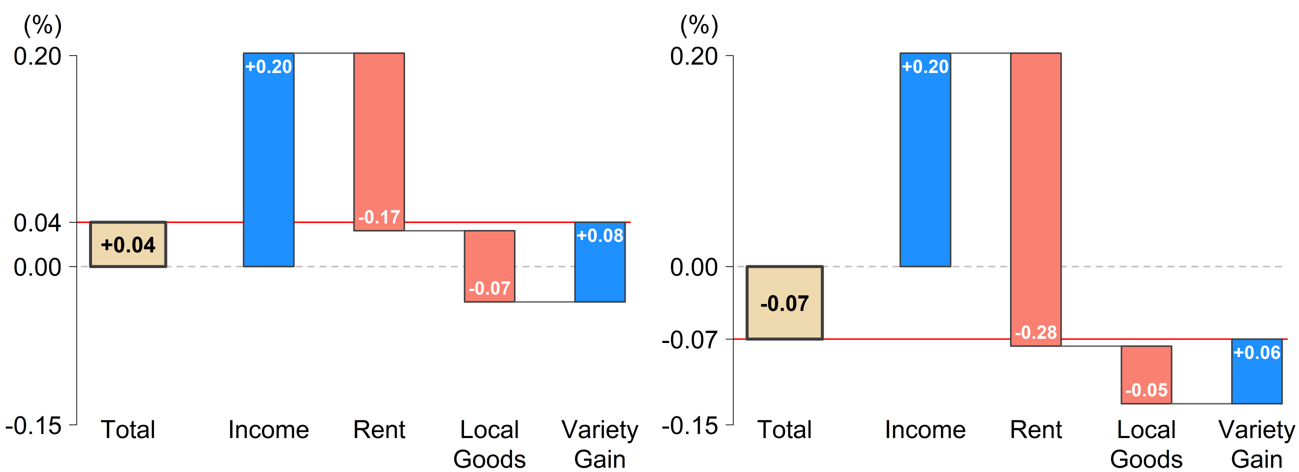
Table 7: Welfare Effect of the Influx of Remote Workers on Local Residents

(a) By Each Type

	A. High-skilled					B. Low-skilled				
	Share (%)	% Income	% CE/Income			Share (%)	% Income	% CE/Income		
			Baseline	$\bar{w}_T$	+Home Value			Baseline	$\bar{w}_T$	+Home Value
	(1)	(2)	(3)	(4)	(5)	(1)	(2)	(3)	(4)	(5)
(a) Always nonemployed	5.31	0.00	–0.16	–0.16	–0.16	8.59	0.00	–0.27	–0.27	–0.27
(b) Newly employed workers	0.06	209.70	0.11	–0.01	0.11	0.10	126.61	0.18	0.09	0.18
(c) Always local service workers	4.23	0.99	0.83	0.83	0.86	4.61	0.99	0.72	0.72	0.78
(% Homeowners)	(56.01)					(41.04)				
(d) Switchers	0.12	–43.54	0.43	0.43	0.43	0.33	–38.49	0.32	0.32	0.32
(e) Always tradable workers	28.48	0.20	0.04	–0.16	0.46	18.76	0.20	–0.07	–0.27	0.29
(% Homeowners)	(62.53)					(45.62)				
(f) Landowners	14.40	3.70	—	—	3.71	14.99	3.70	—	—	3.71
Total	52.61					47.39				
Weighted average		1.34	0.10	–0.05	1.33		1.35	–0.01	–0.12	1.22

(b) By Each Economic Component

A. High-skilled Renters Working in Tradable Sector   B. Low-skilled Renters Working in Tradable Sector



Notes: Panel (a) presents the share (%) of each type of local resident in column (1), the percentage change (%) in nominal income in column (2), and the percentage change (%) in consumption equivalence (CE) relative to baseline nominal income in three different scenarios in columns (3)-(5). Column (3) reports the welfare effects on workers who are all renters (baseline), column (4) explores the scenario where tradable sector wages do not change (factor price equalization), and column (5) incorporates the increase in home value by reporting the weighted welfare effects of both renters and homeowners. Consumption Equivalence (CE) is calculated as follows: $V(income + CE) = V'$. Panel (b) shows the results of the decomposition exercise for high-skilled renters in the tradable sector (0.04 in row (e) and column (3) in panel (a)-A) and for low-skilled renters in the tradable sector (–0.07 in row (e) and column (3) in panel (a)-B) as an example.

Equilibrium Effects. Column (2) of Table 7a summarizes the change in nominal income by type. Income of always nonemployed workers (e.g., unemployment insurance benefits) remains unaffected by the program (0.00%). Newly employed workers experience a remarkable increase in income as they begin working and receive employment income, either in the local service or tradable sectors. This increase is larger for high-skilled workers (209.70%) than for low-skilled workers (126.61%) because high-skilled workers are more likely to get jobs in the tradable sector where the increase in income is greater than in the local service sector. Always local service workers also experience higher income (0.99%) due to the increased labor demand in the local service sector. Switchers experience a drop in income, but their idiosyncratic taste shocks compensate for the difference. Their income loss (not welfare loss) is greater for high-skilled workers (–43.54%) than for low-skilled workers (–38.49%) because high-skilled workers are more likely to have previously worked in the tradable sector where the income was higher compared to the local service sector. Always tradable workers can achieve slightly higher income (0.20%) due to decreased labor supply.[65] Landowners also benefit from higher income (3.70%) due to increased land demand. Row-wise, the percentage change in nominal income is the same for both high-skilled and low-skilled individuals across the board, except for becoming employed workers and switchers. Overall, both high-skilled and low-skilled local residents experience comparable increases in nominal income (1.34% and 1.35%, respectively).

Moreover, all local residents experience higher prices for land (r) and for each local service good (p_S), in addition to the variety gain (M_S). Quantitatively, the prices for land and each local service good increase by 0.84% and 0.96%, respectively. The variety of local service goods, which is measured by the number of establishments, increases by 4.38%.

Welfare Effects. Columns (3), (4), and (5) of Table 7a present the welfare effects of each type of worker by considering the equilibrium effects in different scenarios.[66] Welfare is measured by the percentage of the consumption equivalence (CE) relative to the baseline nominal income. To calculate the consumption equivalence, I first decompose the indirect utility in Equation (11) as follows:

$$V_{ek}(I_{ek}, r, M_S, p_S, \bar{P}_T) = log(I_{ek}) - \alpha_e^H log(r) - \alpha_e^S log(p_S) + \frac{\alpha_e^S}{\varepsilon - 1} log(M_S) - (1 - \alpha_e^H - \alpha_e^S) log(\bar{P}) + Const. \tag{35}$$

Combining the above with Equation (3) gives

$$U_{i,e,k}(I_{ek}, r, M_S, p_S, \bar{P}_T) = V_{e,k}(I_{ek}, r, M_S, p_S, \bar{P}_T) + \xi_{i,e,k} \tag{36}$$

[65] In fact, this depends on the elasticity of labor demand, which is governed by the labor share parameter θ_T in tradable firms' production. However, I consider the alternative scenario in column (denoted as $\bar{w}_T$) in Table 7a where their income does not change (Samuelson, 1948).

[66] For newly employed workers and switchers, I simulate the idiosyncratic shocks and take the average of them.

Next, the definition of CE—i.e., $U_{ek}(I_{ek}+CE)=U'_{ek}$—gives:[67]

$$log\left(\frac{I_{ek}+CE}{I'_{ek}}\right)=-\alpha_e^H log\left(\frac{r'}{r}\right)-\alpha_e^S log\left(\frac{p'_S}{p_S}\right)+\frac{\alpha_e^S}{\varepsilon-1}log\left(\frac{M'_S}{M_S}\right)+\Delta\xi_{i,e,k} \tag{37}$$

$$\Longleftrightarrow\ \frac{CE}{I_{ek}}\approx log\left(1+\frac{CE}{I_{ek}}\right)=log\left(\frac{I'_{ek}}{I_{ek}}\right)-\alpha_e^H log\left(\frac{r'}{r}\right)-\alpha_e^S log\left(\frac{p'_S}{p_S}\right)+\frac{\alpha_e^S}{\varepsilon-1}log\left(\frac{M'_S}{M_S}\right)+\Delta\xi_{i,e,k} \tag{38}$$

Equation (38) shows that higher income $\left(\frac{I'_{ek}}{I_{ek}}\right)$ and a greater variety of local service goods $\left(\frac{M'_S}{M_S}\right)$ lead to a larger consumption equivalence. On the other hand, the higher land price $\left(\frac{r'}{r}\right)$ and the higher local service goods price $\left(\frac{p'_S}{p_S}\right)$ push down the consumption equivalence. For non-switchers, the difference between the unobserved taste remains zero ($\Delta\xi_{i,e,k}=0$).

However, the extent to which each component affects each type varies, resulting in different welfare implications. I provide Figure 7b as an example to illustrate how each economic factor plays out for high-skilled renters working in the tradable sector (in panel A) and low-skilled renters in the tradable sector (in panel B). They reach different conclusions regarding welfare effects (0.04% for high-skilled and –0.07% for low-skilled) despite both high-skilled and low-skilled workers experiencing the same increase in income (0.20%). To reveal the mechanisms behind this, I plot how each economic factor (rent, local service goods price, and variety gain, which correspond to each term in Equation (38)) is translated into the welfare effect for each type of worker. The increase in rents negatively affects low-skilled workers (–0.28%) more than high-skilled workers (–0.17%) because rents take a larger proportion of consumption for low-skilled workers. Conversely, price increases in local service goods have a more adverse effect on high-skilled workers (–0.07%) than on low-skilled workers (–0.05%) due to the larger consumption share of local service goods among high-skilled workers. Lastly, the benefits from the variety gain are greater for high-skilled workers (0.08%) than low-skilled (0.06%).

I turn to describe the comprehensive welfare results reported in columns (3), (4), and (5) under different scenarios:

- Column (3): renters where wages in the tradable sector increase as some workers shift from the tradable to the local service sector (baseline);
- Column (4): renters where wages in the tradable sector remain constant in the spirit of factor price equalization (Samuelson, 1948);
- Column (5): weighted average of renters and homeowners,[68] where wages in the tradable sector increase

[67] The CE for landowners can also be calculated in the same way, with the rent component omitted but the adjusted consumption shares applied.

[68] The percentages of homeowners among local service workers and tradable workers are respectively reported in the fourth and seventh rows in Table 7a.

From column (2) to column (3), higher rents, increased prices for local goods, and variety gains are incorporated into the welfare effects, in addition to the nominal income change (which Figure 7b is applied to). Both high-skilled and low-skilled nonemployed workers experience a decline in welfare (–0.16% and –0.27%, respectively) because they do not see an increase in income but face rising rents and prices for local service goods. Both high-skilled and low-skilled newly employed workers experience improved welfare (0.11% and 0.18%, respectively), primarily due to their higher income. For this group, the change in unobserved taste is also taken into account, as they switch their working sector. Both high-skilled and low-skilled always local service workers also experience enhanced welfare (0.83% and 0.72%, respectively), mainly driven by their higher income. Both high-skilled and low-skilled switchers experience welfare improvement (0.43% and 0.32%, respectively), which falls between that of always local service workers and always tradable workers. Intuitively, this group would not have switched if they had not experienced better outcomes, although not to the same extent as always local service workers.

In column (4), I keep wages in the tradable sector constant while holding everything else equal to column (3). As a result, workers in the tradable sector (including some newly employed workers and all always tradable workers) experience worse outcomes in column (4) compared to column (3). Other workers (nonemployed, always local service workers, and switchers) not tied to the tradable sector do not experience any change. In this scenario, both high-skilled and low-skilled renters are worse off on average as their income does not compensate enough for other negative effects such as rent increases. If each city faces the same tradable goods prices (because of trades) and uses the same technology for production, this ultimately results in wages being equalized across cities without migration of labor (Samuelson, 1948).

Moving from column (3) to column (5), I consider increased home value for homeowners (among workers in local service or tradable sectors) in addition to landowners (who are not working). By the classification of landowners who do not work and receive land income instead, there are no homeowners among nonemployed. In other words, all nonemployed workers are renters. Among always local service workers and always tradable workers, more than half of high-skilled workers are homeowners (56.01% and 62.53%, respectively) but less than half of low-skilled workers are homeowners (41.04% and 45.62%, respectively).[69] In the scenario where the increased home value is incorporated into homeowners' wealth, I exogenously add the home value into the income for this group in the baseline.[70] I then assume that home values increased in the same proportion as the rent increase in the post equilibrium.[71]

[69] I do not consider homeowners among switchers in column (5) to make the calculation simple. However, this simplification will have almost zero impact on the welfare result because this portion represents less than 0.3% of the total population ($0.12\% \times 0.6253 + 0.33\% \times 0.4562 \approx 0.23\%$).

[70] I take the average of home values for each type of worker using the 2011 ACS, which are as follows: \$162,308 for high-skilled always local service workers, \$194,402 for high-skilled always tradable sector workers, \$134,708 for low-skilled always local service workers, and \$103,259 for low-skilled always tradable workers. For the average income for each type of local resident, please see panel A in Table 4.

[71] One might argue that increased home value might not directly contribute to welfare improvement for homeowners unless

Furthermore, these homeowners do not face increased housing expenses (e.g., rising rents), but continue to pay fixed mortgage payments. I report the weighted welfare effect of renters and homeowners on average in rows (a)-(e) in column (5). Considering the increased home values, only the relevant groups to this factor (always local service workers and always tradable workers in rows (c) and (e)) experience an increase in welfare compared to the effects on other types reported in column (3).

All in all, high-skilled workers benefit more from the influx of remote workers induced by the program than low-skilled workers do, on average. This is because high-skilled workers, with a higher share of local service goods consumption, gain more from a wider variety of choices; high-skilled remote workers enhance the choice set of local service goods, which is more advantageous for high-skilled local residents. In contrast, the rise in housing prices negatively affects low-skilled workers more due to their higher expenditure share on housing compared to high-skilled workers. Additionally, increased home values benefit homeowners, the majority of whom are high-skilled workers. Consequently, despite both high-skilled and low-skilled residents experiencing an equivalent increase in nominal income (1.34% and 1.35%, respectively), the positive welfare effect is greater for high-skilled residents (1.33% for high-skilled and 1.22% for low-skilled). This leads to an increase in the welfare gap between the two groups.

8 Subsidizing Remote Workers through Taxation

While Tulsa Remote was readily funded by a non-profit organization, not every Remote Worker Relocation Program enjoys the same level of financial support. In most cases, the program is funded by taxes collected from local residents, sometimes with support from the state government. To examine this mechanism, I introduce a government problem that balances the annual tax revenue (the total taxes collected from both local residents and newly moved-in remote workers) with the program costs (the interest payment that the government rolls over and the annual fixed cost):[72]

$$\tau \times \Big(\underbrace{\sum_{e\in\{h,l\},\, k\in\{S,T\}} w_{ek} \times L_{ek}}_{\text{Workers}} + \underbrace{\sum_{e\in\{h,l\}} \pi_e^{landlords} \times I^{landlords}}_{\text{Landowners}} + \underbrace{w_R \times L_R}_{\text{Newly moved-in remote workers}} \Big) \tag{39}$$
$$= \underbrace{r \times (1.2 \times S) \times R(S) \times \frac{1}{o}}_{Interest\ payment} + \underbrace{(0.4 \times S) \times R(S) \times \frac{1}{o}}_{Annual\ fixed\ cost}$$

where τ is the proportional income tax rate paid by local workers, local landowners, and incoming remote

they sell their property and realize a cash gain, especially when their living conditions do not change. In this interpretation, the welfare calculations for homeowners can be understood as those of renters which are reported in column (3). Homeowners who are working do not pay rent but still have fixed mortgage payments.

[72] In Appendix F.1, I explore the welfare consequences with a government who pays the total installment payment upfront under the scenario that a government did not borrow.

workers, r is a 1-year municipality bond rate of 3.0%,[73] S is the subsidy amount, $R(S)$ is the number of newly relocated remote workers, which increases in S, and o is the remote workers' retention rate, 76%.[74] Referring to Table A2, I incorporate the total cost associated with bringing R number of remote workers. Under a linear relationship, 1.2 times the subsidy amount is spent on the one-time payment (including stipend, initial visit, and coworking space membership), and 0.4 times the subsidy amount is allocated annually for local events and staff salaries.[75] Finally, Equation (39) shows one tradeoff of attracting more remote workers: hosting more remote workers results in increased income remote workers bring to the city, but it also leads to a greater tax burden on local residents.[76]

The number of relocated remote workers is endogenous to the subsidy amount. I model this relationship by imposing the following functional form:

$$R(S) = R_0 \times \left(\frac{w_R + S}{w_R} \right)^{\psi} \tag{40}$$

Here, R_0 represents the number of base remote workers who reside in the city without the subsidy,[77] w_R is the wage of relocated remote workers, and S is the subsidy. The important parameter is the elasticity of the number of relocated remote workers in response to the relative income, which is denoted by ψ in Equation (40). I set $\psi = 3.3$ which is the responsiveness of location choice to utility in Monte, Redding and Rossi-Hansberg (2018). I provide a sensitivity analysis varying ψ in Appendix F.[78]

Figure 8 presents the counterfactual results while varying the subsidy amount. Panel (a) displays the percentage of remote workers moving to the city (relative to the total population of local residents) in response to the subsidy amount on the left y-axis, and the imposed proportional tax rate on local residents in response to the subsidy amount on the right y-axis. The proportional tax rate satisfies the government's balanced budget constraint. With a larger subsidy, more remote workers are induced to relocate, but local residents are required to pay a quadratically increasing tax rate to fund this influx. Panel (b) illustrates the weighted welfare impact of an influx of remote workers on local residents. As the subsidy grows,

[73] The source is: `https://www.municipalbonds.com/bonds/issue/899645ZS7/`

[74] To be accurate, the retention rate reported in Tulsa Remote data is about 76% with the survey response rate, 50%. Therefore, the maximum retention rate is 88% ($\approx 0.5 \times 76\% + 0.5 \times 100\%$) and the minimum retention rate is 38% ($\approx 0.5 \times 76\% + 0.5 \times 0\%$).

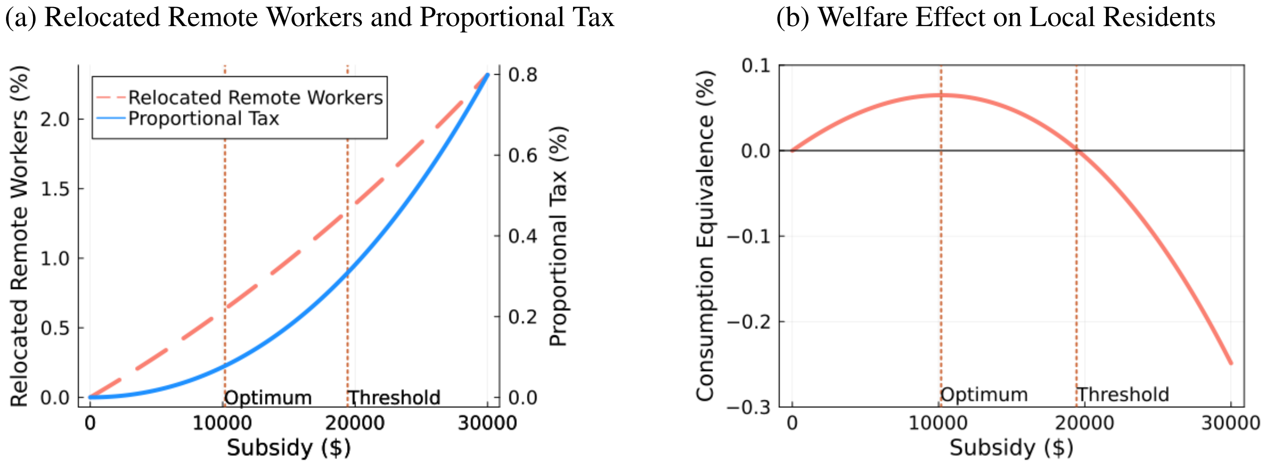
[75] This linear assumption can be validated after more data points from other programs are accumulated. I assume that the amount of program costs, other than the subsidy, linearly increases with the program quality, and the program quality determines the amount of remote workers attracted.

[76] Equation (39) also shows one back-of-the-envelop calculation that a local government can do: attracting remote workers can be beneficial to the local economy as long as the interest payment the government rolls over is smaller than the tax revenue that the government can collect from remote workers conditional on a fairly high retention rate but without any annual fixed cost.

[77] This is 1.69% of the total population in the city of Tulsa (source: 2011 ACS).

[78] In summary, this sensitivity exercise shows that neither the optimal subsidy level nor the subsidy threshold is significantly affected by using a different elasticity. In terms of the optimal welfare effect size, it ranges from 0.02% (when $\psi = 2$) to 0.13% (when $\psi = 10.45$).

Figure 8: Welfare Effect of a Remote Worker Relocation Program Subsidized by Local Tax



Notes: Panel (a) plots the relative relocated remote workers to the local residents (%) on the left y-axis and the proportional tax rate (%) on the right y-axis when the subsidy amount differs. Panel (b) plots the average welfare effect on local residents measured by the relative consumption equivalence to nominal income (%) and weighted by the population mass of each type, as the subsidy amount varies. Relocated remote workers are not included in this welfare calculation.

the benefit of bringing more remote workers becomes larger. More importantly, the welfare benefit of the program becomes reduced by 95% (0.065% at the subsidy amount $10.000) when financed by local residents. This stands in stark contrast to the actual Tulsa Remote, where the average welfare is enhanced by 1.28%, with the key difference being the financial burden on local residents.[79]

Figure 9 explores distributional aspects of the program. Panel (a) reveals uneven consequences of the program across skill types. High-skilled local residents are likely to reap larger benefits, as the increased home value is primarily capitalized on high-skilled homeowners and the variety gain is larger for high-skilled workers. Moving on to panel (b), I shed light on a potential principal-agent problem in program set-up. If a local mayor, who is often a high-skilled landowner, overlooks unequal impacts of the program on marginalized residents, such as nonemployed workers and low-skilled renters,[80] he can overexpand the program. As a result, local residents experience rather worse outcomes, resulting in a welfare loss of about –0.4% on average.

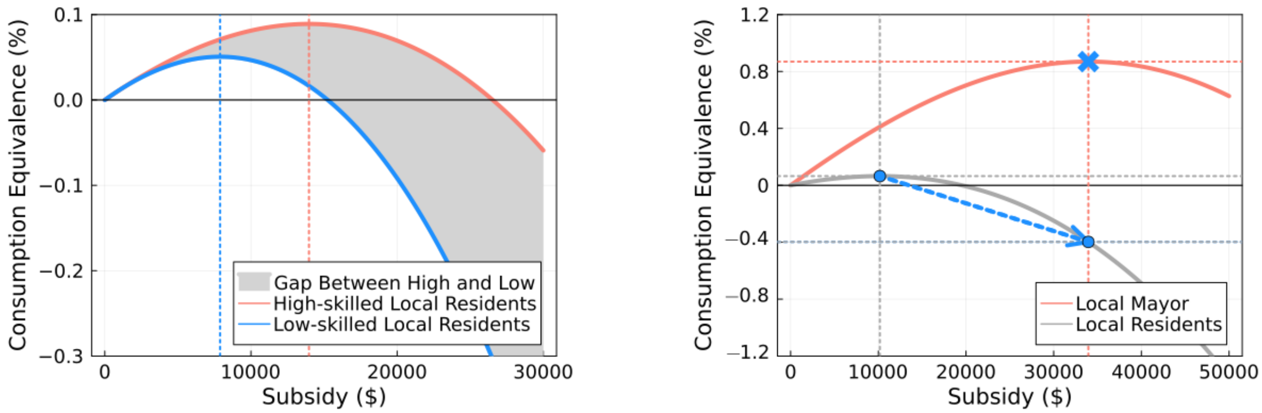
One might question why the local government does not directly provide cash transfers to local res-

[79] However, the counterfactual exercise cannot be directly compared to the actual Tulsa Remote case for several reasons. First, the actual Tulsa Remote program is not known to all remote workers, in contrast to the counterfactual scenario (information friction). Second, the Tulsa Remote program selects individuals who are likely to have higher incomes and stronger attachments to Tulsa (selection). Using the relative income in Equation (40) addresses the rationing of high-income individuals, but selecting stronger attachments to Tulsa is not endogenously modeled. This is simply reflected in the retention rate of 76%.

[80] This is not an unrealistic scenario. For instance, Choi, Kim and Kim (2022) find that congresspeople with more real estate assets in their portfolios are less likely to propose economic bills that tighten the real estate market.

Figure 9: Heterogeneous Welfare Effects of a Remote Worker Relocation Program Subsidized by Local Tax by Skill Type and Landownership

(a) By Skill Type (b) Principal-Agent Problem



Notes: Panel (a) plots the weighted welfare effect of the program on local residents by skill type (high-skilled and low-skilled), measured by the percentage (%) of consumption equivalence relative to nominal income. Panel (b) illustrates how the principal-agent problem in implementing the program can drive negative outcomes for local residents. If a mayor, who is likely to be a high-skilled landowner, focuses on his own interests, he is likely to set a larger subsidy amount (denoted as the second vertical line) than the desirable amount for the local resident on average (denoted as the first vertical line). This results in an average welfare loss of –0.4%.

idents instead of subsidizing remote workers. The benefit of subsidizing remote workers relies on the income they earn by working remotely, which is then brought into and spent within the local economy. By allocating $\$S$ per remote worker, the local economy can take additional $\$w_R$ on average. For instance, the average income of a remote worker ($\$104,600$) is about 10 times greater than the subsidy ($\$10,000$) paid to one remote worker, if such income level of relocated remote workers remains constant.

9 Conclusion

Over the last few decades, distressed areas in the United States and many other countries have struggled to generate economic growth due to various factors, including population loss, lack of investment, and geographic disadvantages. In an effort to revive these specific geographic areas, policymakers have explored place-based policies. Acknowledging numerous prior efforts, this paper contributes by investigating the welfare effects of one such policy, Remote Worker Relocation Programs. Crucially, this paper also offers direct empirical evidence on how the incoming remote workers affect local residents by using the understudied policy variation. This paper then extends the reduced-form results by building and estimating a structural equilibrium model. I find that incoming remote workers have the potential to benefit local residents in destination cities. It is also important to note that nonemployed individuals and renters working in the tradable sector are negatively affected.

However, this paper cautions that attracting remote workers should reflect on multiple factors: equilibrium effects, distributional effects, local economic conditions, and public finance perspective. For example, the asymmetric effect of remote workers between the local service sector and the tradable sector leads to labor reallocation from the tradable to the local service sector. Additionally, the program increases the welfare gap between high-skilled and low-skilled workers. Furthermore, local economic conditions, such as local industry composition and housing supply elasticity, play a key role in welfare calculations. Lastly, if local residents ultimately fund remote workers' relocation through taxes, this reduces the benefits they receive due to the tax burden.

I have left a few aspects for future work. First, this paper does not provide the welfare calculation for local residents in the remote workers' origin cities. The current literature (Althoff et al., 2022) provides evidence that local service workers left behind may suffer from a declined local demand as high-skilled remote workers leave big cities. This suggests that the national implications of this policy can be mitigated, but other sets of local residents in remote workers' origins are not included. Additionally, the theoretical micro-foundations of urban agglomeration economies (Duranton and Puga, 2004) imply that reallocating remote workers from large to small cities can lead to nationwide welfare improvement. Second, this paper does not consider dynamic aspects, such as the relocation of additional remote workers as well as other cities' dynamic responses. The welfare impact on local residents may vary depending on factors such as the retention rate of both remote workers and local residents, or remote workers' influence in drawing their families and friends. Other municipalities also can respond to this movement by proposing higher subsidies to remote workers, which may lead to a bad equilibrium in the national economy in the spirit of Slattery (2019). I anticipate that further research can provide valuable insights for shaping effective policy tools for broader individuals.

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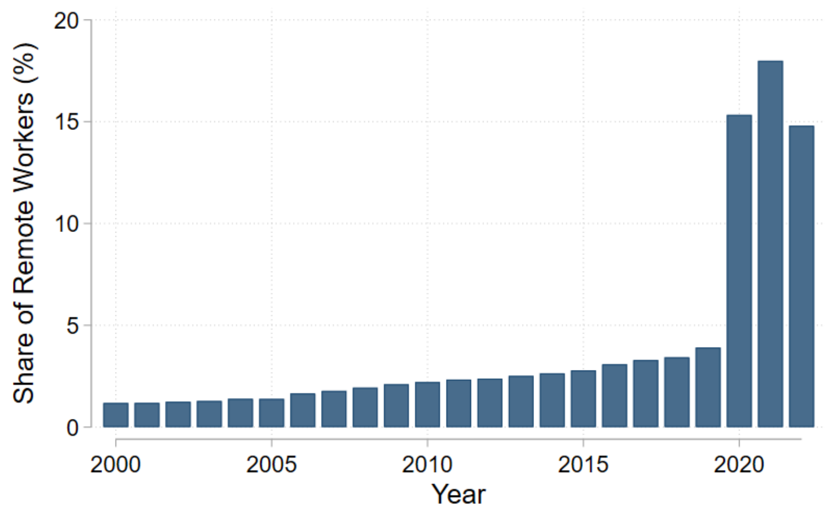
Appendices

A Supplementary Material to Section 2: Institutional Background

A.1 Increasing Trend of Remote Workers

Figure A1: Share of Remote Workers Over Time (2000-2022)



Notes: Remote workers are defined as those who primarily work from home, are more than 18 years old, are not self-employed, and are full-time workers (working $\geq$ 30 hours/week and $\geq$ 40 weeks/year). The share of remote workers is calculated as a percentage of those who are more than 18 years old, are not self-employed, and are full-time workers. The data source is American Community Survey (ACS).

A.2 Remote Worker Relocation Programs in the United States

Table A1: Remote Worker Relocation Programs in United States (September, 2022)

State	Place	Program Name	Start Year*	# of App.	# of Movers	Incentives	Funding Source	Eligibility
AK	Ketchikan	Choose Ketchikan[1]	November, 2021		15 (per one calendar year)	1. Permanent Fund Dividend ($2,000/person per year) 2. No added income tax 3. Fiber optic internet (3 months free) 4. No state sales tax	Ketchikan Chamber of Commerce	1. Must be over the age of 18 2. Must be a domestic US resident or foreign worker of a domestic corporation with full green card status 3. Live outside of Alaska (Alaska residents are not eligible, but former residents are). 4. Provide a W-2 showing earnings of $52,000 per year or more from a full time, remote-eligible employer. 5. Must commit to relocating to Ketchikan within 6 months of approval. 6. Must commit to volunteering 100 hours over the course of a year to share their talents with students or emerging leaders.
https://chooseketchikan.com/								
AL	Shoals	Remote Shoals	June, 2019	3000	87	1. Minimum annual income of $52,000 2. Able to move to the Shoals within 6 months 3. Full-time remote employment or self-employed outside Colbert and Lauderdale Counties 4. 18+ and Eligible to Work in the United States	Shoals Economic Development Authority and Shoals Industrial Development Committee	1. $10,000 cash
https://remoteshoals.com/								
AR	Northwest	Finding NWA's Talent Incentive[2]	November, 2020	66,000+	100	1. $10.000 cash (or Bitcoin) 2. Mountain bike	Northwest Arkansas Council	1. Must be at least 24 with 2 years of work experience 2. Must have full-time employment either remote or self-employed 3. Currently live outside of Arkansas 4. Can relocate within 6 months
https://findingnwa.com/incentive/								

State	Place	Program Name	Start Year*	# of App.	# of Movers	Incentives	Funding Source	Eligibility
GA	Savannah	Savannah Technology Workforce Incentive[3]	May, 2020		50 households/year	1. $2,000 cash	Savannah Economic Development Authority	1. Must be a self-employed, remote worker of technology firms located outside of Chatham county (at least 60 miles from Savannah City Hall), or relocating to take a position with a tech company in Chatham County 2. At least 3 years of verifiable experience 3. Be able to relocate with a minimum 1-year lease or purchase property in Chatham county 4. Be relocating to Chatham County for a minimum of two years
https://seda.org/resources-and-data/incentives-database/creative-incentive/								
HI	Honolulu	Movers and Shakas[4]	November, 2020	90,000 (Cohort 1)	50 (Cohort 1), 50 (Cohort 2)	1. $2,500 cash	Hawaii Executive Collaborative	1. Must be 18+ years old 2. Must live in the continental U.S. 3. Must work remotely and relocate for at least 30 days
https://www.moversandshakas.org/								
IL	Mattoon	Move to Mattoon	June, 2022	100 Inquiries (August 2022)	5 scheduled for 2022	1. $5,000 cash 2. $2,555 gift cards to local businesses 3. $500 voucher for local restaurants 4. Free six-month membership at the YMCA 5. Free 1-gigabit internet for six months from Consolidated Communications 6. 1 year free membership at Elevate	Mattoon in Motion, Mattoon Chamber of Commerce, Local businesses and non-profit organizations	1. Must be a remote worker that works for a a company. Gig-workers (ex: Uber) and self-employed individuals are not eligible. 2. The personal income must be over $45,000. 3. Must live 100 miles from Mattoon, IL and agree to move within 6 months of signing the MOU. 4. Must commit to living in Mattoon, IL for at-least two years. 5. Must agree to provide employment and residency documentation in order to determine eligibility.
https://movetomattoon.org/								
IN	Bloomington	Bloomington Remote	June 2021	150^+ (8 weeks in 2021)	20 (2022)	1. Three-year, full-time coworking membership at the Mill 2. Ambassador program 3. Relocation and real estate services 4. Community leadership opportunities 5. Community-building events 6. Priority banking services	Velocities, Mill with the support of the City of Bloomington and ARPA funds	1. Be 18^+ years old 2. Currently reside outside of Indiana 3. Have full-time remote employment (or self-employment) for a business located outside of Monroe County 4. Be able to relocate to Bloomington within the calendar year 5. Be eligible to live and work in the US
https://www.bloomingtonremote.com/								

State	Place	Program Name	Start Year*	# of App.	# of Movers	Incentives	Funding Source	Eligibility
IN	Daviess / Dubois / Greene County (Southern Indiana)	Choose Southern Indiana[5]	July 2021	$1,000^+$ (August, 2022)	27 (August, 2022)	1. $5,000 cash 2. Self-Guided Drive-Through Safari 3. Go Behind the Scenes at Patoka Lake Winery 4. One-Year Pass to West Boggs Park 5. Two Tickets to Dinner and Show at Abbeydell Hall	Radius Indiana	1. Must currently reside outside the state of Indiana 2. Must be willing to move to Southern Indiana within 6 months 3. Must be willing to stay in Southern Indiana for at least two years 4. Must be a fully remote worker 5. Must have a minimum household income of $40,000
https://www.choosesouthernindiana.com/remote-worker-program								
IN	Greensburg	Get Paid to Live in Greensburg	October, 2021	1,500 (first week)	2 (April, 2022)	1. $5,000 cash 2. "Grandparents on Demand" to babysit 3. YMCA Membership 4. Coworking space 5. Playhouse tickets	Greensburg / Decatur County Economic Development	1. Must relocate to Greensburg, IN within the next 6-12 months 2. Must have a remote position or be self-employed outside of Greensburg 3. Must be at least 18 years old 4. Must be eligible to work in the U.S.
https://www.makemymove.com/get-paid/greensburg-indiana								
IN	Henry County	Get Paid to Live in Henry County	September, 2022		20 (scheduled)	1. $5,000 cash	City of New Castle, Henry County	1. Must relocate to Henry County in 6-12 months 2. Must be self-employed or a full-time employee with remote work privileges 3. Must be 18 years or older 4. Must be a U.S citizen eligible to work in the U.S.
https://www.makemymove.com/get-paid/henry-county-indiana								
IN	Marion	Get Paid to Live in Marion				1. $5,000 cash		1. Must relocate to Marion within the next 6 months 2. Must be self-employed or a full-time employee with remote work privileges 3. Must be 18 years or older 4. Must be a U.S citizen eligible to work in the U.S.
https://www.makemymove.com/get-paid/marion-indiana								
IN	Muncie	Get Paid to Live in Muncie[6]	December, 2021	600 (May, 2022)	45 scheduled by 2023	1. $5,000 cash 2. Coworking space at the Innovation Connector 3. Recreational fitness pass at Ball State University 4. Access to the Ball State Iniversity library 5. Help Desk for connecting to local resources	City of Muncie, State of Indiana	1. Be a remote worker or self-employed 2. Be at least 18 years of age 3. Be eligible to work in the U.S. 4. Relocate to Muncie within the next 6-12 months
https://www.makemymove.com/get-paid/muncie-indiana								

State	Place	Program Name	Start Year*	# of App.	# of Movers	Incentives	Funding Source	Eligibility
IN	Richmond	Get Paid to Live in Richmond	June, 2022		20 (scheduled)	1. $5,000 cash 2. VIP Community Pass	Economic Development Corporation of Wayne County, Richmond Common Council	1. Must relocate to Richmond within the next 6 months 2. Must be self-employed or a full-time employee with remote work privileges 3. Must be 18 years or older 4. Must be a U.S. citizen eligible to work in the U.S.
https://www.makemymove.com/get-paid/richmond-indiana								
IN	Terre Haute	Get Paid to Live in Terre Haute	June, 2022		12 scheduled (for the first year)	1. $5,000 cash	City of Terre Haute, Indiana Economic Development Corporation	1. Must relocate to Terre Haute in 6-12 months 2. Must be self-employed or a full-time employee with remote work privileges 3. Must be 18 years or older 4. Must be a U.S citizen eligible to work in the U.S.
https://www.makemymove.com/get-paid/terre-haute-indiana								
IN	West Lafayette	Work from Purdue	May, 2021	300 (May, 2021)	28 (April, 2022)	1. Up to $5,000 cash 2. Coworking space discount ($1,800) 3. Chamber of Commerce Membership ($375) 4. Continued education discount ($200) 5. Purdue library membership 6. Free campus food and drink 7. Free city bus pass 8. Monthly networking events 9. Free programs by the Foundry 10. Care.com membership 11. Speaker series 12. Up to 10% off moving and storage with PODS	Indiana Economic Development Corporation, Purdue Research Foundation	1. Must have full-time remote employment 2. Must relocate to West Lafayette from outside of Indiana 3. Must possess U.S. citizenship or green card 4. Must be approved and selected by Purdue Research Foundation
https://www.workfrompurdue.com/								

State	Place	Program Name	Start Year*	# of App.	# of Movers	Incentives	Funding Source	Eligibility
KS	Topeka	Choose Topeka	December, 2019		Up to 60/year	1. Up to $5,000 for renters 2. Up to $10,000 for home buyers	Greater Topeka Partnership	1. Move to Topeka for full-time remote position 2. Purchase or rent a home, for primary residence, in Shawnee County within a year of move 3. Eligible to work in the U.S. 4. Limit one relocation incentive per household 5. Minimum 3 months waiting period 6. Remote employer must be located outside Shawnee County
https://choosetopeka.com/choose-topeka/								
KY	Owensboro	Grow the Boro	August, 2022		10 scheduled until 2024	1. $5,000 cash	Greater Owensboro Economic Development Corporation	1. Must be employed full time with a remote position 2. Must relocate to Owensboro within the next 6 months 3. Must be eligible to work in the U.S. 4. Must be 18^+ years old
https://www.makemymove.com/get-paid/owensboro-kentucky								
KY	Paducah	Remote Workers Incentive Program[7]	August, 2021	27 (August, 2022)	4 (August, 2022)	1. Up to $2,500 cash 2. Up to $70/month toward internet expenses for 12 months 3. Waiver of the City of Paducah's 2% payroll tax for 12 months 4. Community partner incentives	City of Paducah	1. Be 21 years old or older 2. Be a U.S. citizen, lawful permanent resident, or have other credentials necessary to work in the U.S. 3. Live at least 100 miles outside the limits of the City of Paducah at the time of application 4. Work full-time for a company in which all offices are located at least 100 miles outside the Paducah city limits 5. Be able to perform a majority of their employment duties remotely from a home office or coworking space located inside the Paducah city limits 6. Acquire primary residency in the City of Paducah within three 3 months of acceptance 7. Agree in writing to retain primary residence in the City of Paducah for at least one year beyond the initial twelve-month program 8. Not be a participant in any other publicly-funded program/initiative.
http://paducahky.gov/remote-workers#								

State	Place	Program Name	Start Year*	# of App.	# of Movers	Incentives	Funding Source	Eligibility
LA	Ruston	Welcome to Ruston	July, 2021	170 (July, 2022)	25 (July, 2022)	1. Must have full-time remote employment or are self-employed outside of Ruston 2. Minimum Annual Income of $52,000, or Family Income of $100,000 3. Can Move to Ruston within 6 months 4. 21+ and Eligible to Work in the United States	City of Ruston, economic development council	1. $10,000 grant awarded over a 3-year period 2. Free lifetime Alumni Foundation membership for returning Louisiana Tech University and Grambling State University graduates 3. Discounted University Athletic Events 4. Community Liaison to assist with move-in and community connections
https://www.welcometoruston.org/home								
MI	Southwest	Move to Michigan[8]	October, 2020		25 (for the first year)	1. $10,000 toward the purchase of the new home 2. $5,000 cash added if a child is placed into a public school 3. First choice community tour 4. About $5,000 in additional perks (2 options)	Cornerstone Alliance	1. Must provide proof of remote employment outside the state of Michigan 2. Must not be a current Michigan resident 3. Must purchase or build a home with a cost of at least $200,000 4. Must purchase or build a home in one of the following locations in Table Note 9 5. Must be considered a full-time Michigan resident, once moved 6. Must consider volunteering on a non-profit board, in local schools or participating in a civic organization in Berrien County.
https://movetomichigan.org/								
MN	Bemidji	218 Relocate Telecommuter Relocation Program	February 1st, 2021		50^{+} (Aug., 2022)	1. Up to $2,500 cash 2. One-year membership to the LaunchPad co-working space ($1,500 value) 3. Free access to the Community Concierge Program, connecting you and your family to the community 4. Teleworking support and tools through Effective Remote Work	Greater Bemidji	1. a full-time employee for a company headquartered outside of the region 2. Must be relocating from a distance of 60 miles or greater from the Bemidji area 3. Must be becoming a full time resident of the Bemidji area (56601 zip code) within one month 4. Must perform the majority (95-100%) of their employment duties remotely (from a home office or co-working space in the Bemidji area, such as the LaunchPad) 5. Must be obtaining internet services through Paul Bunyan Communications.
https://www.218relocate.com/relocation-incentive-package-2/								

State	Place	Program Name	Start Year*	# of App.	# of Movers	Incentives	Funding Source	Eligibility
MS	Natchez / Adams County	Shift South	February, 2021		24 (August, 2022)	1. Up to $2,500 reimbursement for documented relocation expenses 2. $300 stipend monthly for a period of one year	Natchez, Inc. Economic Development	1. Must be employed by an employer outside the Natchez region and have the ability to work remotely 2. Must establish primary residence within the City limits of Natchez, MS and purchase a home valued at no less than $150,000 3. Must maintain ownership and residency of their Natchez, MS home for no less than one year 4. Must be 18 years or older 5. Must be eligible to work within the United States
https://natchezinc.com/city-of-natchez-awards-first-shift-south-incentive/								
NY	Rochester	Greater Roc Remote[9]	February, 2022	500 (August, 2022)	25-30 (December, 2022)	1. $10,000 relocation incentive 2. Up to $9,000 in homebuyer incentives	ROC2025, the Rochester Industries Educational Fund	1. Must be a full-time remote worker 2. Must currently live 300+ miles from downtown Rochester 3. Must be at least 18 years of age 4. Must be able to relocate to Greater Rochester within 6 months of program acceptance 5. Must be eligible to work in the United States
https://www.greaterrocremote.com/program								
OK	Ponca City	Get Paid to Live in Ponca City				1. Coworking space 2. Chamber of Commerce membership 3. City Arts membership 4. Season pass to Ponca City school sporting events 5. Ponca City Leadership Program 6. 12 months free membership to the Ponca City Country Club		1. Must be relocating from outside of Ponca City 2. Must be able to bring your remote job with you
https://www.makemymove.com/get-paid/ponca-city-oklahoma								
OK	Tulsa	Tulsa Remote	November, 2018	33,190 (July, 2022)	About 1,900 (September, 2022)	1. Can move to Tulsa within the next 12 months 2. Full-time remote employment or are self-employed outside of Oklahoma 3. 18+ years old 4. Eligible to work in the United States	George Kaiser Family Foundation, Oklahoma State Government	1. $10,000 cash 2. Free one-year membership at 36 Degrees North coworking space 3. Local community events
https://tulsaremote.com/								

State	Place	Program Name	Start Year*	# of App.	# of Movers	Incentives	Funding Source	Eligibility
TN	Johnson City	Johnson City Remote program[10]	April, 2021	52 (May-June, 2021)	20-25 (first year)	1. $2,500 cash 2. $500 cash referral bonus 3. New bike (up to $500) 4. New spa or hot tub (up to $1,000) 5. Discounted coworking space (Spark Plaza)	Northeast Tennessee Regional Economic Partnership, Northeast Tennessee Tourism Association, Visit Johnson City	1. Must relocate to Johnson City within 6 months of acceptance 2. Need to be a full-time remote worker 3. Must have a minimum annual income of $50,000 4. Must be 24^+ and eligible to work in the U.S. 5. Must consent to a background check if accepted 6. Remote Workers in Greene, Washington, Carter, Johnson, Hawkins, Unicoi, Sullivan, and Hancock counties in Tennessee or Washington, Lee, Scott, Smyth, and Russell counties in Virginia are not eligible to apply.
https://visitjohnsoncitytn.com/remote-workers/								
TX	Beaumont	Beaumont remote worker program		0	0	1. One year membership for two to the Christus Health and Wellness Center ($2,000 value) 2. $500 off a new car or $300 off a used car at Philpott Motors 3. Free first-time pest control treatment 4. 1 year of free oil changes	Beaumont Economic Development Foundation	1. Must relocate to Beaumont within the next 12 months 2. Must have a remote work position or be self-employed 3. Must be 18 years or older 4. Must be eligible to work in the U.S.
https://www.bmtecon.org/copy-of-job-opportunities-rtu								
VT	Statewide	Remote Worker Grant Program[11]	January, 2019		435	1. $10,000 over two years 2. Coworking space	Vermont Agency of Commerce and Community Development	1. Must be a remote worker with a company located outside of the state 2. Must move to Vermont and stay for two years
https://thinkvermont.com/relocation-incentives/								
WV	Beckley	Beckley Remote	May, 2021		5 (2022) 5 (2023 scheduled)	1. $ 5,000 cash 2. Free outdoor recreation 3. Housing support 4. Free coworking space 5. Social programming	Beckley Common Council	1. Must relocate to Beckley within 6 months 2. Must have a full-time remote work position or be self-employed outside of the state of West Virginia 3. Must be 18 years or older 4. Must be eligible to work in the U.S.
https://liveinbeckley.com/								

State	Place	Program Name	Start Year*	# of App.	# of Movers	Incentives	Funding Source	Eligibility
WV	Morgantown, Greenbrier Valley, Eastern Panhandle, and Greater Elkins	Ascend West Virginia	Early 2020	$20,000^{+}$ (November, 2022)	98 (Morgantown), 37 (Greenbrier Valley)[12]	1. $12,000 cash over two years 2. Free outdoor recreation 3. Coworking space 4.Social programming	Donation by Brad D. Smith	1. Full-time remote employment 2. Have to relocate to the areas designated within six months of notification of acceptance 3. Be 18 years or older 4. Reside full-time outside of West Virginia and be a U.S. citizen
https://ascendwv.com/ https://governor.wv.gov/News/press-releases/2021/Pages/Ascend-West-Virginia-announces-inaugural-class-of-remote-workers.aspx								

Table Notes
* Start year indicates when the program was launched or announced.

[1] • Benefits: Once a remote worker becomes a resident of Alaska, the state will pay a program member after a year of residence. Every year, each Alaska resident will receive money from the Alaska Permanent Fund Dividend. The amount varies each year, but can be as high as $2,000 per person. • Selection process: The Ketchikan Chamber Remote Team reviews new applications at the beginning of each month. If an applicant is a monthly finalist, Choose Ketchikan sets up a video interview. If an applicant is qualified and highly motivated, the team may extend an invitation to you for an amazing, locally-curated, four-day Ketchikan experience.

[2] 89 trailing spouses/partners and children have moved along. The application process has ended. Northwest Arkansas Council also launched a partnership with Airbnb to help potential residents explore the region and "try before they buy."

[3] Eligibility criteria: Experienced technology workers with no fewer than three years of verifiable experience are eligible. The incentive is available to individuals who are choosing to relocate to Chatham County for a minimum of two years, and are self-employed or remote workers for technology firms located elsewhere (at least 60 miles from Savannah City Hall), as well as new hires of technology companies located in the region. To be eligible, participants must relocate to Chatham County with a minimum one-year lease or property purchase, and they must have resided in Chatham County for at least 30 days. Applicants must apply and provide verifiable receipts or other documentary proofs, such as a utility bill in their names and a Chatham County address or a valid Georgia driver's license.

[4] As the pandemic ravaged the tourism industry in 2020, a group of volunteer CEOs from different industries took it upon themselves to help the community and explore ways to build resilience in the economy. They created a temporary resident program to attract remote workers to actively contribute to Hawaii. Since then, two groups have run programs. The first cohort program was launched in late 2020, and the second cohort program was launched in early 2022. As of September 2022, the program does not accept applications anymore.

[5] To date, the Choose Southern Indiana initiative has received over 1,000 applications, and the 27 recipients along with their families account for more than 70 new residents, who will bring over $1.2 million in annual income to the communities. Additionally, an economic impact increase of over $750,000 can be attributed to this initiative, which measures revenue from property taxes, local household spending and other socioeconomic factors (source: Radius Indiana).

[6] The city and the state respectively contribute $250,000 to fund the program. The city's portion comes from the Mayor's Economic Development Income Tax (EDIT)

Funds.

[7] • Eligibility criteria: The availability of Remote work must be evidenced by written documentation from their employer. The primary residency in the City of Paducah must be evidenced by a lease with a physical address or a deed of conveyance of real estate which includes a home. • Funding and Marketing: The City has budgeted $100,000 for the incentives and marketing with the goal of reaching workers in the following cities: Atlanta, Georgia; Austin, Texas; Charlotte, North Carolina; Chicago, Illinois; Houston, Texas; and Louisville, Kentucky (Source: City Commission Meeting Highlights - July 27, 2021). • Approval: The Board approved an ordinance providing the criteria for the Remote Workers Incentive Program. The goal is to attract to Paducah approximately 25 full-time remote workers from 100 miles or more outside Paducah (Source: City Commission Meeting Highlights - August 10, 2021).

[8] Additional options include car service, an annual pass for the South Shore Rail, athletic club, economic club, practice golf, coworking space, two VIP passes to KitchenAid Senior PGA Championship, and an annual pass to Berrien County parks. • Eligibility Criteria: The following locations include the City of St. Joseph, the City of Benton Harbor, St. Joseph Charter Township, Royalton Township, Benton Charter Township, Oronoko Charter Township, Lake Charter Township, Lincoln Charter Township, or the Village of Stevensville. A full-time Michigan resident can be evidenced by Michigan driver's license or claiming Michigan home as primary residence.

[9] • Round 1 of Greater ROC Remote will serve as a pilot, with a recruitment target of 25-30 remote workers. Over the next three years, the program seeks to relocate up to 600 participants, not counting significant others, partners, and/or children that may also relocate with participants. • Eligibility criteria: "Greater Rochester Area" is defined as any area inside any of the New York state counties of Monroe, Genesee, Livingston, Ontario, Orleans, Seneca, Wayne, Wyoming, or Yates.

[10] Applicants earning $50,000 to $60,000 would receive $2,500 to move to the area, people earning $61,000 to $70,000 would receive $3,500 and people earning $71,000 to $80,000 would receive $5,000. If a remote worker refers a successfully accepted candidate into the program, a referer must also be a remote worker residing in the Northeast Tennessee region in order to receive the $500 referral bonus (Any remote worker currently residing in the counties of Greene, Washington, Carter, Johnson, Hawkins, Unicoi, Sullivan, or Hancock are eligible for a referral bonus of a successfully accepted candidate).

[11] Since 2018, the Vermont Legislature has created three different relocation incentives, awarding $1,780,000 to attract new residents to the state, bolster the workforce, and provide support to Vermont employers. In total, these three programs have assisted 435 new workers and their families in living and working in Vermont. After all funds for the first round were awarded on a first-come, first-served basis, applicants were notified in January 2020.

• 2018 New Remote Worker Grant Program: Enacted in 2018, Vermont's inaugural worker incentive program focused specifically on remote workers. With total funding of $500,000, grants of up to $10,000 (a maximum of $5,000 per year) were provided on a first-come, first-served basis to those becoming full-time residents of Vermont on or after January 1, 2019. To be eligible, an applicant was required to be a full-time employee of a business with its domicile or primary place of business within or outside Vermont who would perform a majority of employment duties remotely from a home office or a co-working space located in Vermont. This program's funds were exhausted by January 30, 2020.

• 2019 New Worker Relocation Incentive Program: In 2019, the state's second worker incentive program was enacted with an overall funding level of $670,000. Instead of focusing on remote workers, this program targeted relocating workers becoming full-time Vermont residents on or after January 1, 2020. On a first-come, first-served basis, this program provided base grants not exceeding $5,000, and enhanced grants not exceeding $7,500 for workers who relocated to certain economically distressed areas of the state. The ACCD reported that the program was fully subscribed as of October 7, 2020.

• 2021 New Relocating Employee Incentives Program: The newest incentive, enacted in 2021, combines elements of the first two programs, targeting new residents taking qualifying jobs with Vermont employers as well as new residents who will remotely for out-of-state employers. Relocating workers must become full-time residents on or after July 1, 2021, while remote workers must become full-time residents on or after February 1, 2022. Under this program, $480,000 is available for relocating workers, and $130,000 is available for remote workers. As with the New Worker Relocation Incentive Program, base grants cannot exceed $5,000, and enhanced grants for those locating in certain economically distressed areas of the state cannot exceed $7,500.

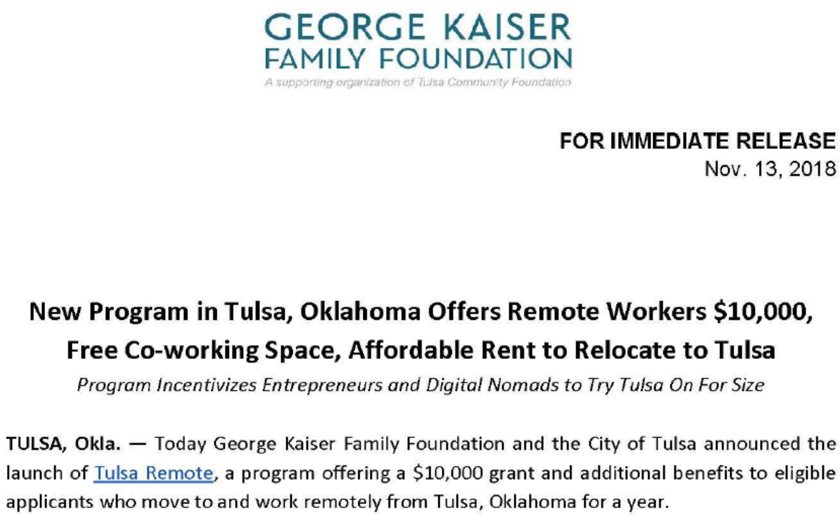
[12] The program plans to welcome more than 1,000 new remote workers to the state over the next five years. The program was founded through a $25 million gift to West Virginia University by Smith, the former executive chairman of Intuit, and his wife, Alys.

A.3 Tulsa Remote

This section describes how the Tulsa Remote program has been initiated and operated.

Figure A2: Tulsa Remote

(a) Press Release: Tulsa Remote Announcement



GEORGE KAISER FAMILY FOUNDATION

A supporting organization of Tulsa Community Foundation

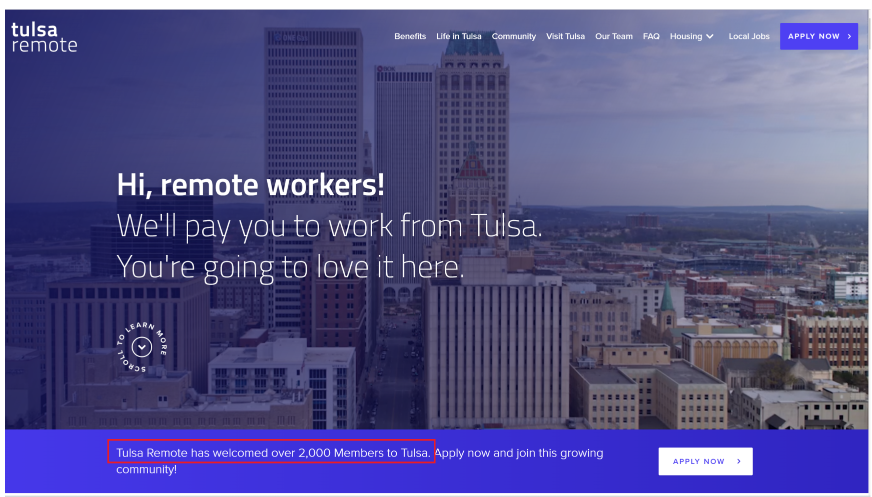
FOR IMMEDIATE RELEASE
Nov. 13, 2018

New Program in Tulsa, Oklahoma Offers Remote Workers $10,000, Free Co-working Space, Affordable Rent to Relocate to Tulsa

Program Incentivizes Entrepreneurs and Digital Nomads to Try Tulsa On For Size

TULSA, Okla. — Today George Kaiser Family Foundation and the City of Tulsa announced the launch of Tulsa Remote, a program offering a $10,000 grant and additional benefits to eligible applicants who move to and work remotely from Tulsa, Oklahoma for a year.

(b) Tulsa Remote Website



Notes: Panel (a) shows the press release that Tulsa Remote was announced in November 2018, and Panel (b) shows a snapshot of the Tulsa Remote website where remote workers can apply (source: Tulsa Remote, LLC (2023a)).

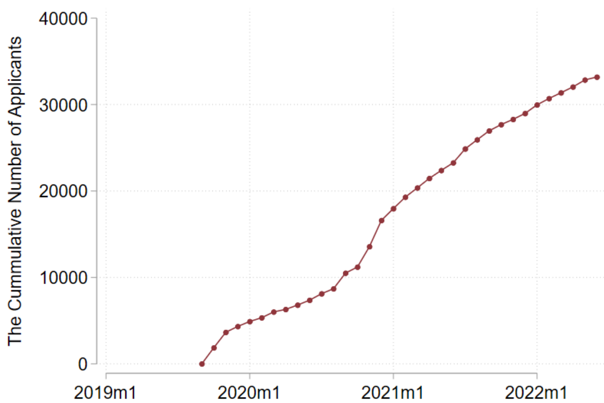
Table A2: Tulsa Remote Program Cost per Participant

Program Expenses	Estimated Cost
Stipend (Subsidy)	$10,000
Initial visit	$1.000
Coworking space membership	$1,000
Events and programming	$1,000
Program staff salaries	$3,000
Total	$16,000

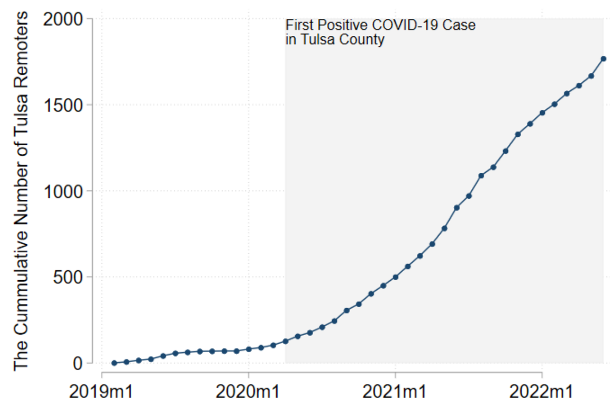
Source: Tulsa Remote

Figure A3: The Number of Applicants and Tulsa Remoters, and Program Selection

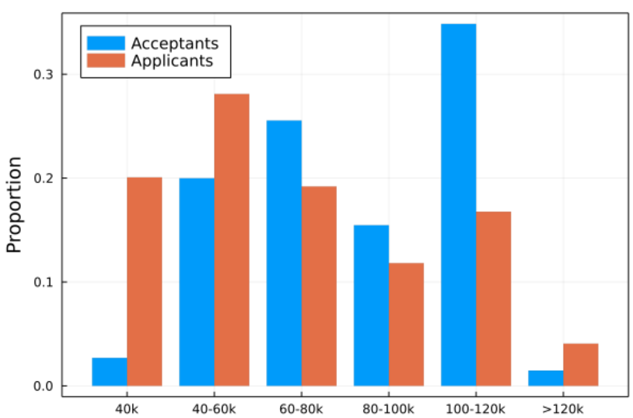
(a) The Cumulative Number of Applicants



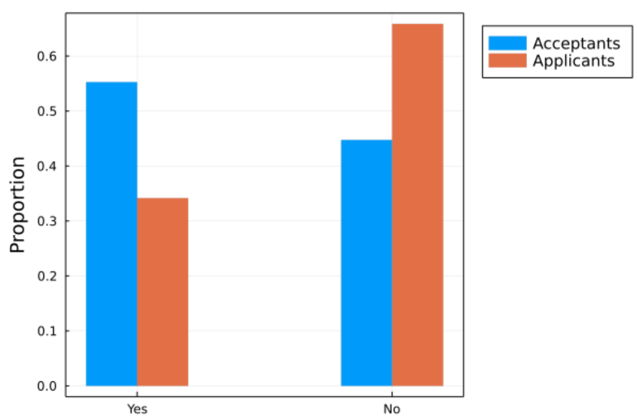
(b) The Cumulative Number of Tulsa Remoters



(c) Income Distribution



(d) Do you have friends/family in Tulsa?



Notes: Panel (a) shows the cumulative number of program applicants, and Panel (b) shows the cumulative number of Tulsa Remoters. The number of applicants before September 2019 is missing (Source: Tulsa Remote). Panel (a) shows the income distribution of the acceptants into the Tulsa Remote program and that of the applicants. Panel (b) shows the proportion of acceptants and applicants who answered 'yes' or 'no' to the question of "Do you have friends/family in Tulsa?"

Figure A4: Fieldwork: Documenting the Coworking Spaces (36 Degrees North)

(a) Basecamp: Entrance

(b) Basecamp: Board

(c) Basecamp: Meeting Booth

(d) Camp II: Meeting Room

Notes: 36 Degrees North has two locations in downtown Tulsa. The membership includes high-speed WiFi, free printing, copying and scanning, personal desks, and free coffee.

B Supplementary Material to Section 3: Data

I present a summary of the data used in this paper in Table B1 and elaborate on each dataset.

Table B1: Summary of Data Used in this Paper

Information of Interest	Main Objective	Year	Observation Unit
A. Tulsa Remote			
a. Summary statistics of Tulsa Remoters	Moments in structural estimation	2020-2022	Aggregate
b. Residential distribution of Tulsa Remoters	Variation in event study design	2020-2022	Zip code
B. American Community Survey (ACS)			
a. Summary statistics of remote workers	Descriptive	2017-2018	Individual
b. Population, income per capita, and non-employment in Tulsa	Event study design	2015-2019 (2021)	Census tract
c. Summary statistics of local residents in Tulsa	Moments in structural estimation	2011†	Individual
C. Current Population Survey (CPS)			
a. Consumption pattern of remote workers (Supplements)	Descriptive	April 2001	Individual
b. Industry sector switching behavior	Robustness	2014-2019	Individual
D. LEHD Origin-Destination Employment Statistics			
a. Employment (by workplace census tract) of local residents	Event study	2015-2019	Census tract
b. Origin-Destination linkage	Decomposition		Census tract
E. SafeGraph			
a. Consumption (total number of visits, visitors)	Event study	2015-2019	Place
F. YTS			
a. Total number of establishments	Event study	2015-2019	Establishment
G. FHFA HPI			
a. Housing price	Event study	2015-2019	Zip code

Notes: † The city variable for Tulsa is available until 2011. The income of local residents by sectors and skill types are CPI-adjusted to 2018.

American Community Survey (ACS). I use the ACS to examine both remote workers and local residents. The descriptive characteristics of remote workers are analyzed using individual-level 1-year ACS (2017-2018) before COVID-19. The summary statistics of local residents (in Panel A of Table 3) are derived from 5-year ACS spanning from 2011-2015 to 2014-2018. These 5-year ACS estimates are also utilized to estimate the population growth in downtown Tulsa after the program's implementation. Additionally, summary statistics of local residents within the city limit of Tulsa, such as labor share and income by sector and skill types, along with the shares of renters and homeowners, are employed as data moments to estimate the baseline equilibrium in structural estimation.

Current Population Survey (CPS) Supplements. The CPS Food Security Supplement (April 2001) and Work Schedules Supplement (May 2001) are equipped to examine the food consumption patterns of remote workers compared to non-remote workers. I link the remote work information from the Work Schedules Supplement to the food spending information from the CPS Food Security Supplement based on the CPS personal ID. By doing so, I contrast the food spending of remote workers to that of non-remote workers; however, I do not have information on the food spending of Tulsa Remoters, a selected group of remote workers. I note that the year in the analysis is 2001 because the CPS Work Schedules Supplement is not available for recent years. However, the nature of remote workers has not significantly changed in the last few decades before the COVID-19 pandemic.

Current Population Survey (CPS). I use CPS to understand the individuals' labor market status transitions and job-switching behavior between the local service sector and the tradable sector, on a monthly basis. Employing the 4-8-4 rotating pattern of the CPS, I construct a transition matrix for industry sectors at a monthly frequency as presented in Table C5.

LEHD Origin-Destination Employment Statistics. I use the LEHD Origin-Destination Employment Statistics (LODES) (U.S. Census Bureau, 2019) to examine the impact of the Tulsa Remote program on local employment. LODES is one of the statistical data products provided by the Longitudinal Employment-Household Dynamics (LEHD) program as the part of the Center for Economic Studies at the U.S. Census Bureau. Under the Local Employment Dynamics (LED) partnership, states agree to share Unemployment Insurance earnings data and the Quarterly Census of Employment and Wages (QCEW) data with the U.S. Census Bureau. Then the LEHD program combines these administrative data, additional administrative data, and data from censuses and surveys. The LODES data is organized into three components: Origin-Destination (OD), Residence Area Characteristics (RAC), and Workplace Area Characteristics (WAC). The OD data is about the number of jobs totaled by a home census block and a workplace census block, as well as by year, job type, and segment. The job type bins include all jobs, primary jobs, all private jobs, private primary jobs, all federal jobs, and federal primary jobs. The segments are workers by age ($\leq$ 29 years old, 30-54 years old, and $\geq$ 55 years old), earnings (< \$1250/month, \$1251-3333/month, > \$3333/month), and three industry groups (trades, goods, and services). The RAC/WAC data provides the number of jobs totaled by home/workplace census block, as well as by year, job type, segment, and demographic characteristics. The segments are workers by age, earnings, and two-digit NAICS code. Among the three, I use the WAC data for primary analysis to study the effect of remote workers on employment in their corresponding workplace and the OD data for additional analysis of employment changes in the workplace area by residents and commuters. Following Couture and Handbury (2020), I aggregate the job counts at the tract level to minimize the impact of noise infusion. The summary statistics of the number of jobs (headcounts) are provided in Panel B of Table 3, which covers the years 2015 to 2018.

SafeGraph. To detect the consumption effect of incoming remote workers in Tulsa, I use SafeGraph, a monthly data set available from 2018. SafeGraph offers information on consumer spending patterns by analyzing billions of anonymous and aggregated location data points generated by mobile devices. The key variables used are place latitude and longitude, NAICS code, and consumer visits from January 2018 to December 2019.

Your-economy Time Series. I also use the Your-economy Time Series (YTS) data to examine local business activity, thus bolstering the employment effect evidenced in the LODES data. The YTS is a yearly panel of U.S. establishments that conduct commercial activity and are in-business. The data is assembled using historical business files from Infogroup (currently known as, Data Axle) as underlying sources of information. I extract the total number of establishments by census tract and NAICS code from 2014-2019.

Housing Prices Data. I leverage Federal Housing Finance Agency (FHFA) Housing Price Index (HPI)

(Bogin, Doerner and Larson, 2019) to assess the impact of Tulsa Remote on housing price in Tulsa. The FHFA HPI provides an annual measure of changes in single-family home prices across the entire U.S., based on data provided by Fannie Mae and Freddie Mac. The analysis covers the period from 2015 to 2019, and the geographic unit of analysis is the zip code.

C Supplementary Material to Section 4: Descriptive and Reduced-Form Analyses

C.1 Table 2: The Food Consumption Patterns of Remote Workers

Linkage. The remote worker indicator (‘wswkhm’) comes from the CPS Work Schedules Supplement (May 2001), and the outcome variables (food spending) are based on the CPS Food Security Supplement (April 2001). Using the variable ‘cpsidp’, the remote work information can be linked to the observations in April 2001.

Variables Used. The variables taken from the CPS Food Security Supplement are: (i) ‘fsspdrest’ (the total amount spent by the household spent on food at restaurants in the past week), (ii) ‘fsspdmkt’ (the total amount the household spent on food at grocery stores or supermarkets in the past week), and (iii) ‘fsulxpns’ (the usual weekly amount a household spends on food). To be specific, the outcome variables of each column are as follows:

- Column (1): ‘fsspdrest’ being larger than 0
- Column (2): log(1+‘fsspdrest’)
- Column (3): log(1+‘fsspdmkt’)
- Column (4): log(1+‘fsulxpns)

The regressions are weighted by using ‘fssuppwth,’ the weight specific to the Food Security Supplement.

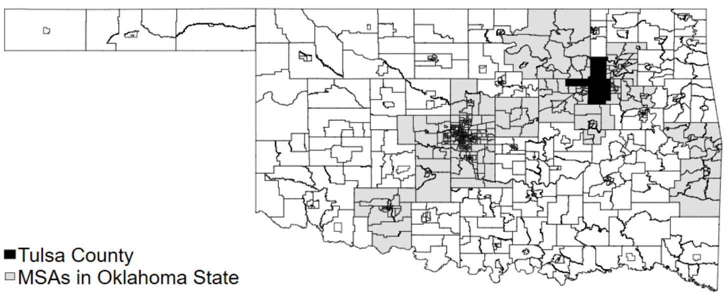
C.2 Maps

Figure C1: Zoom-in: Downtown Tulsa

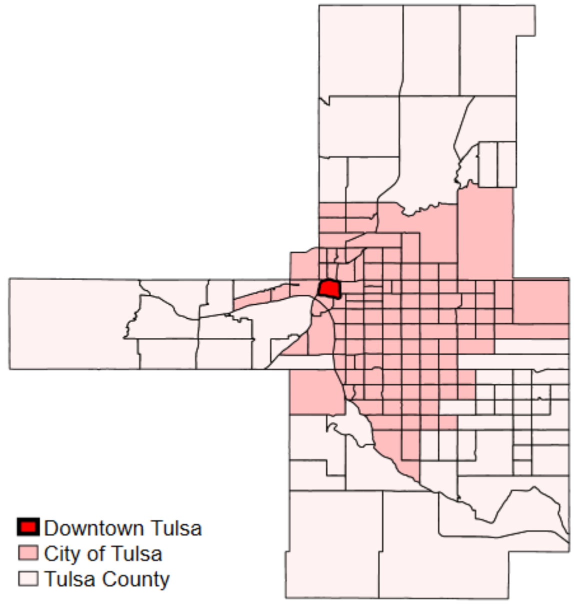
Notes: This figure shows that Interstate 244 and Interstate 444 surround downtown, known as the Inner Dispersal Loop. The map is sourced from the Oklahoma Department of Transportation to provide geographic context for downtown Tulsa.

Figure C2: Map of Oklahoma and Tulsa County

(a) Oklahoma by Census Tract



(b) Tulsa County by Census Tract



Notes: Panel (a) displays the MSAs in Oklahoma, a sample used in Equation (2). In Panel (b), there is a zoomed-in map of Tulsa County illustrating the geographic boundaries of downtown Tulsa and the city of Tulsa.

C.3 Empirical Results

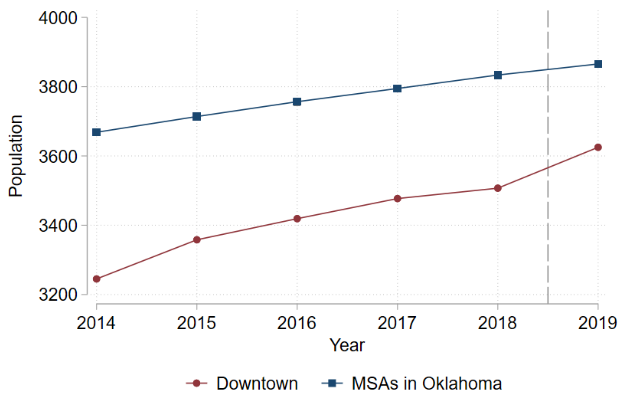
Table C1: Event Study Results: Population Growth in Tulsa (Longer Periods)

	Downtown	Rest of Tulsa
2015	0.01	0.01
	[0.00, 0.02]	[-0.00, 0.02]
2016	0.00	0.00
	[-0.00, 0.01]	[-0.01, 0.01]
2017	0.01	-0.00
	[0.00, 0.01]	[-0.01, 0.01]
2019	0.03	-0.00
	[0.02, 0.04]	[-0.01, 0.01]
2020	-0.02	-0.01
	[-0.03, -0.01]	[-0.02, 0.01]
2021	0.04	0.02
	[0.03, 0.04]	[0.01, 0.04]

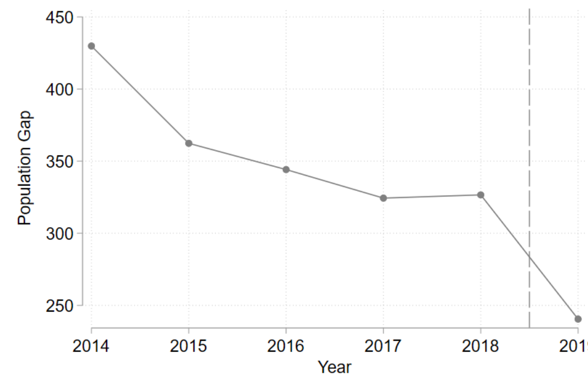
Notes: Table reports $\hat{\beta}_t^D$ and $\hat{\beta}_t^R$, corresponding to Figure C4. The 95% confidence intervals are based on census tract-clustered wild bootstrap with 9,999 replications and a six-point weight distribution (Webb, 2013).

Figure C3: Including Lag to Address Population Growth Momentum

(a) Population Trend



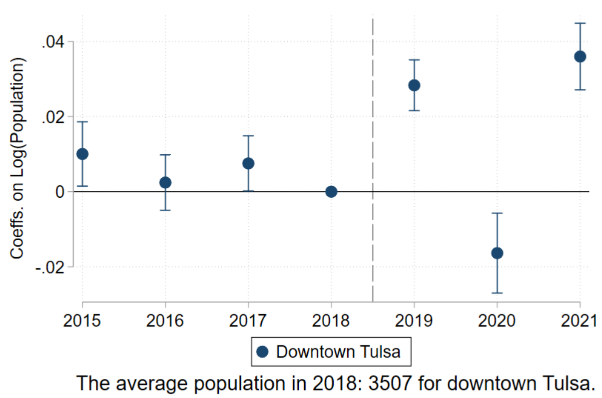
(b) Population Gap



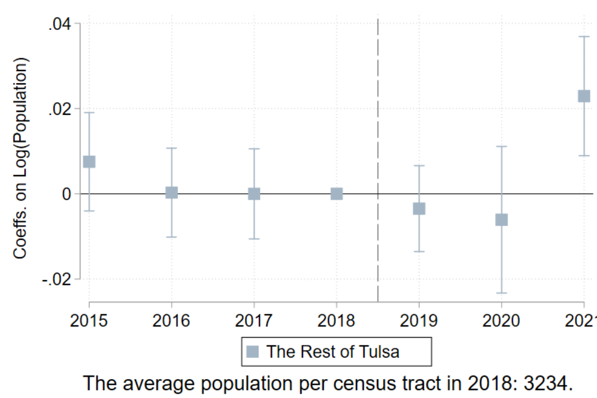
Notes: Panel (a) shows the population on average in downtown Tulsa and in the other MSAs in Oklahoma over time. Panel (b) shows the gap between the two. The population in downtown Tulsa and the population in other MSAs in Oklahoma show a parallel trend in the second order, not in the first order. Ding and Li (2019) also says that "when the parallel trends assumption does not hold, the lagged-dependent-variable regression adjustment approach produces the most efficient and least biased estimates among these three methods." Therefore, I include the lag outcome variable on the left-hand side in the Equation (2) for the population outcome. The coefficient of the lag variable is about 0.7, which demonstrates a high serial correlation. Including lag or not does not change the magnitude of the coefficient of interest (β^D_{2019}) significantly (0.028 with the lag and 0.027 without lag).

Figure C4: Event Study Results: Population Growth in Tulsa (Longer Periods)

(a) Downtown Tulsa



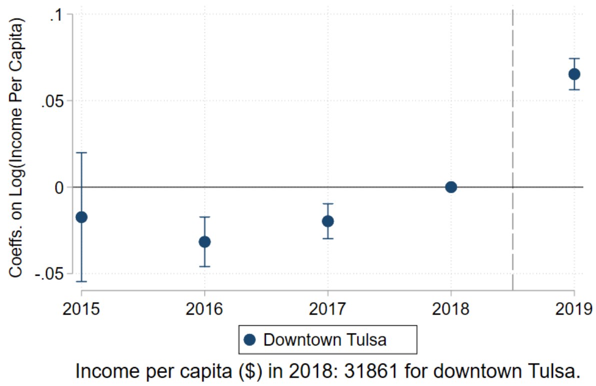
(b) Rest of Tulsa



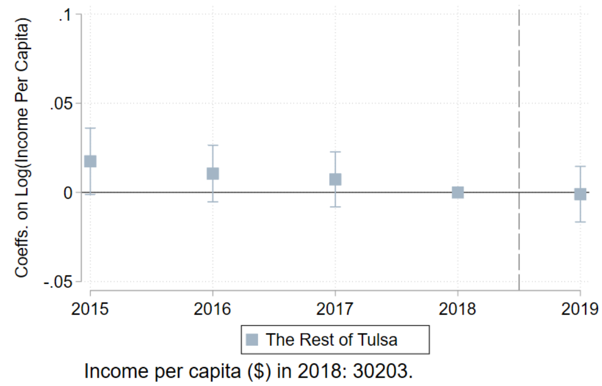
Notes: In panel (a) and (b), I plot the event study coefficients ($\hat{\beta}^D_t$ and $\hat{\beta}^R_t$ respectively) in Equation (2) with a lagged outcome variable, extended up to 2021. The 95% confidence intervals are based on census tract-clustered wild bootstrap with 9,999 replications and a six-point weight distribution (Webb, 2013).

Figure C5: Event Study Analysis: Effect of Tulsa Remote on Income Per Capita and Nonemployment

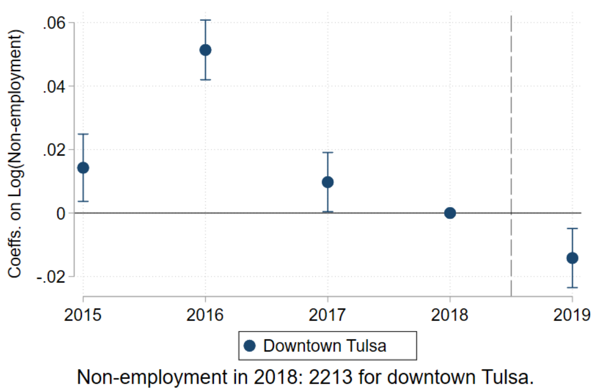
(a) Income Per Capita: Downtown Tulsa ($\hat{\beta}^D$)



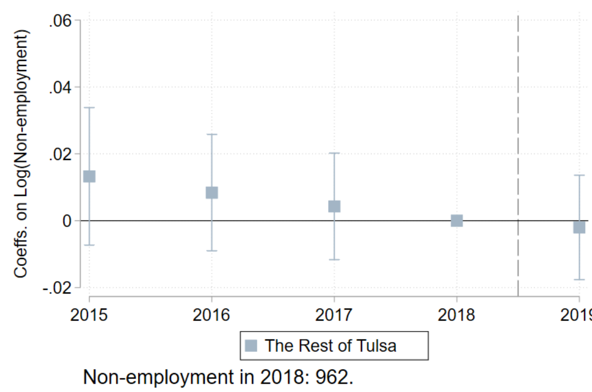
(b) Income Per Capita: Rest of Tulsa ($\hat{\beta}^R$)



(c) Nonemployment: Downtown Tulsa ($\hat{\beta}^D$)

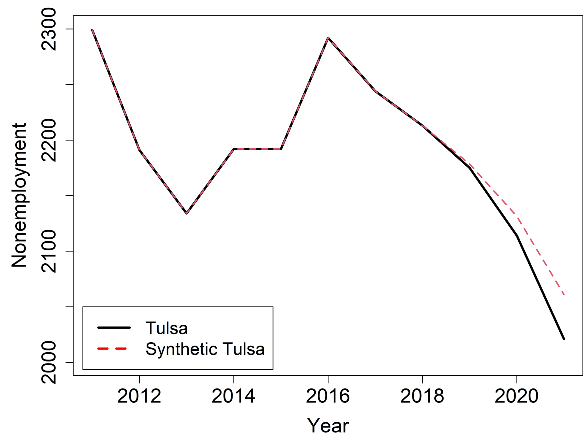


(d) Nonemployment: Rest of Tulsa ($\hat{\beta}^R$)



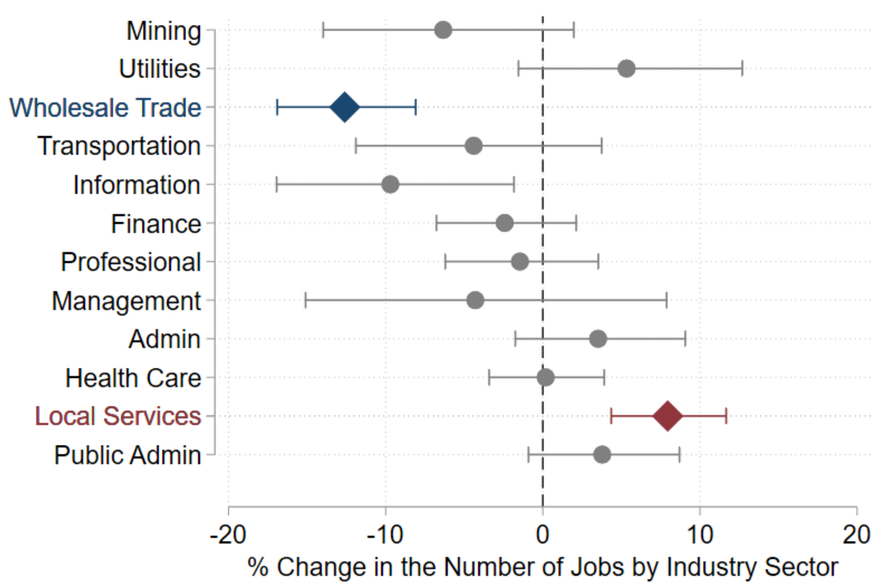
Notes: In panels (a) and (b), I present β_t^D estimates (in circles) and β_t^R estimates (in squares) from Equation (2) using income per capita as the outcome variable. Similarly, I present β_t^D estimates (in circles) and β_t^R estimates (in squares) respectively using nonemployment as the outcome variable in panels (c) and (d). The 95% confidence intervals are based on census tract-clustered wild bootstrap with 9,999 replications and a six-point weight distribution (Webb, 2013). The data source is ACS 5-year estimates.

Figure C6: Synthetic Control Analysis: Nonemployment



Note: The top three census tracts used for a synthesized control are 400090966100, 400270201202, and 400110958900. Amjad, Shah and Shen (2018)'s method is used.

Figure C7: Local Employment Effect by Industry Sector (two digits of NAICS code)



Note: The industry sectors with the employment composition more than 3% are included.

Table C2: Event Study Analysis: Local Employment

	A. Local Service		B. Construction	
	Downtown (1)	Rest (2)	Downtown (3)	Rest (4)
2015	-0.02	0.05	-0.06	-0.16
	[-0.07,0.04]	[-0.06,0.15]	[-0.13,0.00]	[-0.35,0.04]
2016	0.04	0.09	-0.18	-0.20
	[-0.00,0.09]	[0.00,0.17]	[-0.23,-0.13]	[-0.35,-0.05]
2017	0.02	0.03	-0.19	-0.10
	[-0.02,0.06]	[-0.03,0.09]	[-0.24,-0.15]	[-0.21,0.00]
2019	0.08	-0.01	0.13	-0.06
	[0.04,0.11]	[-0.07,0.06]	[0.09,0.18]	[-0.17,0.05]
Counterfactual Baseline	2991	–	666	–
# of Observations	3342		3263	
	C. Wholesale Trade		D. Manufacturing	
	Downtown (1)	Rest (2)	Downtown (3)	Rest (4)
2015	0.03	0.06	-0.26	-0.08
	[-0.04,0.10]	[-0.11,0.24]	[-0.35,-0.17]	[-0.26,0.10]
2016	-0.05	0.13	-0.17	-0.07
	[-0.12,0.02]	[-0.03,0.29]	[-0.24,-0.10]	[-0.22,0.08]
2017	0.01	0.02	-0.06	-0.05
	[-0.04,0.06]	[-0.12,0.16]	[-0.12,0.00]	[-0.21,0.11]
2019	-0.13	-0.06	0.07	-0.12
	[-0.19,-0.08]	[-0.20,0.07]	[0.01,0.13]	[-0.28,0.05]
Counterfactual Baseline	928	–	420	–
# of Observations	2990		2642	

Notes: This table presents results from the regression in Equation 2 with four different outcome variables: the number of jobs in the service sector (accommodation and food services (NAICS 72), and other services (NAICS 81)) in column A, construction in column B, wholesale trade in C, and manufacturing in panel D. Panel A corresponds to Figure 4a and Figure 4b, and panel C corresponds to Figure 4c and Figure 4d. Outcomes are the log of the number of jobs per working census tract in each industry in each year. Year and census tract fixed effects are included. Columns (1) and (3) report results for each year for Tulsa Downtown ($\hat{\beta}^D$ coefficients) and columns (2) and (4) report results for each year for the rest of Tulsa ($\hat{\beta}^R$ coefficients). Below each coefficient, I report the 95% confidence intervals estimated using census tract-clustered wild bootstrap with 9,999 replications and a six-point weight distribution as in Webb (2013). The counterfactual baseline provides the mean number of jobs in downtown netting out the program effect in downtown in the post-period (2019).

C.4 Summary of Local Shock Effects from Previous Literature

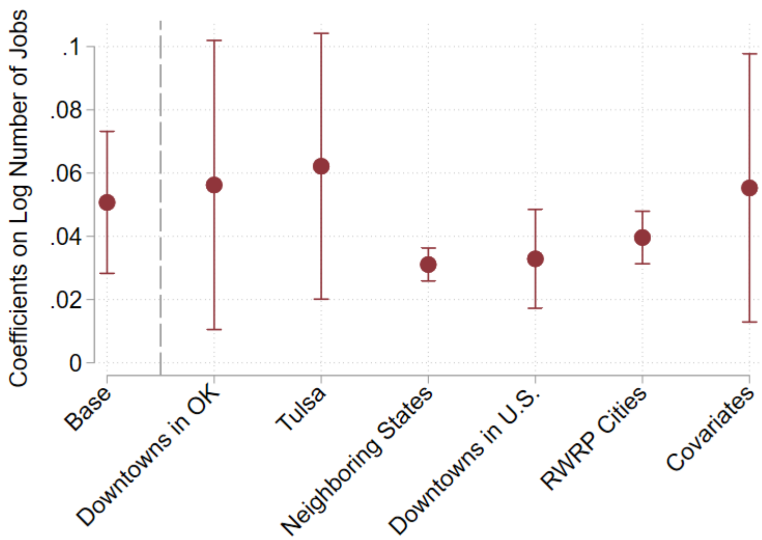
Table C3: Summary of Local Demand Effects from Previous Literature

Paper	Variation Context	Main Findings	Data	Methodology
Moretti (2010)	Nationwide employment growth (shift share)	+1.6 job multiplier (tradables on non-tradables) + 2.5 job multiplier (skilled tradables on non-tradables)	Census 1980, 1990, 2000	IV
Faggio and Overman (2014)	Public sector employment growth (shift share)	+0.5 jobs in non-tradable sector –0.4 jobs in tradable sector	English Local Authority data (2003-2007)	OLS, IV
Becker, Heblich and Sturm (2021)	West German government after WWII	+1 jobs in private sector	Census employment data (1925-1987)	DID, SC

C.5 Robustness Analysis

Employment Increase in Local Service Sector. The first five analyses are about using different control groups: (i) the Central Business Districts (downtowns) in Oklahoma, (ii) the rest of Tulsa, (ii) the MSAs in neighboring states, (iv) the Central Business Districts (downtowns) in the United States, and (v) the cities that implemented Remote Worker Relocation Programs after Tulsa Remote. The last one is about adding the time-varying covariates to the Equation (2). These include the proportion of male, age 15-24, age 25-44, age 45-64, (non-Hispanic) White, (non-Hispanic) Black, Hispanic, above high school, and the employed. Figure C8 summarizes the robustness results, presenting only the normalized $\hat{\beta}^D_{2019}$.

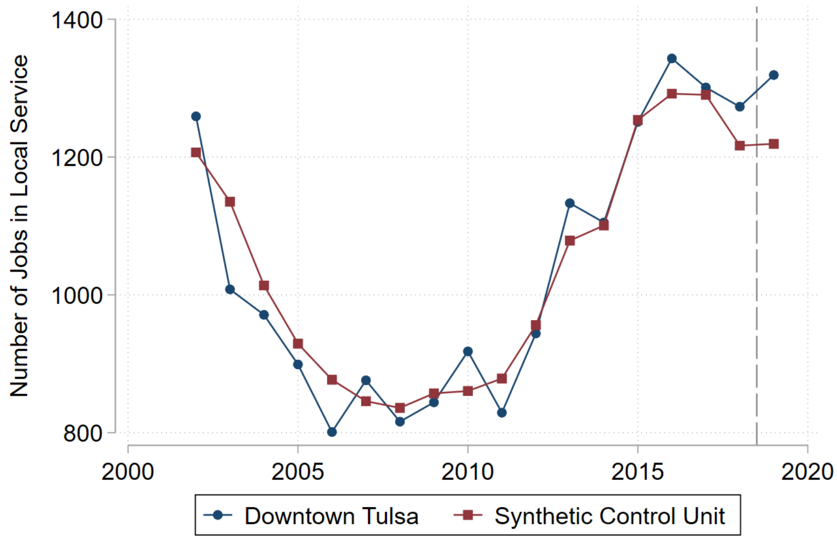
Figure C8: Robustness Analysis: Number of Jobs in Local Service Sector



Notes: The figure plots the results from the six robustness checks described above. Each plot shows the coefficient from an estimation scaled by the standard deviation of the outcome variable. The base case is the main specification, which is the same as the estimate in panel (a) of Figure 4, but normalized by the standard deviation of $y_{c,t}$; then I vary the control group from (i) the Central Business Districts in Oklahoma ('Downtowns in OK'), (ii) the rest of Tulsa ('Tulsa'), (iii) the MSAs in neighboring states ('Neighboring States'), (iv) the Central Business Districts in the United States ('Downtowns in U.S.'), to (v) the cities that implemented Remote Worker Relocation Programs after Tulsa implemented the program ('RWRP Cities'); and then I add the covariates ('Covariates'). The bars indicate census tract clustered wild bootstrap 95% confidence intervals.

Synthetic Control Analysis. I employ a synthetic control method (Abadie, Diamond and Hainmueller, 2010) in an effort to find the most comparable group in a longer horizon as well as concerning the single treated unit.

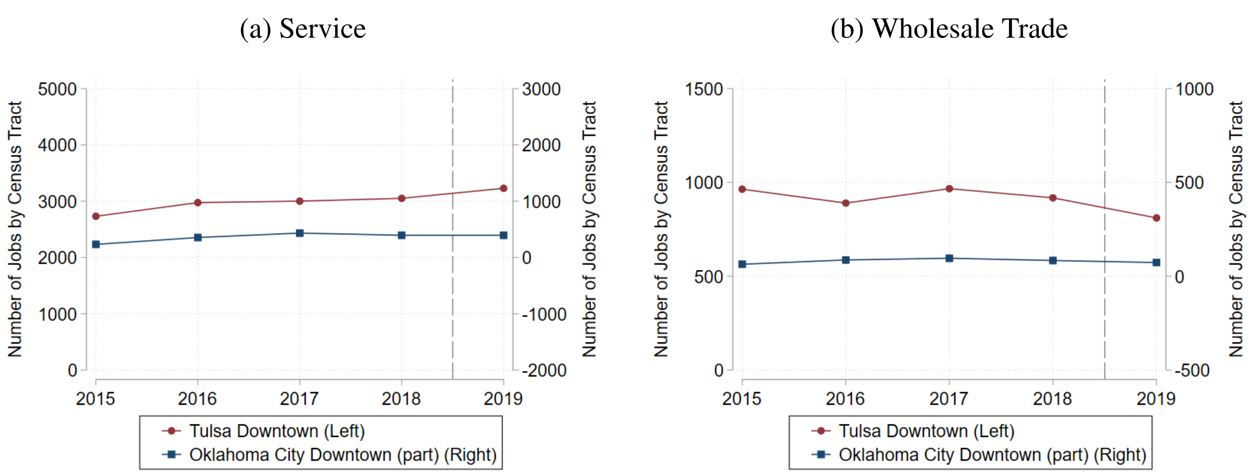
Figure C9: Synthetic Control Analysis: Employment in Local Service Sector



Notes: The plot shows the number of jobs in the local service sector over the years (2002-2019). The synthetic control unit is a mixture of the following census tracts: 45019000700, 12011042500, 17031320400, 17031320100, and 55087010100.

Raw Data Plots.

Figure C10: Descriptive Analysis: Number of Jobs in Each Workplace Census Tract



Notes: Panel (a) shows the time series plot of the number of jobs in the service sector in two census tracts: downtown Tulsa (geo ID: 40143002500) and the center (subpart) of downtown in Oklahoma City (geo ID: 40109103200). Panel (b) shows the time series plot of the number of jobs in the wholesale trade sector for both downtown Tulsa and the center of downtown in Oklahoma city.

C.6 Heterogeneity Analysis

Table C4: Heterogeneous Effect of Tulsa Remote on Number of Jobs by Earnings

	High		Medium		Low	
	Downtown (1)	Rest (2)	Downtown (3)	Rest (4)	Downtown (5)	Rest (6)
	A. Local Service					
2015	-0.16	0.09	-0.02	0.02	0.04	0.05
	[-0.22, -0.10]	[-0.05, 0.22]	[-0.07, 0.04]	[-0.11, 0.14]	[-0.03, 0.10]	[-0.07, 0.17]
2016	-0.01	0.05	0.03	0.06	0.07	0.06
	[-0.07, 0.04]	[-0.06, 0.15]	[-0.02, 0.08]	[-0.04, 0.15]	[0.01, 0.12]	[-0.04, 0.16]
2017	-0.11	0.05	0.05	-0.02	0.03	0.01
	[-0.16, -0.06]	[-0.07, 0.16]	[0.00, 0.09]	[-0.10, 0.05]	[-0.01, 0.07]	[-0.06, 0.09]
2019	0.03	0.02	0.06	-0.03	0.09	0.01
	[-0.01, 0.08]	[-0.08, 0.11]	[0.02, 0.10]	[-0.11, 0.05]	[0.05, 0.14]	[-0.07, 0.09]
Counterfactual Baseline	494	–	1320	–	1201	–
# of Obs.	3021		3241		3240	
	B. Wholesale Trade					
2015	0.14	0.13	-0.09	0.05	0.09	-0.04
	[0.06, 0.21]	[-0.06, 0.33]	[-0.18, -0.01]	[-0.16, 0.26]	[-0.01, 0.18]	[-0.26, 0.18]
2016	0.14	0.22	-0.24	0.06	-0.27	-0.03
	[0.07, 0.21]	[0.04, 0.39]	[-0.32, -0.15]	[-0.13, 0.25]	[-0.36, -0.18]	[-0.21, 0.15]
2017	0.11	0.09	0.00	0.02	-0.32	-0.00
	[0.05, 0.17]	[-0.06, 0.23]	[-0.07, 0.07]	[-0.14, 0.17]	[-0.41, -0.24]	[-0.18, 0.17]
2019	-0.09	-0.02	-0.29	-0.18	-0.30	-0.09
	[-0.15, -0.04]	[-0.15, 0.11]	[-0.35, -0.23]	[-0.35, -0.00]	[-0.38, -0.21]	[-0.30, 0.12]
Counterfactual Baseline	573	–	339	–	48	–
# of Obs.	2782		2555		2245	

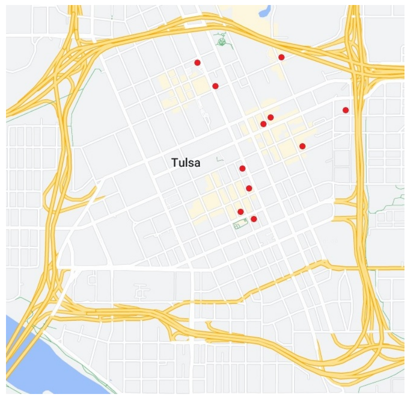
Notes: This table presents results from the regression in Equation (2) with six different outcome variables: the number of local service jobs in high, medium, and low earning groups in panel A, and the number of wholesale trade jobs in high, medium, and low earning groups in panel B. Outcomes are the log of the number of jobs per working census tract in each industry in each year. Year and census tract fixed effects are included. Columns (1), (3), and (5) report the results for each year for Tulsa Downtown ($\hat{\beta}^D$ coefficients) and columns (2), (4), and (6) report the results for each year for the rest of Tulsa ($\hat{\beta}^R$ coefficients). Below each coefficient, I report the 95% confidence intervals estimated using census tract-clustered wild bootstrap with 9,999 replications and a six-point weight distribution as in Webb (2013). The counterfactual baseline provides the mean number of jobs in downtown netting out the program effect in downtown in the post-period (2019).

C.7 Varieties of Goods

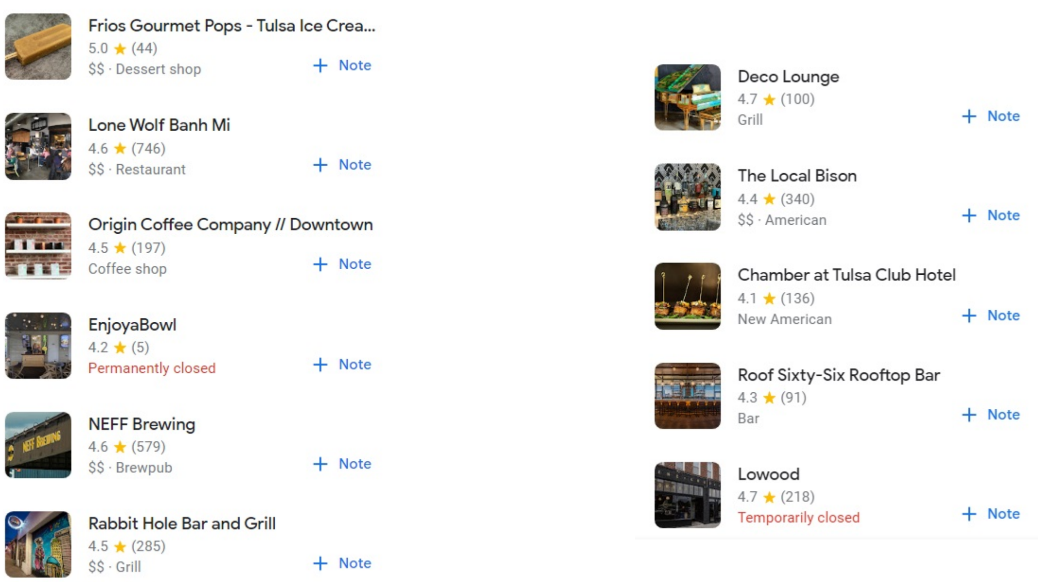
To provide direct evidence of variety gain, Figure C11 shows the map of newly opened local service establishments along with a corresponding list. Figure C12 presents experts from Google reviews for some local service establishments. The reviews illustrate the utility gain resulting from the increased choices of local service goods.

Figure C11: Newly opened local service establishments in downtown Tulsa in 2019

(a) Location in Downtown Tulsa

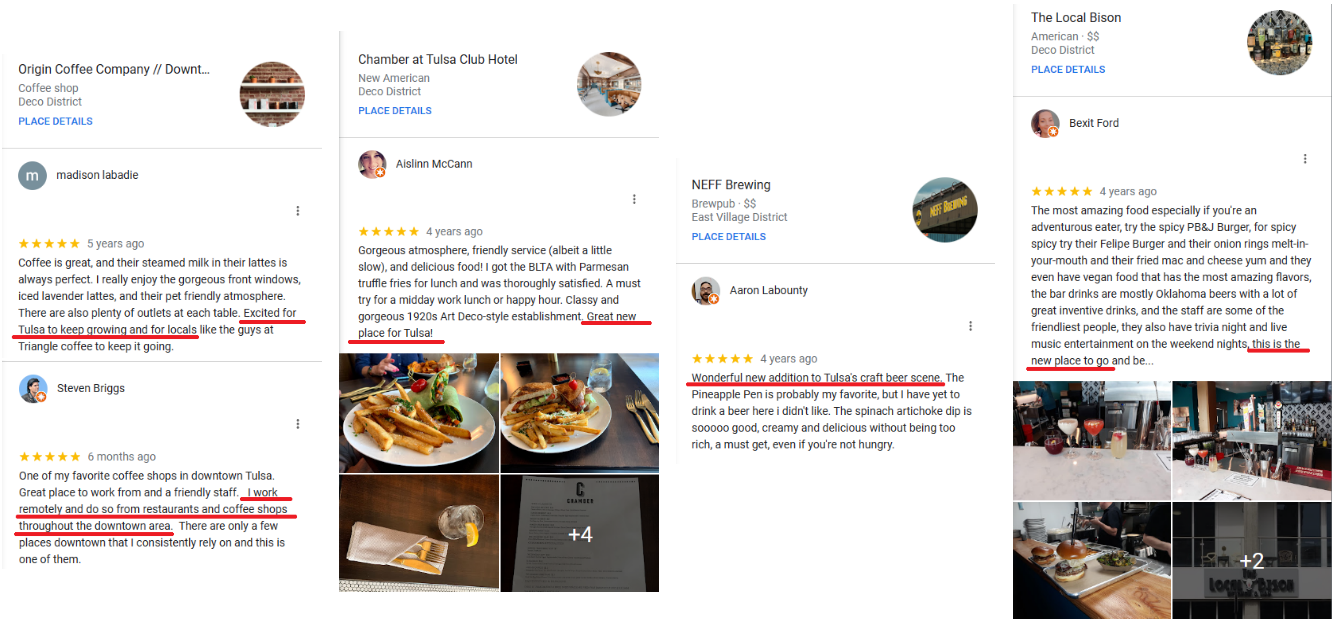


(b) The List of Establishments



Notes: I collect the list of establishments that opened in downtown Tulsa in 2019 using the YTS and Google map.

Figure C12: Google Review Excerpts: Evidence of Gains from Varieties



Notes: I excerpt some of the Google reviews for local service establishments that opened in downtown Tulsa in 2019.

C.8 Additional Analysis

Consumer Visits. To analyze consumer visits, I run a regression:

$$\begin{aligned} y_{i,m} = \alpha_i + \gamma_m &+ \beta^D \times \mathbf{1}(\text{Downtown})_{z(i)} \times \mathbf{1}(\text{Post})_m \\ &+ \beta^R \times \mathbf{1}(\text{Rest})_{z(i)} \times \mathbf{1}(\text{Post})_m + \varepsilon_{i,m} \end{aligned} \tag{41}$$

where i is place, m is year-month, and s is industry sector. $\mathbf{1}(\text{Post})_m$ is 1 if the year-month m falls within the period from February 2019 to December 2019. As SafeGraph data is available from 2018, I cannot include the year-by-year dummy variables. Three outcome variables are considered: log(visits), log(weekend visits), and log(visitors). Due to the data availability, the control group is Oklahoma City. Inference is based on census tract clustered wild bootstrap.

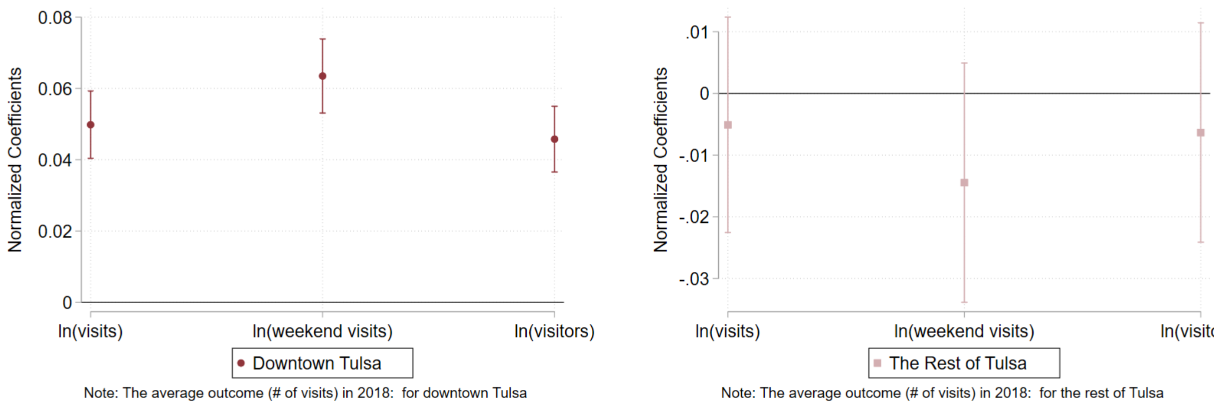
Housing Price. Next, I conduct the event study analysis on housing prices by using Federal Housing Finance Agency's Housing Price Index, similar to Equation (2):

$$\begin{aligned} y_{z,t} = \alpha_z + \gamma_t &+ \sum_{\substack{t=2015,\\ t\neq 2018}}^{2019} \beta_t^D \mathbf{1}(\text{Downtown})_z \mathbf{1}(\text{Year})_t \\ &+ \sum_{\substack{t=2015,\\ t\neq 2018}}^{2019} \beta_t^R \mathbf{1}(\text{Rest})_z \mathbf{1}(\text{Year}_t) + \varepsilon_{z,t} \end{aligned} \tag{42}$$

The difference between Equation (42) and Equation (2) is that the geographic unit is based on zip code, due to the geography unit available in data.

Figure C13: Additional Analysis: Consumer Visits by Industry (from SafeGraph)

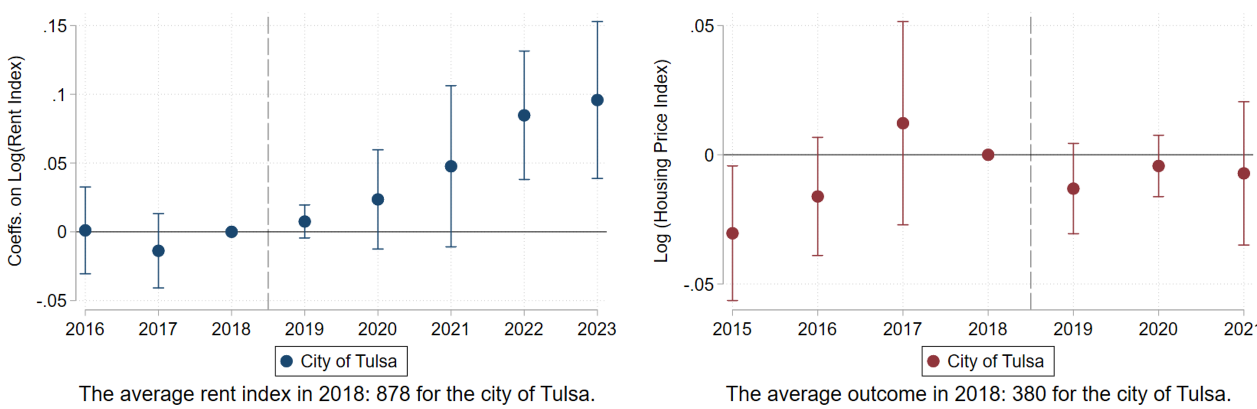
(a) Downtown Tulsa (b) Rest of Tulsa



Notes: Panel (a) reports the $\hat{\beta}^D$ coefficients and Panel (b) reports the $\hat{\beta}^R$ coefficients. Data is from SafeGraph.

Figure C14: Additional Analysis: Rent Price Index and Housing Price Index

(a) Rent Price Index (b) Housing Price Index



Notes: Panel (a) reports the $\hat{\beta}_t^D$ coefficients and Panel (b) reports the $\hat{\beta}_t^R$ coefficients. Data is from Federal Housing Finance Agency (FHFA) (Bogin, Doerner and Larson, 2019).

Transitions in Labor Market Activity. Table C5 presents transitions among non-employment, working in the local service sector, and working in the tradable sector. The primary focus of the table is to examine the frequency of transitions from non-employment to working in the local service sector and from working in the tradable sector to the local service sector. First, this analysis shows that labor reallocation among these three states within one year is not uncommon. Second, it is worth noting that the conditional inflows to the local service sector, whether from non-employment or the tradable sector, are greater among low-skilled individuals than among high-skilled individuals.

Table C5: Working Sector Transition Matrix (Monthly Frequency)

	A. High-skilled			
	Nonemployed$_t$ (32.04%)	Local Service$_t$ (4.52%)	Tradable$_t$ (63.44%)	(100%)
Non-employed$_{t-1}$	0.9337	0.0066	0.0597	1.0
Local Service$_{t-1}$	0.0508	0.9064	0.0429	1.0
Tradable$_{t-1}$	0.0325	0.0027	0.9648	1.0
	B. Low-skilled			
	Nonemployed$_t$ (52.26%)	Local Service$_t$ (7.32%)	Tradable$_t$ (40.43%)	(100%)
Non-employed$_{t-1}$	0.9494	0.0102	0.0404	1.0
Local Service$_{t-1}$	0.0748	0.8873	0.0378	1.0
Tradable$_{t-1}$	0.0556	0.0064	0.9381	1.0

Notes: The table is based on the Current Population Survey, 2014-2019. The number of individuals used is 1,454,003 and the number of observations is 8,281,617. The local service sector includes "Traveler accommodation," "Recreational vehicle parks and camps, and rooming and boarding houses," "Restaurants and other food services," "Drinking places, alcoholic beverages," "Automotive repair and maintenance," "Car washes," "Electronic and precision equipment repair and maintenance," "Commercial and industrial machinery and equipment repair and maintenance," "Personal and household goods repair and maintenance and footwear and leather goods repair," "Barber shops," "Beauty salons," and "Nail salons and other personal care services." The tradable sector includes the remaining industries.

Absence of Empirical Evidence on Spatial Reallocation. To test the spatial reallocation in response to the influx of remote workers, I run the following regression using LODES data:

$$log(commuters)_{o,d,t} = \omega_o + \delta_d + \gamma_t + \sum_{\substack{t=2015,\\ t\neq 2018}}^{2019} \beta_t^D \times \mathbf{1}(\text{Downtown})_d \times \mathbf{1}(\text{Year})_t + \varepsilon_{o,d,t} \tag{43}$$

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 error.

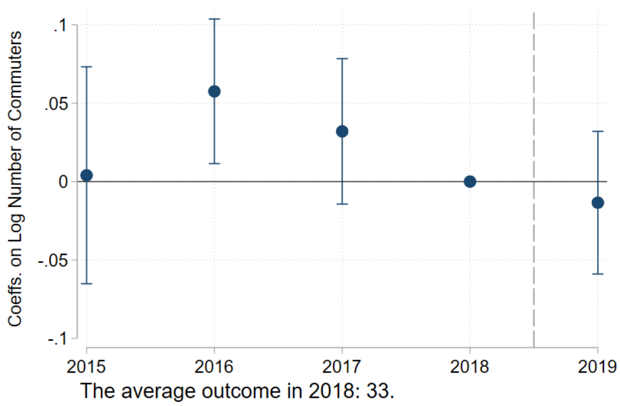
Next, I run the following regression to detect the effect on the total number of jobs in the city of Tulsa.

$$log(emp)_{i,t} = \alpha_i + \gamma_t + \sum_{\substack{t=2015,\\ t\neq 2018}}^{2019} \beta_t^D \times \mathbf{1}(\text{Tulsa})_i \times \mathbf{1}(\text{Year})_t + \varepsilon_{i,t} \tag{44}$$

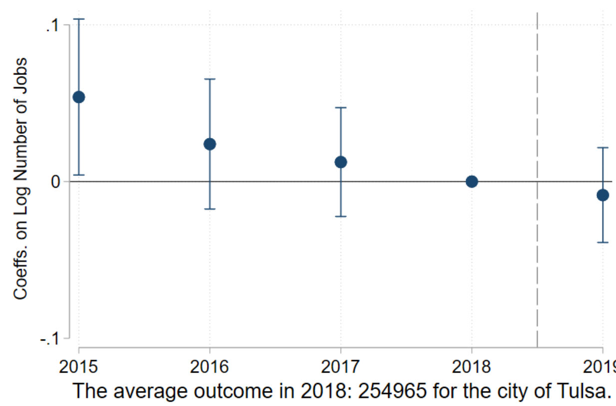
α_i is the workplace census tract fixed effect, γ_t is the year fixed effect, and the outcome variable, $log(emp)_{i,t}$ is the log of the total number of jobs in workplace census tract i in year t. The inference is based on census tract clustered robust standard error.

Figure C15: Absence of Empirical Evidence on Spatial Reallocation

(a) Total Number of Commuters



(b) Total Number of Jobs



Notes: Panel (a) reports the $\hat{\beta}_t^D$ coefficients in Equation (43) and Panel (b) reports the $\hat{\beta}_t^D$ coefficients in Equation (44). The data is from LODES OD and WAC.

D Supplementary Material to Section 5: A Local Economy Model of Labor Market, Goods Market, and Land Market

D.1 Workers

Labor Supply. Solving a worker's labor supply problem in Equation (3) gives the following closed-form solutions:

$$L_{e,\phi} = \pi_e \times \pi_{e,j(k)=\phi} \tag{45a}$$

$$L^{supply}_{e,S} = \pi_e \times \pi_{e,j(k)=W} \times \pi_{e,S|j=W} \tag{45b}$$

$$L^{supply}_{e,T} = \pi_e \times \pi_{e,j(k)=W} \times \pi_{e,T|j=W} \tag{45c}$$

where $\pi_{e,j(k)=\phi}$ is the share of individuals of skill type e not working, and $\pi_{e,j(k)=W}$ is the share of individuals working. They are characterized as:

$$\begin{aligned}
\pi_{e,j(k)=\phi} &= Pr(V_{e,k=\phi} + \xi_{i,e,k=\phi} > V_{e,k=S} + \xi_{i,e,k=S} \text{ and } V_{e,k=\phi} + \xi_{i,e,k=\phi} > V_{e,k=T} + \xi_{i,e,k=T}) \\
&= \frac{exp(\frac{V_{e,\phi}}{\sigma})}{exp(\frac{V_{e,\phi}}{\sigma}) + exp\Big((1-\rho_e)log\big(\sum_k exp(\frac{V_{e,k}+\mu_{e,k}}{\sigma(1-\rho_e)})\big)\Big)} \\
&= \frac{(w_{e,\phi})^{\frac{1}{\sigma}}}{(w_{e,\phi})^{\frac{1}{\sigma}} + \Big((w_{e,S}\mu_{e,S})^{\frac{1}{\sigma(1-\rho_e)}} + (w_{e,T}\mu_{e,T})^{\frac{1}{\sigma(1-\rho_e)}}\Big)^{(1-\rho_e)}}
\end{aligned} \tag{46a}$$

$$\begin{aligned}
\pi_{e,j(k)=W} &= Pr(V_{e,k=S} + \xi_{i,e,k=S} > V_{e,k=\phi} + \xi_{i,e,k=\phi} \text{ or } V_{e,k=T} + \xi_{i,e,k=T} > V_{e,k=\phi} + \xi_{i,e,k=\phi}) \\
&= \frac{exp\Big((1-\rho_e)log\big(\sum_k exp(\frac{V_{e,k}+\mu_{e,k}}{\sigma(1-\rho_e)})\big)\Big)}{exp(\frac{V_{e,\phi}}{\sigma}) + exp\Big((1-\rho_e)log\big(\sum_k exp(\frac{V_{e,k}+\mu_{e,k}}{\sigma(1-\rho_e)})\big)\Big)} \\
&= \frac{\Big((w_{e,S}\mu_{e,S})^{\frac{1}{\sigma(1-\rho_e)}} + (w_{e,T}\mu_{e,T})^{\frac{1}{\sigma(1-\rho_e)}}\Big)^{(1-\rho_e)}}{(w_{e,\phi})^{\frac{1}{\sigma}} + \Big((w_{e,S}\mu_{e,S})^{\frac{1}{\sigma(1-\rho_e)}} + (w_{e,T}\mu_{e,T})^{\frac{1}{\sigma(1-\rho_e)}}\Big)^{(1-\rho_e)}}
\end{aligned} \tag{46b}$$

Note that the logit structure still holds with the inclusive value of working ($j = W$), i.e., $I_{e,j(k)=W} = log\big(\sum_k exp(\frac{V_{e,k}+\mu_{e,k}}{\sigma(1-\rho_e)})\big)$. Next, $\pi_{e,S|j=W}$ is the share of individuals working in the local service sector conditional on working, and $\pi_{e,T|j=W}$ is the share of individuals working in the tradable sector conditional on working. Therefore, they are characterized as:

$$\begin{aligned}
\pi_{e,S|j=W} &= Pr(V_{e,k=S} + \xi_{i,e,k=S} > V_{e,k=T} + \xi_{i,e,k=T}) \\
&= \frac{exp(\frac{V_{e,S}+\mu_{e,S}}{\sigma(1-\rho_e)})}{\sum_k exp(\frac{V_{e,k}+\mu_{e,k}}{\sigma(1-\rho_e)})} \\
&= \frac{\left(w_{e,S}\mu_{e,S}\right)^{\frac{1}{\sigma(1-\rho_e)}}}{\left(w_{e,S}\mu_{e,S}\right)^{\frac{1}{\sigma(1-\rho_e)}} + \left(w_{e,T}\mu_{e,T}\right)^{\frac{1}{\sigma(1-\rho_e)}}} \qquad (47a)
\end{aligned}$$

$$\begin{aligned}
\pi_{e,T|j=W} &= Pr(V_{e,k=T} + \xi_{i,e,k=T} > V_{e,k=S} + \xi_{i,e,k=S}) \\
&= \frac{exp(\frac{V_{e,T}+\mu_{e,T}}{\sigma(1-\rho_e)})}{\sum_k exp(\frac{V_{e,k}+\mu_{e,k}}{\sigma(1-\rho_e)})} \\
&= \frac{\left(w_{e,T}\mu_{T}\right)^{\frac{1}{\sigma(1-\rho_e)}}}{\left(w_{e,S}\mu_{e,S}\right)^{\frac{1}{\sigma(1-\rho_e)}} + \left(w_{e,T}\mu_{e,T}\right)^{\frac{1}{\sigma(1-\rho_e)}}} \qquad (47b)
\end{aligned}$$

Within the lower level (conditional on working), the logit structure holds again.

Consumption. I solve the consumer's utility maximization problem and derive Marshallian demand functions for local service goods (see Equation (9)). The Lagrangian problem is written as:

$$\mathscr{L} = \left(Q_{ek}^S\right)^{\rho} - \lambda\left(\int_{\omega} p(\omega)q_{ek}(\omega)d\omega - \alpha_e^S(w_{ek} - T)\right)$$

By taking the first derivative with respect to $q_{ek}(\omega)$, I have:

$$q_{ek}(\omega) = \left(\frac{\lambda p(\omega)}{\rho}\right)^{\frac{1}{\rho-1}}$$

Furthermore, the ratio of the above demands for two varieties ω_i and ω_j generate:

$$\frac{q_{ek}(\omega_i)}{q_{ek}(\omega_j)} = \left(\frac{p(\omega_i)}{p(\omega_j)}\right)^{\frac{1}{\rho-1}}$$

which leads to

$$q_{ek}(\omega_i) = q_{ek}(\omega_j)\left(\frac{p(\omega_i)}{p(\omega_j)}\right)^{-\varepsilon}$$

If I multiply the above by $p(\omega_i)$ and integrate over the variety ω_i, then the left-hand side becomes the total expenditure across all varieties of the consumer of skill type s and in industry sector k.

$$\alpha_e^S(w_{ek} - T) = q_{ek}(\omega_j) \cdot p(\omega_j)^{\varepsilon} \int_{\omega_i} p(\omega_i)^{1-\varepsilon} d\omega_i$$

By rearranging the above, I have Marshallian demand for the variety ω_j:

$$q_{ek}(\omega_j) = \frac{\alpha_e^S \cdot I_{ek} \cdot p(\omega_j)^{-\varepsilon}}{\int_{\omega_i} p(\omega_i)^{1-\varepsilon} d\omega_i}$$

Using the price index of all non-tradable goods varieties $P_S \equiv \left(\int_0^{M_S} p(\omega)^{1-\varepsilon} d\omega\right)^{\frac{1}{1-\varepsilon}}$, the Marshallian demand for the variety ω is finally summarized as:

$$q_{ek}(\omega) = \left(\frac{p(\omega)}{P_S}\right)^{-\varepsilon} \cdot \frac{\alpha_e^S \cdot I_{ek}}{P_S}$$

The consumption demand for immobile landlords is derived in a similar manner. In other words, the demand for local service goods $q(\omega)$ for immobile landlords is

$$q_e^{landlords}(\omega) = \left(\frac{p(\omega)}{P_S}\right)^{-\varepsilon} \cdot \frac{\frac{\alpha_e^S}{\alpha_e^S+\alpha_e^T} \bar{I}_e^{landlords}}{P_S}$$

where $\bar{I}^{landlords} = \bar{I}_l^{landlords} + \bar{I}_h^{landlords} = r \cdot H$ holds.

D.2 Firms

Price Per Variety. Local service firms maximize their profits as:

$$\max_{p_S(\omega), y_S(\omega), \eta_S(\omega), h_S(\omega)} \pi_S(\omega) = p_S(\omega) y_S(\omega) - \lambda_S \cdot \eta_S(\omega) - r \cdot h_S(\omega) - F$$

Accordingly, I have:[81]

$$\frac{\partial \pi(\omega)}{\partial p(\omega)} = q(\omega) + (p(\omega) - MC)\frac{\partial q(\omega)}{\partial p(\omega)} = 0$$
$$\iff p = MC + \frac{-q(\omega)}{\frac{\partial q(\omega)}{\partial p(\omega)}}$$

By plugging $\frac{\partial q(\omega)}{\partial p(\omega)} = \left(\frac{1}{\sigma-1}\right) \cdot \frac{MC}{-q}$ into the above (which is derived from the Marshallian demand in Appendix D.1), I have:

$$p(\omega) = \left(\frac{\sigma}{\sigma-1}\right) \cdot MC$$

The price of local service goods is a markup of marginal cost.

[81] I sometimes suppress the subscript S to keep it simple.

The marginal cost (which is also the unit cost) is given by the following cost minimization problem:

$$MC_S = \min_{\eta_S(\omega), h_S(\omega)} \lambda_S \cdot \eta_S(\omega) + r \cdot h_S(\omega) \tag{48}$$

$$\text{s.t.} \quad A_S \cdot \eta_S(\omega)^{\theta_S} \cdot h_S(\omega)^{1-\theta_S} \leq 1 \tag{49}$$

$$= \frac{1}{A_S} \cdot \Big(\frac{\lambda_S}{\theta_S}\Big)^{\theta_S} \cdot \Big(\frac{r}{1-\theta_S}\Big)^{1-\theta_S} \tag{50}$$

Factor Costs. The first order conditions with respect to η_S and h_S solving the profit maximization problem in equation 12 give:

$$\frac{\partial \pi}{\partial \eta} = 0 \iff \frac{\partial p}{\partial \eta} \cdot q + p \cdot \frac{\partial q}{\partial \eta} = \lambda_S \iff \frac{\partial p}{\partial q} \cdot \frac{\partial q}{\partial \eta} \cdot q + p \cdot \frac{\partial q}{\partial \eta} = \lambda_S$$
$$\frac{\partial \pi}{\partial h} = 0 \iff \frac{\partial p}{\partial h} \cdot q + p \cdot \frac{\partial q}{\partial h} = r \iff \frac{\partial p}{\partial q} \cdot \frac{\partial q}{\partial h} \cdot q + p \cdot \frac{\partial q}{\partial h} = r$$

I rearrange the above two equations as:

$$\Big(\frac{\partial p}{\partial q} \cdot q + p\Big) \frac{\partial q}{\partial \eta} = \lambda_S$$
$$\Big(\frac{\partial p}{\partial q} \cdot q + p\Big) \frac{\partial q}{\partial h} = r$$

By plugging $\frac{\partial p}{\partial q} = \big(\frac{1}{\sigma-1}\big) \cdot \frac{MC}{-q}$ and $p = \big(\frac{\sigma}{\sigma-1}\big) \cdot MC$, I have:

$$MC \cdot \frac{\partial q}{\partial \eta} = \lambda_S$$
$$MC \cdot \frac{\partial q}{\partial h} = r$$

Finally, by multiplying η and h to the above equations respectively, I obtain the labor and land costs, which are θ_S and $(1-\theta_S)$ shares of total costs excluding the fixed operating cost:

$$\theta_S \cdot MC \cdot y = \lambda_S \cdot \eta$$
$$(1-\theta_S) \cdot MC \cdot y = r \cdot h$$

Proof for Proposition 1. Free entry condition gives zero profit:

$$\begin{aligned}
0 &= p \cdot q - MC_S \cdot q - F \\
&= \Big(\frac{1}{\sigma-1}\Big) MC_S \cdot q - F \\
&= \Big(\frac{1}{\sigma-1}\Big) MC_S \cdot \Big(\frac{p}{P_S}\Big)^{-\sigma} \cdot \frac{\alpha_S \cdot \bar{I}^{residents} + \big(\frac{\alpha_S}{\alpha_S+\alpha_T}\big) \cdot \bar{I}^{landlords}}{P_S} - F \\
&= \Big(\frac{1}{\sigma-1}\Big) MC_S \cdot \Big(\frac{p}{M_S^{\frac{1}{1-\sigma}} p}\Big)^{-\sigma} \cdot \frac{\alpha_S \cdot \bar{I}^{residents} + \big(\frac{\alpha_S}{\alpha_S+\alpha_T}\big) \cdot \bar{I}^{landlords}}{M_S^{\frac{1}{1-\sigma}} p} - F \\
\iff M_S &= \frac{\alpha_S \cdot \bar{I}^{residents} + \big(\frac{\alpha_S}{\alpha_S+\alpha_T}\big) \cdot \bar{I}^{landlords}}{\sigma F} \\
\text{where} \quad & \bar{I}^{residents} = \sum_s \sum_k w_{sk} \cdot L_{sk},\ \bar{I}^{landlords} = \alpha_H \bar{I}^{residents} + M_S \cdot (1-\theta_S) p_S y_S + (1-\theta_T) \bar{P}_T Y_T
\end{aligned}$$

E Supplementary Material to Section 6: Estimation Procedure and Results

E.1 Estimation Procedure: Indirect Inference

I define a 11-dimensional parameter Θ as follows:

$$\Theta = \{\sigma, \rho_h, \rho_l, \mu_{h,S}, \mu_{l,S}, \mu_{h,T}, \mu_{l,T}, \alpha_h^S, \alpha_l^S, \tau^S, \tau^T\} \tag{51}$$

Table E1 presents the summary of 11 data moments.

Table E1: Data Moments

Notation	Description	Source	Observation Unit
$\%\Delta L_\phi$	Percentage change in not-employed	5-year ACS	Census tract
$\%\Delta L_{h,S}$	Percentage change in local service employment (high)	LODES WAC SE03	Census tract
$\%\Delta L_{l,S}$	Percentage change in local service employment (low)	LODES WAC SE01&SE02	Census tract
$L_{h,S}$	Share of local service employment (high)	1-year ACS	Individual
$L_{l,S}$	Share of local service employment (low)	1-year ACS	Individual
$L_{h,T}$	Share of tradable sector employment (high)	1-year ACS	Individual
$L_{l,T}$	Share of tradable sector employment (low)	1-year ACS	Individual
$w_{h,S}$	Income of local service sector workers (high)	1-year ACS	Individual
$w_{l,S}$	Income of local service sector workers (low)	1-year ACS	Individual
$w_{h,T}$	Income of tradable sector workers (high)	1-year ACS	Individual
$w_{l,T}$	Income of tradable sector workers (low)	1-year ACS	Individual

Notes: 'High' refers to high-skilled workers, and 'low' refers to low-skilled workers. The share of non-employment among each type of worker ($L_{e,\phi}$) is not listed as a data moment because this is redundant, i.e., $L_{e,S}$ and $L_{e,T}$ provide sufficient information ($L_{e,\phi} = \pi_e - L_{e,S} - L_{e,T}$ for $e \in \{h,l\}$). Income for the non-employed for each type of worker ($w_{h,\phi}$, $w_{l,\phi}$) is also not included as they are not an equilibrium object.

To construct data moments, four different datasets are used: (i) 5-year ACS, (ii) LODES WAC SE01 and SE02 (low earning group), (iii) LODES WAC SE03 (high earning group), and (iv) 1-year ACS. The number of individuals in 1-year ACS is 2,531 –i.e., $N = 2,531$.

Construction of the Generalized Method of Moments Estimator. I define a vector-valued function $g(X_i;\Theta)$ for an observation i and a candidate parameter vector Θ as follows:

$$g(X_i;\Theta) = \begin{pmatrix} \mathbf{1}\{e_i = h\}\mathbf{1}\{k_i = S\} - L_{h,S}(\sigma, \rho_l, \mu_{l,S}, \mu_{l,T}, w_{h,S}(\Theta), w_{l,S}(\Theta), w_{h,T}(\Theta), w_{l,T}(\Theta)) \\ \mathbf{1}\{e_i = l\}\mathbf{1}\{k_i = S\} - L_{l,S}(\sigma, \rho_l, \mu_{l,S}, \mu_{l,T}, w_{h,S}(\Theta), w_{l,S}(\Theta), w_{h,T}(\Theta), w_{l,T}(\Theta)) \\ \mathbf{1}\{e_i = h\}\mathbf{1}\{k_i = T\} - L_{h,T}(\sigma, \rho_l, \mu_{l,S}, \mu_{l,T}, w_{h,S}(\Theta), w_{l,S}(\Theta), w_{h,T}(\Theta), w_{l,T}(\Theta)) \\ \mathbf{1}\{e_i = l\}\mathbf{1}\{k_i = T\} - L_{l,T}(\sigma, \rho_l, \mu_{l,S}, \mu_{l,T}, w_{h,S}(\Theta), w_{l,S}(\Theta), w_{h,T}(\Theta), w_{l,T}(\Theta)) \\ \mathbf{1}\{e_i = h\}\mathbf{1}\{k_i = S\}w_i - w_{h,S}(\alpha_h^S, \alpha_l^S, \tau^S, L_{h,\phi}(\Theta), L_{h,S}(\Theta), L_{h,T}(\Theta)) \\ \mathbf{1}\{e_i = l\}\mathbf{1}\{k_i = S\}w_i - w_{l,S}(\alpha_h^S, \alpha_l^S, \tau^S, L_{l,\phi}(\Theta), L_{l,S}(\Theta), L_{l,T}(\Theta)) \\ \mathbf{1}\{e_i = h\}\mathbf{1}\{k_i = T\}w_i - w_{h,T}(\alpha_h^S, \alpha_l^S, \tau^T, L_{h,\phi}(\Theta), L_{h,S}(\Theta), L_{h,T}(\Theta)) \\ \mathbf{1}\{e_i = l\}\mathbf{1}\{k_i = T\}w_i - w_{l,T}(\alpha_h^S, \alpha_l^S, \tau^T, L_{l,\phi}(\Theta), L_{l,S}(\Theta), L_{l,T}(\Theta)) \end{pmatrix} \tag{52}$$

The moment function g measures the difference between the data and model moments for observation i at parameter Θ. Note that $E[g(X_i;\Theta^*)] = 0$ holds for the true model parameter Θ^*. Consequently, the generalized method of moments estimator $\hat{\Theta}$ is obtained as a minimizer of an empirical analog of the norm of $E[g(X_i;\Theta^*)]$, i.e., $\hat{\Theta}$ solves:

$$\hat{\Theta} = \arg\min_{\Theta} \left\| \frac{1}{N}\sum_{i=1}^{N} g(X_i;\Theta) \right\|^2 \tag{53}$$

Hansen (1982) showed that, under some regularity conditions, $\hat{\Theta}$ is asymptotically normal as the sample size N grows to infinity:

$$\sqrt{N}(\hat{\Theta}-\Theta^*) \xrightarrow{D} N\Big(0,(G^TG)^{-1}G^T\Omega G(G^TG)^{-1}\Big),$$

where

$$\begin{aligned}\Omega &= E\left[g(X;\Theta^*)g^T(X_i;\Theta^*)\right]\\ G &= E\left[\frac{\partial}{\partial\Theta^T}g(X;\Theta)\right]\Bigg|_{\Theta=\Theta^*}.\end{aligned}$$

In other words, Ω and G are the variance matrix of g and its Jacobian matrix evaluated at the true parameter values Θ^*, respectively. Therefore, a variance estimator of $\hat{\Theta}$ is given by:

$$\frac{1}{N}(\hat{G}^T\hat{G})^{-1}\hat{G}^T\hat{\Omega}\hat{G}(\hat{G}^T\hat{G})^{-1} \in \mathrm{R}^{dim(\Theta)\times dim(\Theta)} \tag{54}$$

where

$$\hat{\Omega} = \tfrac{1}{N}\textstyle\sum_{i=1}^{N}\left\{g(X_i;\hat{\Theta})g^T(X_i;\hat{\Theta})\right\} \quad \in \mathrm{R}^{dim(g)\times dim(g)} \tag{55}$$

$$\hat{G} = \tfrac{1}{N}\textstyle\sum_{i=1}^{N}\tfrac{\partial}{\partial\Theta^T}g(X_i;\Theta)\Big|_{\Theta=\hat{\Theta}} \quad \in \mathrm{R}^{dim(g)\times dim(\Theta)} \tag{56}$$

In other words, $\hat{\Omega}$ is the sample mean of the outer product of g and $\hat{G}$ is the sample mean of the Jacobian matrix of g. I calculated the Jacobian matrix based on the numerical differentiation using the centered differencing method. Specifically, the jth column of $\hat{G}$, denoted by $\hat{G}_j$, is obtained by

$$\hat{G}_j = \frac{N^{-1}\sum_{i=1}^{N}g(X_i;\hat{\Theta}+\varepsilon e_j) - N^{-1}\sum_{i=1}^{N}g(X_i;\hat{\Theta}-\varepsilon e_j)}{2\varepsilon}$$

where ε is chosen as a very small number (10^{-6}), and e_j is the jth unit vector, i.e., $e_j = (0,\ldots,0,1,0,\ldots,0)^T$.

E.2 Elasticity of Labor Supply

Extensive Margin. As there are two industry sectors, I consider two types of elasticities of labor supply in the extensive margin: (i) the elasticity of labor supply in response to the relative wage in the local service sector to not working and (ii) the elasticity of labor supply in response to the relative wage in the tradable sector to not working. After plugging Equations (46a), (46b), (47a), and (47b) into Equations (45a), (45b), and (45c), I calculate the log of the fraction of working to not working as follows:

$$log\left(\frac{L_{e,S}+L_{e,T}}{L_{e,\phi}}\right) = log\left(\frac{\left((w_{e,S}\mu_{e,S})^{\frac{1}{\sigma(1-\rho_e)}} + (w_{e,T}\mu_{e,T})^{\frac{1}{\sigma(1-\rho_e)}}\right)^{(1-\rho_e)}}{(w_{e,\phi})^{\frac{1}{\sigma}}}\right) \tag{57}$$

$$= (1-\rho_e)log\left(\left(\frac{w_{e,S}}{w_{e,\phi}}\mu_S\right)^{\frac{1}{\sigma(1-\rho_e)}} + \left(\frac{w_{e,T}}{w_{e,\phi}}\mu_T\right)^{\frac{1}{\sigma(1-\rho_e)}}\right) \tag{58}$$

To get the elasticities, I take the derivative of the above with respect to $log\big(\frac{w_{e,S}}{w_{e,\phi}}\big)$ and $log\big(\frac{w_{e,T}}{w_{e,\phi}}\big)$ respectively. Therefore, I have:

$$\frac{\partial log\left(\frac{L_{e,S}+L_{e,T}}{L_{e,\phi}}\right)}{\partial log\left(\frac{w_{e,k}}{w_{e,\phi}}\right)} = \frac{1}{\sigma}\cdot\frac{\left(\frac{w_{e,k}}{w_{e,\phi}}\mu_k\right)^{\frac{1}{\sigma(1-\rho_e)}}}{\left(\frac{w_{e,S}}{w_{e,\phi}}\mu_S\right)^{\frac{1}{\sigma(1-\rho_e)}} + \left(\frac{w_{e,T}}{w_{e,\phi}}\mu_T\right)^{\frac{1}{\sigma(1-\rho_e)}}} \tag{59}$$

$$= \frac{1}{\sigma}\cdot\frac{\left(w_{e,k}\mu_k\right)^{\frac{1}{\sigma(1-\rho_e)}}}{\left(w_{e,S}\mu_S\right)^{\frac{1}{\sigma(1-\rho_e)}} + \left(w_{e,T}\mu_T\right)^{\frac{1}{\sigma(1-\rho_e)}}} \quad \text{for } k\in\{S,T\} \tag{60}$$

when all else equal.

Intensive Margin. Conditional on working, I consider the elasticity of substitution of labor supply between the local service sector and the tradable sector. By dividing Equation (45b) by Equation (45c) and taking the log of it, I have:

$$log\left(\frac{L_{e,S}}{L_{e,T}}\right) = \frac{1}{\sigma(1-\rho_e)} \times log\left(\frac{w_{e,S}\mu_{e,S}}{w_{e,T}\mu_{e,T}}\right) \tag{61}$$

Therefore, the elasticity of labor supply substitution is $\frac{1}{\sigma(1-\rho_e)}$.

Comparison to Previous Literature. To compare the estimates reported in Table 6, I provide various labor supply elasticities found in previous literature in Table E2. In terms of extensive margin, Chetty et al. (2011) gives a point estimate of the extensive margin labor supply elasticity as 0.26 based on meta-analyses of existing micro quasi-experiments. This means that a 1% increase in wage leads to a 0.26% increase in labor. To convert this interpretation into what I provided in Table 6, I calculate the percentage of the relative labor supply increase in response to a 1% increase in wage.

Table E2: Labor Supply Elasticities in Previous Literature

Paper	Value	Interpretation
A. Extensive margin		
Chetty et al. (2011)	0.26	Steady state labor supply elasticity
B. Intensive margin		
Card et al. (2018)	2 for high-skilled 5 for low-skilled	Firm-specific labor supply elasticity
Dhyne et al. (2022)	3.5	Firm-specific labor supply elasticity (Belgium)
Huneeus, Kroft and Lim (2021)	5.5	Labor supply elasticity (Chile)
Kroft et al. (2020)	3.5-4.1	Construction sector labor supply elasticity
Lamadon, Mogstad and Setzler (2022)	4.6	Market-level labor supply elasticity
	6.5	Firm-specific labor supply elasticity

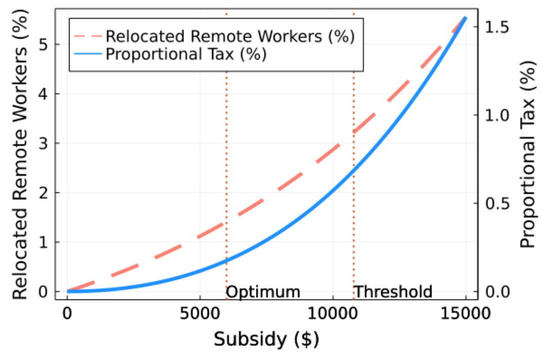
F Supplementary Material to Section 8: Subsidizing Remote Workers through Taxation

F.1 Sensitivity Analysis on ψ

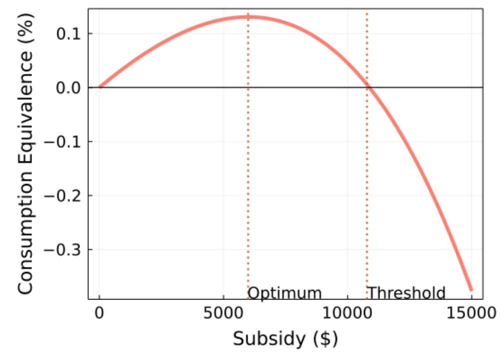
Figure F1: Sensitivity Analysis of Figure 8

(a) A Smaller Geographic Unit ($\psi = 10.45$)

Relocated Remote Workers and Proportional Tax

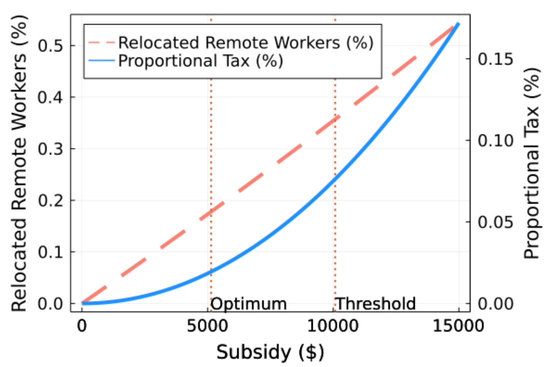


Welfare Effect on Local Residents

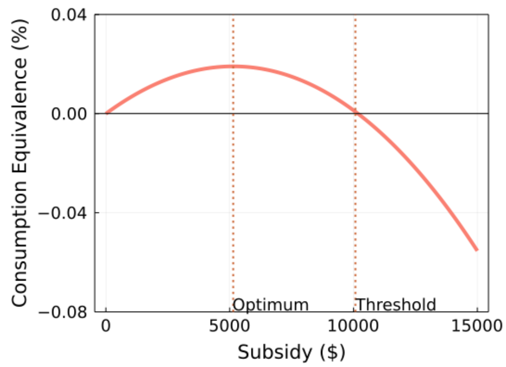


(b) A Larger Geographic Unit ($\psi = 2$)

Relocated Remote Workers and Proportional Tax



Welfare Effect on Local Residents



Notes: Panel (a) presents the same set of plots as Figure 8 when $\psi = 10.45$, and panel (b) is when $\psi = 2$. For the left panels, the percentage of relocated remote workers relative to the local residents (%) is shown on the left y-axis, and the progressive tax rate ($) is shown on the right y-axis. For the right panels, the weighted welfare effect on local residents is shown. Newly relocated remote workers are not included in this welfare calculation. Two vertical lines denote (i) the optimal subsidy ($5,995 for $\psi = 10.45$ and $5,142 for $\psi = 2$) and (ii) the subsidy threshold ($10,778 for $\psi = 10.45$ and $ 10,077 for $\psi = 2$). The optimal subsidy is where the effect size is maximized. The threshold is the subsidy at which receiving more remote workers is no longer beneficial to local residents on average. Applying different elasticity values is intended to explore the welfare effects with different geographic units. For example, $\psi = 10.45$ is used for the census tract geographic unit and $\psi = 2$ is used for the county geographic unit. If $\psi = 10.45$, the percentage of relocated remote workers reaches approximately 2.87% when the subsidy amount is set at $10,000, which is exactly matched with the Tulsa Remote case. In summary, this sensitivity exercise shows that using a different elasticity does not significantly alter the optimal level of subsidy and the threshold subsidy. In terms of the size of the optimal welfare effect, it ranges from 0.02% (when $\psi = 2$) to 0.13% (when $\psi = 10.45$).