Remote Work and Consumer Cities

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Abstract

The rapid adoption of remote work reduced the physical presence of workers in urban centers, weakening cities' traditional role as centers of production. We highlight that cities' role as centers of consumption remained robust and, with greater time flexibility from workers, may have grown in importance. We present a stylized model showing that the amenity value premium of dense urban areas can serve as an anchoring force for urban foot traffic despite residential suburbanization. Using detailed mobile-device foot traffic data, we find that while remote work reduced visits to former commuting destinations, it simultaneously increased visits to amenity-rich urban hot spots. Our findings suggest that remote work accelerated the transition of urban centers from commuting destinations to leisure destinations.

Keywords: Amenities, Consumer Cities, Central City, WFH, Remote Work, Work from Home, Commuting, Retail, Foot Traffic, Consumption

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1 Introduction

The COVID-19 pandemic triggered an unprecedented remote work revolution. At its peak, as many as 60% of U.S. workers worked from home, and by mid-2024, 29% of paid working hours continued to be supplied away from the office, according to the Survey of Working Arrangements and Attitudes (SWAA) (Barrero et al., 2021). With the widespread adoption of remote and hybrid work, daily commutes to urban office districts have fallen sharply. Because office work sites are disproportionately concentrated in dense city centers, this shift inevitably reduced the foot traffic and ancillary economic activity that commuters once brought into downtown areas, while also fueling net out-migration from cities to suburbs (Liu and Su, 2021; Gupta et al., 2021; Althoff et al., 2022; Ramani and Bloom, 2021). The resulting population loss further eroded demand for urban amenities and local businesses, compounding pressures on urban prosperity (Monte et al., 2023; Gupta et al., 2023). As remote and hybrid arrangements appear likely to persist, many observers warn of a bleak urban future, raising concerns of an "urban doom loop" driven by declining economic activity and downward spirals in local public finance (Nieuwerburgh, 2022).

That said, prevailing discussions about the future of cities are heavily premised on their role as centers of *production*. If dense urban cores are primarily valued as sites where workers congregate to produce, then the spatial dispersion of work enabled by remote arrangements would indeed diminish their importance. Yet cities have increasingly been recognized not only as places of production but also as centers of *consumption* and leisure (Glaeser et al., 2000; Glaeser, 2011; Jedwab et al., 2022). Workers choose to visit and reside in cities not just for job proximity but to access urban amenities. Research shows that even before the pandemic, location choices have shifted toward valuing amenity access rather than proximity to high-productivity workplaces per se (Glaeser and Gottlieb, 2006; Couture and Handbury, 2020). Thus, as the workplace function of cities wanes relative to their amenity function, the trajectory of urban vitality may hinge less on production and more on the strength of cities as centers of consumption.

In this paper, we show that although remote work has persisted and commuting trips have only partially recovered, visits and consumer spending at urban consumption amenities rebounded strongly after the pandemic's peak. In particular, while remote work has continued to suppress foot traffic in neighborhoods dominated by commuting-related destinations such as Central Business Districts (CBDs), visits to large clusters of consumption amenities recovered robustly after an initial decline. We demonstrate that these concentrated amenity clusters serve as powerful magnets for urban foot traffic, even in the absence of pre-pandemic levels of inbound commuters. Furthermore, we present evidence that the flexibility afforded by remote work increased residents' willingness to travel to major amenity centers, reinforcing the elevated foot traffic in urban neighborhoods, despite *residential* suburbanization.

To demonstrate the mechanisms through which remote work adoption affects foot traffic and residential population patterns, we develop a stylized spatial equilibrium model of remote work and local amenity provision with two locations: an urban core and a suburb. Our framework relaxes several common assumptions implicitly embedded in most analyses of remote work. Once these often-implicit common assumptions are relaxed, the model generates predictions that differ sharply from those of the conventional frameworks.

The first common assumption is that the urban core attracts visits ultimately as a commuting destination, with other activities primarily arising endogenously from foot traffic derived from commuter flows (Su, 2020; Davis et al., 2021; Delventhal et al., 2021; Delventhal and Parkhomenko, 2022; Richard, 2024). In this view, a permanent decline in commuting would imply a long-run decline in all other urban economic activities. We relax this assumption by allowing the urban core to provide an *exogenous* amenity premium that persists even as commuter presence falls. The second common assumption is that amenity demand originates solely from local residents. If this holds, suburbanization induced by remote work would necessarily reduce visits to urban amenities. We relax this assumption by allowing residents to *travel* across locations for leisure, enabling the urban amenities to attract inbound visits from suburban residents. The third common assumption is that remote work leaves residents' time for amenities unchanged. With a fixed leisure-time budget, households would reduce their urban visits as they relocate outward, even if they travel to amenities sometimes. We relax this assumption by allowing remote work adoption to increase leisure time, thereby opening up the possibility that remote work can potentially *raise* the likelihood that suburban residents travel into the urban core to enjoy its amenities.

Because remote work adoption surged concurrently with the onset of the pandemic, we stress that its effects on foot traffic and residential patterns are distinct from those of the pandemic-induced aversion to amenities. It is therefore important not to conflate the two. In our framework, the pandemic generated a *combination* of shocks to the spatial equilibrium: a temporary rise in aversion to amenities due to heightened disease-transmission risk, and a permanent increase in remote work adoption. Once the pandemic subsides, the amenity aversion dissipates, but remote work adoption remains elevated relative to its pre-pandemic level because of its persistence.

Under our model framework, the temporary pandemic-induced surge in amenity aversion strongly reduces foot traffic across all locations, with especially large effects in the urban location, and simultaneously induces some residential suburbanization. Hence, the sharp decline in urban foot traffic observed during the peak of the pandemic cannot be attributed solely to remote work adoption. If urban amenities retain their amenity value premium and residents are willing to travel for leisure, once the temporary aversion dissipates after the pandemic ends, the model predicts a strong rebound in amenity foot traffic, especially at urban amenities. If we further account for workers' expanded leisure time due to the reduced commuting burdens under remote work, foot traffic to urban amenities may eventually even rise *above* its pre-pandemic level.

Whether urban amenities ultimately anchor or even amplify foot traffic depends on the relative strength of the above-mentioned factors. To assess the extent to which these theoretical predictions are borne out in practice, we analyze geographically detailed foot traffic data based on mobile devices, consumer spending data, and housing data.

We show that both survey-reported time spent and mobile-device-based foot traffic at amenity establishments recovered strongly after collapsing during the peak of the pandemic. In particular, the recovery of foot traffic and consumer transactions was more pronounced in urban-center amenities. Notably, the rebound in urban amenity visits outpaced the recovery of commuter traffic, indicating that the resurgence of urban amenity foot traffic was not mechanically driven by the return to on-site work.

In contrast, the re-urbanization of the residential population and housing demand has been far weaker, if present at all. The rent and housing value gradient with respect to distance from city centers has shown no signs of recovery. Consistent with residents continuing to suburbanize while amenity visits become more spatially concentrated in urban centers, we find that visitors to urban amenities are increasingly non-local inbound travelers from suburban areas.

However, analyzing locations in binary terms, urban centers versus suburbs, creates difficulties in identifying whether the recovery of amenity traffic and consumer spending in urban centers reflects genuine renewed demand for urban amenities, or instead a byproduct of a rebound in commuting trips. This empirical challenge arises because urban centers disproportionately host *both* clusters of office work sites with high potential for remote work adoption and clusters of high-value amenities.

To empirically demonstrate that the recovery and surge in foot traffic are driven by the anchoring effect of urban amenities, we zoom in to the census tract level and analyze foot traffic and spending data at this finer geographic resolution. For each tract, we separately compute (i) the expected shock to commuter presence, based on the local industrial composition and the share of jobs with high potential for remote adoption, and

(ii) the value of nearby amenities, measured by pre-pandemic foot traffic density to amenity establishments in the surrounding area. This approach allows us to disentangle the effects of commuter losses from the anchoring role of urban amenities.

Controlling for neighborhood characteristics and time effects, our regression analysis shows that neighborhoods with larger expected reductions in commuter presence experienced disproportionate and persistent declines in amenity foot traffic and consumer spending (both in transaction volume and spending amount), well beyond the peak of the pandemic. In contrast, neighborhoods with very high amenity value, while suffering larger initial drops during the pandemic peak, experienced a disproportionate rebound in foot traffic beginning in late 2021. This rebound made foot traffic and consumer spending at amenities even more spatially concentrated in high-amenity neighborhoods than before the pandemic. Moreover, in neighborhoods facing large negative commuter shocks, visitors are no more likely to travel from farther away. In high-amenity hot spots, however, the recovery has been fueled disproportionately by non-local visitors coming from more distant neighborhoods.

In contrast to the patterns for foot traffic and spending, rents in neighborhoods near amenity hot spots declined disproportionately in 2020 and showed only a modest recovery after 2021. Although the rent premium around amenity centers has returned to its pre-pandemic level, it has not risen beyond that baseline. This stands in sharp contrast with foot traffic around amenity hot spots, which surged after 2021 and became even more spatially concentrated near amenity clusters. These results are consistent with the model's prediction that amenities anchor *foot traffic*, and may even draw more of it as remote work expands workers' time budgets, but that these forces do not translate into residential location choices to the same extent.

Finally, we test whether the surge in foot traffic and consumer spending at amenity hot spots is *specifically* driven by the increased time flexibility afforded by widespread remote work. Using individual-level mobile device data on movements, we show that remote work days have a positive same-day effect on the fraction of non-work time that workers spend in high-value amenity hot spots. This effect is especially pronounced for workers who live and work outside urban centers. To address potential measurement error from conflating vacation days with remote work, we alternatively identify routine remote work days using a rolling-window approach based on adjacent weeks. The results remain robust: workers are more likely to spend time in amenity hot spots on the days of the week when they routinely work remotely. Moreover, we find strong intertemporal patterns in visiting behavior. Anticipating a routine remote work day significantly increases time spent in amenity hot spots on the preceding day, suggesting that remote work boosts demand for amenities partly by relaxing workers' time constraints over a multi-day window.

Our paper adds to the list of recent papers and articles discussing remote work's effect on the demand for city neighborhoods. Since 2020, researchers have noted that the pandemic has led to a wave of suburbanization among high-skilled workers, attributed to the sudden availability of virtual work options (Liu and Su, 2021; Gupta et al., 2021; Althoff et al., 2022; Ramani and Bloom, 2021; Delventhal et al., 2021). The decreased commute to the workplace not only weakened the relative demand for housing in city centers and populous urban areas, but also led to persistently empty commercial real estate, including offices and the brick-and-mortar retail spaces near these offices, and spurred a surge in online retail (Rosenthal et al., 2022; Duguid et al., 2023). Gupta et al. (2023) show that the persistently low and subdued expectations can even trigger financial concerns regarding the health of CRE debts. Other papers feature a variety of models to study the equilibrium effects of remote work on cities (Delventhal and Parkhomenko, 2022; Davis et al., 2021; Behrens et al., 2021; Brueckner et al., 2021; Liu and Su, 2023; Richard, 2024). The common focus of these papers dwells on studying the impact of remote work on *productivity* and wages offered by cities. Compared with most existing discourse, our paper presents a rosier prospect for cities by showing that dense urban neighborhoods' amenities may serve as an important anchor and may attract more economic activities as a result of the relaxed time budgets.

Our paper also contributes to the study of the role of amenities in shaping cities and neighborhoods. Over the last two decades, more attention has been paid to the role of consumption in cities. Glaeser et al. (2000) highlight the evolution of cities' role as a place for consumption. Since then, researchers studying changes in cities and neighborhoods have often emphasized how endogenous change in location-specific amenities plays a key role in shaping neighborhoods in equilibrium after an exogenous shock (Diamond, 2016; Su, 2022; Qian et al., 2023; Almagro and Domínguez-Iino, 2023; Hoelzlein, 2023). Our paper argues that amenities play a key role in understanding cities' future in the world of remote work.

Finally, this paper also adds to the general study of the agglomeration economies of *consumption*. Since Krugman (1979, 1980), increasing returns to scale with consumers has been recognized as an important determinant of the geography of economic activities. In particular, Handbury and Weinstein (2015) and Handbury (2021) show that the agglomeration effect of consumption creates a well-being premium (price index discount) associated with the size of the local consumer base – cities. Other papers show that dense neighborhoods enjoy stronger amenity value also through accessing a larger variety of services (Couture, 2016; Su, 2022). Consistent with these insights, the twin agglomeration economies of production and consumption jointly generate the anchoring force pulling people into city neighborhoods as a place to work, consume, and live, as modeled by many versions of the quantitative spatial models (QSM) featuring cities and neighborhoods (Ahlfeldt et al., 2015; Redding and Rossi-Hansberg, 2017; Monte et al., 2018; Heblich et al., 2020; Severen, 2023; Tsivanidis, 2023). Our paper highlights that, while remote work diminishes the agglomeration economies of production in cities and disperses productive activities in tradeable service sectors, the agglomeration economies of consumption remain in the era of remote work, serving as an anchoring force of increased importance for cities.

The rest of the paper is organized as follows. Section 2 presents a stylized model and its key predictions. Section 3 describes the data and how we construct the variables. Section 4 discusses the empirical tests and their implications. Section 5 concludes.

2 Stylized Model of Remote Work and Local Amenity Provision

We present a stylized spatial equilibrium model to illustrate how remote work adoption and shifts in amenity preferences can reshape visiting patterns to urban and suburban amenities, the provision of amenities across locations, and the equilibrium distribution of population between city centers and suburbs. The model highlights that a sufficiently high inherent amenity premium in city centers may anchor foot traffic despite the remote work shock, and it characterizes the conditions under which remote work could *increase* demand for urban amenities.

We adopt a simplified variation of the Alonso-Muth-Mill Model with two locations $j = u, s$, representing typical urban and suburban locations (Alonso, 1964; Mills, 1967; Muth, 1969; Brueckner, 1987). The urban location is where tradable goods and services are produced, such as office-based service production.[1] Amenities are provided in both urban and suburban locations. Workers choose their residential location and, conditional on this choice, decide which locations to visit for amenities, taking travel costs into account.

2.1 Workers' problem

The economy consists of a total population N. Workers choose to reside in either the urban location ($j = u$) or the suburban location ($j = s$), with N_u denoting the urban population and $N_s = N - N_u$ the suburban population. Let $\tau_{j'|j}$ represent the travel time from residential location j to destination j'. For simplicity,

[1] The urban location does not necessarily correspond to the central city; it may also represent suburban employment centers, such as office parks.

we assume that the urban location u is the sole commuting destination, with commuting time to the physical workplace longer for suburban residents ($\tau_{u|s}$) than for urban residents ($\tau_{u|u}$).

Conditional on their residential choice, workers decide where to consume amenities, either in the urban or suburban location. We denote by $x_{j'|j}$ the fraction of workers residing in j choosing to visit location j' for amenities, and by $a_{j'}$ the value of amenities provided in location j'.

2.1.1 Amenity Choice

Workers make two decisions: where to reside and where to consume amenities. We begin with the amenity choice problem. Conditional on their residential location j, each worker derives utility from the choice of amenity destination. A worker may choose to visit the urban location (u), the suburban location (s), or not visit any location at all. The utility of worker i residing in j and visiting j' is given by

$$U_{i,j'|j} = \underbrace{\alpha_L \ln\left(\tau - \theta_c \tau^c_{u|j} - \tau_0 - \theta_a \tau_{j'|j}\right) + a_{j'}}_{\bar{U}_{j'|j}} + \varepsilon^a_{i,j'|j}\sigma_a.$$

The utility from choosing a location reflects the net leisure time available after accounting for various time costs. Specifically, it equals total non-work time (τ) minus the mean commuting time cost ($\tau^c_{u|j}$), the fixed cost of visiting amenities (τ_0), which captures quality-of-life considerations such as the risk of disease transmission during the pandemic, and the travel time cost to the amenity location j' ($\tau_{j'|j}$).

The mean commuting time, $\tau^c_{u|j}$, is defined as the *average* travel time from a worker's residence j to the workplace u, conditional on the prevailing remote work arrangement. Commuting time is modeled as a function of travel distance and the share of work hours performed on-site:

$$\tau^c_{u|j} = \omega_c \tau_{u|j},$$

where ω_c denotes the fraction of aggregate work hours conducted on-site, and $1 - \omega_c$ represents the share of hours worked remotely. The effect of the remote work revolution on commuting is captured by an exogenous reduction in ω_c.

If the worker chooses not to visit amenities, the utility is:

$$U_{i,0|j} = \alpha_L \ln\left(\tau - \theta_c \tau^c_{u|j}\right) + \varepsilon^a_{i,0|j}\sigma_a.$$

The logarithmic functional form over net leisure time generates a key feature of the model: the marginal disutility of amenity travel depends on workers' commuting burden. When commuting time $\tau^c_{u|j}$ declines exogenously due to remote work adoption, workers' total non-work time endowment increases, thereby reducing both the disutility of the fixed cost of visiting amenities and the marginal disutility of additional travel, which reduces workers' sensitivity to leisure travel time. This mechanism allows remote work adoption to influence not only the demand for amenities but also workers' sensitivity to travel time.

In addition to the utility derived from leftover net leisure time, workers obtain amenity value $a_{j'}$ from visiting destination j', along with an idiosyncratic preference shock $\varepsilon^a_{i,j'|j}$, assumed to follow a Type-I Extreme Value distribution. The parameter σ_a denotes the scale (standard deviation) of the idiosyncratic component. Thus, conditional on their residential location, workers may choose to visit amenities in either u or s, or choose to remain at home.

Thus, the fraction of workers living in j visiting j' is the following

$$x_{j'|j} = \frac{\exp\left(\bar{U}_{j'|j}/\sigma_a\right)}{\exp\left(\bar{U}_{j'|j}/\sigma_a\right) + \exp\left(\bar{U}_{j''|j}/\sigma_a\right) + \exp\left(\bar{U}_{0|j}/\sigma_a\right)}.$$

Given the equilibrium level of amenity provision in each location and the travel time, workers living in location j derive the following expected utility from amenity provision:

$$\bar{U}^a_j = \ln\left(\exp\left(\bar{U}_{j'|j}/\sigma_a\right) + \exp\left(\bar{U}_{j''|j}/\sigma_a\right) + \exp\left(\bar{U}_{0|j}/\sigma_a\right)\right).$$

2.1.2 Residential Location Choice

Workers make location choices, taking the expected utility $\bar{U}^a_j$ from amenity provisions in each location as given. The upper level of worker i's utility of *living* in j takes the form of a Cobb-Douglas form, combining log utility from numeraire consumption ($\ln C$), housing consumption ($\ln H$), and the lower-tier amenity value $\bar{U}^a_j$, together with an idiosyncratic preference shock ε_{ij} drawn from a Type-I Extreme Value distribution. σ is the standard deviation of the idiosyncratic component of the utility. κ is the housing expenditure share. The utility that worker i will get living in location j is given by:

$$U_{ij} = (1-\kappa)\ln C + \kappa \ln H + \bar{U}^a_j + \varepsilon_{ij}\sigma,$$

Each worker faces the following budget constraint:

$$C + R_j H = I,$$

where I is income, and R_j is the housing rental price in location j. Solving the utility maximization problem with respect to C and H yields the indirect utility of worker i in location j:

$$V_{ij} = V_0 - \kappa \ln R_j + \bar{U}_j^a + \varepsilon_{ij}\sigma.$$

Workers choose the location that maximizes their utility. As a result, the population residing in location j is given by:

$$N_j = N \frac{\exp\left(\left(V_0 - \kappa \ln R_j + \bar{U}_j^a\right)/\sigma\right)}{\exp\left(\left(V_0 - \kappa \ln R_j + \bar{U}_j^a\right)/\sigma\right) + \exp\left(\left(V_0 - \kappa \ln R_{j'} + \bar{U}_{j'}^a\right)/\sigma\right)}. \tag{1}$$

2.2 Amenity Demand and Provision

We assume that foot traffic to amenities in each location is generated by leisure visits from both urban and suburban residents. In addition, amenities in the urban location receive extra visits tied to on-site work, such as lunch breaks or commute-chained trips. To capture this, we assume that each suburban resident contributes an ϕ amount of visits to urban amenities whenever working onsite in the urban location.[2]

Hence, the total foot traffic in urban amenity locations is

$$M_u = N_u x_{u|u} + N_s \left(\omega_c \phi + x_{u|s}\right), \tag{2}$$

and the foot traffic in suburban amenity locations is

$$M_s = N_u x_{s|u} + N_s x_{s|s}. \tag{3}$$

To capture how amenity provision adjusts to shifting demand, we model the amenity value in each location as the sum of an exogenous component (a_{j0}) and an endogenous component that depends on local foot traffic ($\beta_a M_j$):

$$a_j = a_{j0} + \beta_a M_j. \tag{4}$$

[2]This amount is equivalent to a ϕ fraction of the suburban worker's total non-work leisure time.

The exogenous component is assumed to be higher in urban locations ($a_{u0} > a_{s0}$), reflecting the inherent advantages of dense urban areas in producing consumption amenities, due to their built environment, agglomerated infrastructures, and path dependence (Couture et al., 2023). The urban premium in exogenous amenity value, $a_{u0} - a_{s0}$, plays a key role in determining whether urban foot traffic can remain anchored in city centers following a shock to commuter flows.

The endogenous component increases with local foot traffic: higher M_j enhances the amenity value of location j. This mechanism captures the increasing returns to scale in amenity provision that are standard in quantitative spatial models. Prior to widespread remote work adoption, urban locations benefited from heavy exogenous foot traffic due to commuting, which in turn amplified urban amenity values through this endogenous channel. The parameter β_a governs the strength of this amplification, determining the extent to which foot traffic shapes local amenity values.

2.3 Housing Market

Housing supply is assumed to be inelastic, so local rental prices increase with population (housing demand). Let N_j denote the population in location j. The inverse housing supply curve is specified as

$$R_j = \exp\left(r_{0j} + \rho_j \ln(N_j)\right), \tag{5}$$

where ρ_j denotes the inverse elasticity of housing supply in location j. We allow ρ_j to vary across locations, consistent with evidence that denser urban areas typically exhibit less elastic housing supply (Baum-Snow and Han, 2020).

2.4 Spatial Equilibrium

The spatial equilibrium in the two-location economy is defined by local foot traffic M_u, M_s, and population N_u (and $N - N_u$), which simultaneously clear all amenity and housing markets. For the amenity markets to clear, two conditions must hold:

1. Foot traffic generated by urban residents (given by equation 2) and suburban residents (given by equation 3) must be consistent with the equilibrium level of endogenous amenity provision (equation 4 must hold),

2. The population distribution across locations (given by equation 1) must be consistent with the equilibrium levels of housing rents (equation 5 must hold).

2.5 How Our Model Differs from the Usual Frameworks

Before turning to the comparative statics, we highlight several key features of our framework that depart from typical urban frameworks in which people study the impact of remote work. These departures are central to generating the ambiguous effects of remote work on urban foot traffic, which earlier frameworks typically do not.

***Exogenous* Urban Amenity Premium** Much of the literature on the future of cities under remote work implicitly assumes that urban foot traffic in major cities is driven primarily by commuting. Even when urban amenities are discussed, the underlying view is that their value is largely endogenous, ultimately arising from the provision sustained by commuter-driven foot traffic.

Under this assumption, widespread adoption of remote work reduces commuter inflows exogenously, diminishing not only the urban foot traffic directly chained with commuting trips but also the additional amenity foot traffic supported by high urban amenity value endogenously generated by the commute-chained trips. Together, these effects imply a sharp decline in urban foot traffic and associated economic activity.

In contrast, our model incorporates both an endogenous and an *exogenous* component of amenity value in urban locations. We show that if the exogenous urban amenity premium is sufficiently large, it can anchor substantial foot traffic in urban areas, even in the face of large remote work shocks.

Residents *Travel* for Amenities Even in models that explicitly incorporate exogenous urban amenity premium, demand for amenities is typically assumed to be purely local—that is, only residents consume the amenities of their own location. As a result, amenity values are modeled solely as a function of the number or composition of local residents. Under this assumption, migration from urban to suburban areas in response to remote work inevitably generates an endogenous decline in both amenity value and foot traffic in urban locations. This decline occurs even when urban areas offer a substantial amenity premium.

In our model, we relax this assumption by allowing residents of either location to choose amenities in either j or j', subject to travel costs that differ based on distance. With this modification of the assumption, we continue to show that widespread adoption of remote work induces residential suburbanization because of the reduced need to commute. However, if the urban location provides a sufficiently large amenity premium, it can continue to retain foot traffic, as suburban residents will still *travel* to the urban location to consume amenities despite living outside.

Amenity Demand is *Endogenous* to the Time Budget Lastly, much of the discussion on remote work's impact on urban foot traffic implicitly assumes that individuals' overall time spent visiting amenities is unaffected by remote work. Under this assumption, as households relocate to the suburbs, even if some continue to visit urban amenities, such visits are drawn from a fixed leisure-time budget, implying that urban locations inevitably lose foot traffic in the long run.

In contrast, our model explicitly incorporates a time budget that adjusts endogenously with commuting time. As remote work becomes more prevalent, workers gain net leisure time and become less constrained in their leisure and travel decisions. Consequently, remote work can increase the overall likelihood of amenity visits. Moreover, if the urban amenity premium is sufficiently large, the reduced sensitivity to travel costs can generate disproportionately higher demand for *urban* amenities among suburban residents.

2.6 Comparative Statics

We posit that the pandemic brings dual immediate shocks to the economy:

1. A surge in remote work adoption:[3] $\omega_c \downarrow$
2. An increase in aversion toward visiting amenities due to the risks of disease transmission:[4] $\tau_0 \uparrow$

After the pandemic subsided, the temporary aversion toward visiting amenities outside of homes would likely have *lifted*. This means that τ_0 would have recovered largely to the pre-pandemic level. However, the increased adoption of remote work remained persistently higher than the pre-pandemic level. Hence, post-pandemic, while ω_c will remain at a reduced level, the elevated τ_0 is expected to have come back down. In this section, we explore how changes in ω_c and τ_0 affect the equilibrium.

[3]The surge in remote work adoption is represented by an exogenous decrease in the size of ω_c - the fraction of work time on urban worksites.

[4]The shock of reduced amenity demand is captured by an exogenous increase in τ_0 - the fixed cost of visiting amenities vis-a-vis staying at home, and the eventual recovery of amenity preference is captured by a reversal of such an increase.

2.6.1 The Effect of Remote Work Shock - $\omega_c \downarrow$

Effect on Residential Migration First, we discuss remote work's effect on the migration of the residential population:

Proposition 1. *If the commuting time saving $\tau_{u|s} - \tau_{u|u}$ is sufficiently large and the leisure travel cost θ_a is sufficiently small, an increase in remote work (i.e., $\omega_c \downarrow$) leads to net migration from the urban to the suburban location—i.e., a reduction in population N_u in the urban location u and an increase in population N_s in the suburban location.*

Please see Appendix A1.1 for the proof.

The rise of remote work affects migration through several channels:

First, remote work reduces the average commuting time required of workers, thereby diminishing the relative commuting advantage of living in an urban location compared to a suburban location. This equalizing effect on commuting costs drives suburbanization of the *residential population*.

Second, as fewer commuters travel to the urban location and as part of the local customer base migrates outward, visits to urban amenities decline. This generates an endogenous reduction in urban amenity value, further eroding the attractiveness of urban residence and amplifying population loss.

But, at the same time, remote work expands residents' effective time budgets, which can increase their willingness to travel for leisure activities. In particular, the relaxed time constraint reduces the marginal disutility of leisure travel time, allowing suburban residents to more frequently choose urban amenities. This channel may offset the decline in foot traffic from the loss of chained commuting trips and, in some cases, even raise urban amenity visits and amenity values, thereby mitigating the loss of urban desirability.

However, if the commuting-time saving $\tau_{u|s} - \tau_{u|u}$ from living in the urban location is sufficiently large and the marginal cost of leisure travel θ_a is sufficiently small, the offsetting time-budget effect will be secondary to the commuting effect. The intuition is that when θ_a is small, urban amenities can attract substantial foot traffic from suburban residents. Yet the same condition implies that access to amenities would be more equal across locations, so urban residence provides little additional advantage. Hence, if $\tau_{u|s} - \tau_{u|u}$ is large, the commuting-time saving effect of remote work dominates and drives residential migration patterns.

Effect on Foot Traffic The impact of remote work on amenity foot traffic is shaped by two starkly opposing forces, yielding an ambiguous net effect even under highly plausible conditions.

Proposition 2. *The increase in remote work (i.e., $\omega_c \downarrow$) reduces urban amenity foot traffic M_u if ϕ is sufficiently large. But, if ϕ is small and cross-location commuting time $\tau^c_{u|s}$ sufficiently long and urban amenity premium $a_{u0} - a_{s0}$ sufficiently high, an increase in remote work could raise urban amenity foot traffic M_u.*

Please see Appendix A1.1 for the proof.

The effect of remote work adoption on amenity foot traffic can be understood as the interaction of several opposing forces:

First, as remote work reduces the number of commuters to urban locations, urban amenities lose visits that were previously chained with commuting trips. The parameter ϕ governs the extent to which amenity visits are tied to commuting. Thus, when ϕ is large, an increase in remote work produces a substantial decline in urban amenity foot traffic. This reduction, in turn, endogenously lowers the amenity value of urban locations, further reinforcing the decline in urban amenity visits.

Second, because leisure travel incurs a positive cost ($\theta_a > 0$), amenities are disproportionately visited by local residents. Consequently, the net migration of population from urban to suburban locations shifts amenity foot traffic outward as well.

On the other hand, remote work relaxes workers' time budgets. If commuting times for suburban residents are long, remote work generates substantial gains in available leisure time, which increases the demand for amenities and reduces the disutility of leisure travel. When the urban amenity premium $a_{u0} - a_{s0}$ is high, this channel can significantly boost foot traffic to urban amenities.

Hence, the overall effect of remote work on urban amenity visits depends on the relative strength of these mechanisms. If the loss of commuters and residents dominates, remote work reduces urban amenity foot traffic. If the expanded time-budget effect dominates, remote work increases urban amenity foot traffic.

Proposition 3. *The increase in remote work (i.e., $\omega_c \downarrow$) raises suburban amenity foot traffic M_s when the urban amenity premium $a_{u0} - a_{s0}$ is not too large or when ϕ is sufficiently large. Conversely, if the urban amenity premium $a_{u0} - a_{s0}$ is large enough and ϕ is small, then an increase in remote work could instead reduce suburban amenity foot traffic M_s.*

Please see Appendix A1.1 for the proof.

The effect of remote work on suburban amenity foot traffic operates through a similar but distinct set of channels:

First, net migration from urban to suburban locations shifts the residential base outward, directly raising foot traffic at suburban amenities.

Second, as remote work reduces commuting to urban centers and urban amenities lose visits that were previously chained with commuting trips, the relative attractiveness of suburban amenities rises, further boosting suburban foot traffic.

On the other hand, remote work also expands leisure time, which increases overall demand for amenities and lowers the disutility of leisure travel. This channel raises visits to both urban and suburban amenities. However, if the urban amenity premium $a_{u0} - a_{s0}$ is sufficiently large, the increased amenity demand driven by relaxed time budgets may flow disproportionately toward urban amenities, diverting visits away from suburban locations.

Hence, the net effect of remote work on suburban amenity foot traffic depends on the relative strength of these mechanisms. If migration, the loss of urban commuters, and the general increase in leisure time dominate, remote work raises suburban foot traffic. If the relaxation of time budgets instead amplifies the pull of high urban amenity premiums, suburban foot traffic will decline.

2.6.2 The Effect of Amenity Preference Change - $\tau_0 \uparrow$

Because the rise of remote work coincided with the onset of the pandemic, which both accelerated remote work's widespread adoption and likely influenced migration and amenity demand through its own channel, it is essential to disentangle the effects of the pandemic itself from those of remote work. Failing to do so risks conflating the pandemic-driven impact with the long-term effects of remote work adoption.

We posit that the pandemic triggered a temporary surge in aversion to visiting amenities, primarily due to heightened concerns over disease transmission. This surge in amenity aversion can substantially alter both local population dynamics and amenity visitation patterns.

We summarize these implications in the following propositions:

Proposition 4. *An increase in amenity aversion ($\tau_0 \uparrow$) reduces amenity foot traffic in both urban and suburban locations (M_u and M_s), provided that the urban amenity premium $a_{u0} - a_{s0}$ is sufficiently large and the aversion shock is strong enough. In this case, the decline in M_u exceeds that in M_s — i.e., urban amenity* *foot traffic falls more sharply than suburban amenity foot traffic.*

See Appendix A1.2 for the proof.

Provided that the endogenous amenity parameter is not so large as to preclude a stable equilibrium, and that the urban location offers a sufficiently strong amenity premium, a large increase in amenity aversion (τ_0) lowers foot traffic across all locations, with particularly strong effects in the urban area. The mechanism is straightforward: a higher τ_0 reduces the probability that residents visit any amenities, raising instead the likelihood of staying home. Because greater aversion also heightens sensitivity to leisure travel costs, it disproportionately discourages non-local trips. Since urban locations typically draw a large share of inbound visitors due to their high amenity premium, the loss of such trips depresses their foot traffic most severely. Hence, even absent remote work, we would expect amenity visits to decline everywhere during the pandemic, and most sharply in urban centers.

Moreover, as residents broadly reduce their demand for amenities, the value of close access to high-quality urban amenities falls. This diminishes the relative attractiveness of urban residence compared with suburban residence, thereby inducing suburbanization of the residential population:

Proposition 5. *An increase in amenity aversion ($\tau_0 \uparrow$) induces net migration from the urban location (u) to the suburban location (s) — i.e., a decline in the urban population N_u and a corresponding rise in the suburban population N_s, provided that β_a is sufficiently small, the urban amenity premium $a_{u0} - a_{s0}$ is sufficiently large, and the aversion shock is strong enough.*

See Appendix A1.2 for the proof.

2.7 Model Predictions of the Pandemic and Post-Pandemic Foot Traffic Patterns

From the comparative statics, it is clear that while the residential migration effects of the pandemic and remote work move in the same direction, their effects on urban amenity *foot traffic* differ sharply. Hence, if the pandemic effect itself is ignored and the dramatic decline in urban amenity visits during the pandemic is attributed entirely to remote work, we risk misidentifying the true effect of remote work once pandemic conditions subside.

To account for the dual shocks, we analyze the dynamics of population and foot traffic under their combined influence during the pandemic and its aftermath. Specifically, we posit that the pandemic introduced a *temporary* rise in amenity aversion ($\tau_0 \uparrow$) alongside a *permanent* increase in remote work adoption ($\omega_c \downarrow$). Once the pandemic wanes, the temporary aversion shock dissipates, while the rise in remote work persists.

At the height of the pandemic, a large increase in amenity aversion dominated, reducing foot traffic across all locations, with disproportionately large declines in urban amenities.[5] At the same time, both the rise in τ_0 and the decline in ω_c induce net out-migration from urban to suburban locations.

When the pandemic subsides, the aversion shock dissipates, reversing its depressing effect on foot traffic and generating a broad rebound in amenity visits, particularly a strong rebound in urban areas.

In the post-pandemic period, however, the dynamics of foot traffic are governed primarily by remote work, since its adoption remains persistently higher than pre-pandemic levels. Based on Proposition 2, if the urban amenity premium is sufficiently high and the commuting-time savings from remote work are large enough, urban amenity foot traffic may not only recover but even exceed its pre-pandemic benchmark.

Turning to residential migration, the urban location is expected to recover only a modest amount of population once the aversion dissipates. A full reversal is unlikely, as the residential suburbanizing effect of remote work endures as a first-order force. Thus, in the long run, once τ_0 has fully normalized, residents will remain disproportionately suburbanized. Nevertheless, foot traffic to urban amenities is likely to rebound more strongly than in foot traffic in suburban amenities and may even overshoot pre-pandemic levels, if the urban amenity premium is high enough. In this sense, remote work is expected to transform urban locations more into leisure *travel* destinations, even as the residential population shifts outward.

3 Data

3.1 SafeGraph Foot Traffic Data

To test the effect of remote work on foot traffic at amenities, we use SafeGraph Foot Traffic data to measure monthly visits to both office establishments and consumption amenity establishments. Each business point of interest (POI) is linked to foot traffic records through a unique establishment identifier. The dataset, which is proprietary, is compiled from multiple sources, including mobile devices, WiFi connections, and sensors. A valuable feature is that visits are reported by duration—for example, 5–20 minutes versus longer

[5] As Proposition 2 shows, the standalone effect of remote work adoption on urban amenity foot traffic could be positive. If τ_0 is not sufficiently high, the combined effect of remote work and increased aversion to urban foot traffic could even be positive. We return to this case when discussing the post-pandemic period. However, at the peak of the pandemic, it is reasonable to assume that the surge in τ_0 was large enough to drive urban amenity visits to very low levels.

than 4 hours. This allows us to distinguish office visits, which generally exceed one hour, from visits to consumption amenities, which are typically shorter.

An important caveat is that SafeGraph sold the data to Advan after the end of 2022. Although the basic format of the data remained unchanged after the sale, Advan implemented several rounds of major corrections to establishment polygons and foot-traffic assignment algorithms. These adjustments introduced structural discontinuities in the data over time. Because the revisions were designed to improve accuracy by eliminating duplicate visit counts, each algorithmic change produced abrupt upward or downward shifts in foot traffic at the neighborhood level, depending on the nature of the local adjustment.

To smooth out the structural breaks in the data, we implement a simple imputation procedure at the tract level. Specifically, for each break month identified nationally, we assume that local foot traffic remains unchanged during that period. Operationally, we multiplicatively rescale the foot traffic in the subsequent month and onward so that no growth is recorded over the break months. The detailed adjustment procedure is provided in Appendix A4.

The implicit assumption behind our multiplicative rescaling is that, in months without structural breaks, the growth rate of tract-level foot traffic observed in the raw data provides an unbiased estimate of the true growth rate. While the level of foot traffic may be affected by measurement error stemming from the cumulative effects of idiosyncratic POI assignment algorithms, these errors are assumed not to distort month-to-month growth.

We argue that the multiplicative rescaling procedure introduces minimal bias in measuring foot traffic trajectories. In our summary statistics, all foot traffic measures are normalized to pre-pandemic levels, which eliminates idiosyncratic cross-sectional differences in levels. What matters for our analysis is the cumulative growth of foot traffic over time. In the regression analysis, log foot traffic serves as the outcome variable, with census tract fixed effects included in all specifications. This ensures that any persistent cross-sectional level differences across tracts are differenced out, leaving only within-tract variation relevant for our empirical analysis.

3.2 SafeGraph Spend data

To complement the SafeGraph foot traffic data, we draw on SafeGraph Spend data. Unlike foot traffic, which is derived from mobile device pings, the Spend data records monthly establishment-level transactions, including transaction counts, dollar volumes, and unique customers. In our analysis, we use business transaction counts from the Spend data as an additional measure of visits to consumption amenities.

These proprietary data are compiled from a variety of payment sources, including credit and debit card networks as well as electronic payment platforms. The coverage is narrower, encompassing roughly 10% of the businesses included in the foot traffic dataset.

3.3 Global Wireless Solutions - Mobile Consumer Panel

To study how remote work causally affects residents' trip choices, specifically the frequency, location, and distance of visits, we use mobile-level panel data from Global Wireless Solutions (GWS). The GWS dataset provides anonymized panel data on Android users' mobile device activity, recorded 24 hours a day, 7 days a week, over several months for a rolling sample of approximately 60 thousand users at any given time. All users included in the sample opted in voluntarily through a rewards app available on the Google Play Store. Participation required installation of the app and completion of an onboarding process, including explicit permission settings.

The data span from early 2019 to mid-2024, but the period with a consistent sample size and composition extends only through mid-2023. Accordingly, we restrict our analysis to data from 2019 through mid-2023. Each observation corresponds to a device ping, which contains the timestamp, geographic location, and information on mobile applications in use. For our purposes, the longitudinal sequence of geolocation pings across a large user base allows us to construct trip profiles at the individual level and analyze how travel behavior responds to different work arrangements.

3.4 Housing and Rent Data

To disentangle the effects of reduced commuting and the scale of consumption amenities on housing demand, we analyze housing price and rent data at the Zip Code level. Housing price data are obtained from Redfin, a national real estate brokerage. We use monthly median sale prices and listing prices at the Zip Code level, disaggregated by residential property type. These measures are compiled from multiple sources, including local Multiple Listing Services (MLS) and assessments by Redfin-affiliated real estate agents. To strengthen coverage, we supplement these data with the Zillow Home Value Index (ZHVI), which tracks the typical home value and market changes for homes between the 35th and 65th percentiles of the value distribution. For rent prices, we use the Zillow Observed Rent Index (ZORI), which provides monthly Zip

Code–level measures of typical asking rents.

3.5 American Time Use Survey (ATUS)

We use the American Time Use Survey (ATUS) to measure the overall time people devote to commuting and to traveling to consumption amenities outside the home, with particular attention to changes before and after 2020. Conducted by the Census Bureau for the Bureau of Labor Statistics, the ATUS provides detailed information on how a representative sample of Americans allocate their time across daily activities, including commuting, dining out, and socializing, as well as the locations where these activities occur. Each respondent records a 24-hour activity diary, which forms the basis of the dataset.

4 Empirical Evidence

4.1 Remote Work Persistence and Amenity Visit Recovery

To validate the model's predictions, we begin documenting the trajectory of commuting trips and amenity foot traffic since 2020. Figure 1 plots the frequency and the average time U.S. residents spend on work-related travel (primarily commuting) and amenity-related travel, normalized to 2012 levels, using the American Time Use Survey (ATUS). Before 2020, both types of travel remained relatively stable. In 2020, however, they both collapsed sharply, consistent with findings from pandemic-era studies, with the frequency and time spent in amenity trips dropping much more severely. However, beginning in 2021, their trajectories diverged: while commuting time has remained relatively steady and well below pre-pandemic levels, reflecting the persistence of remote work, time spent on amenity-related travel rebounded quickly and has risen steadily from its 2020 trough.

We complement the ATUS evidence with SafeGraph foot traffic data to document changes in commuting and amenity visits. Unlike ATUS, which is survey-based, the SafeGraph data are derived from mobile device geolocations. A challenge, however, is that the data do not directly distinguish between work-related and amenity-related trips. To address this, we classify commuting visits as trips to establishments outside the amenity industries that last longer than one hour, and amenity visits as trips lasting less than one hour to establishments in amenity-related industries. Specifically, we define amenity establishments as those in the following NAICS codes: 722 (Restaurants); 445, 446 (Grocery); 440–459 excluding 445 and 446

(Non-Grocery Retail); 713 (Gyms); 812 (Personal Care); 512 (Movie Theaters); and 712 (Recreation and Entertainment).[6]

Figure 2a plots the number of commuting trips and visits to urban consumption amenities. The patterns mirror those in the time-use data. Commuting trips collapsed to unprecedented lows in 2020 and, despite some modest recovery, have remained depressed through 2024. By contrast, visits to amenities rebounded more strongly.

4.1.1 Rebounding Amenity Activities in Urban Centers

Not only has the overall demand for amenities recovered more, but urban centers in particular have experienced a faster rebound relative to suburban areas. Figure 2b plots the trajectories of amenity foot traffic in urban centers and suburbs, where we define urban centers as census tracts within a 5-mile radius of the downtowns of the associated MSAs. Foot traffic fell much more sharply in urban centers at the height of the pandemic, yet their recovery was also faster than that of suburban amenities. Strikingly, the rebound in urban amenity visits has outpaced the recovery of urban commuting trips, indicating that the resurgence of urban foot traffic cannot be explained solely by the return of commuters.

Moreover, when we examine individual MSAs with dense urban centers and well-known urban amenity offerings, the disproportionate recovery of urban amenity foot traffic becomes even more pronounced. Figure 3 presents the trajectories for New York, Chicago, San Francisco, and Washington MSAs. In all four MSAs, both commuting and amenity trips to urban centers collapsed precipitously at the onset of the pandemic, with declines larger than the national average. Commuting trips have since partially rebounded but remain far below pre-pandemic levels as of 2024. In contrast, amenity visits to urban centers in New York and Chicago surged past both suburban amenity foot traffic and urban commuting traffic, nearly regaining their pre-pandemic levels by mid-2024. In San Francisco, the overall recovery has been weaker, yet urban amenity visits still outpaced suburban amenity traffic and urban commuting traffic. In Washington, urban amenity foot traffic rebounded disproportionately and surpassed urban commuting trips, though it remained below suburban amenity traffic. Taken together, these patterns reveal that the recovery of urban amenity visits has been especially strong in MSAs where we would expect a high level of amenity value due to their exogenous urban layouts.

[6] The time-duration assumption underlying these definitions is that consumers generally spend relatively short periods at amenity destinations such as stores and restaurants, while commuting visits typically involve employment shifts lasting at least one hour.

Besides foot traffic data, we also analyze consumer spending data from SafeGraph Spend data. Figure 2c plots the share of consumer spending transaction volume occurring in establishments in the urban centers. The graph shows a clear dip in 2020, meaning that business establishments in urban centers saw a precipitous, outsized drop in consumer presence during that time. However, urban centers started to reclaim their share of consumer spending starting in 2021, and as of mid-2024, merchants in urban centers claim a *higher* fraction of consumer transactions than even before the pandemic.

Consistent with the prediction of the model, Figure 2d shows that the average distance to home for visitors coming to amenities in urban centers surged after 2021. This suggests that after the peak of the pandemic, an increasing fraction of visits to amenities in city centers are made by residents of the suburbs.

This rising distance to home by urban amenity visitors is consistent with the results from Figure 4a, where we plot the population change in urban core counties and the suburban counties of a few select MSAs since 2020.[7] We see a pattern of continuing residential suburbanization since 2020.

Furthermore, Figure 4b plots rent levels in urban centers versus suburbs, normalized to 2019 Q1. Since the start of the pandemic, rent growth in the suburbs has far outpaced that in urban centers, and the gap has continued to widen through 2024. Similarly, Figure 4c shows listed home values, also normalized to 2019 Q1, and reveals the same pattern: suburban home value growth began pulling ahead of urban counterparts in 2020, with the divergence widening steadily by 2024. These results indicate a sustained suburbanization of residential housing demand, with no sign of reversal as of 2024.

This pattern aligns with the model's prediction that the persistent adoption of remote work leads suburbanized *residents* to remain suburbanized. At the same time, the anchoring value of urban amenities enables urban locations to continue attracting amenity *foot traffic*, even with fewer residents in proximity, so long as individuals are willing to travel for leisure. The effect is especially pronounced in MSAs with well-known premium urban amenities, where urban amenity foot traffic has nearly fully recovered. These findings provide suggestive evidence that remote work, by relaxing time budgets, may have increased demand for premium urban amenities.

[7] We select MSAs where county division is fine enough to designate some counties as distinctly urban and other counties as distinctly suburban. They include New York, San Francisco, Denver, Baltimore, Boston, Philadelphia, and Washington. New York includes the four boroughs (all other than Staten Island) as urban counties. Other MSAs include only the core central county as the urban county, and the rest are suburban counties.

4.2 Spatial Tests of Model Mechanisms

The limitation of testing our model predictions using foot traffic patterns based on binary locations — urban vs. suburban is that it may not be enough to rule out alternative explanations. For example, a sharp drop in amenity foot traffic in urban centers during the peak of the pandemic could reflect either the sudden adoption of remote work or a surge in amenity aversion, since both shocks occurred simultaneously. Similarly, in the aftermath of the pandemic, it is difficult to infer from the recovery or lack of recovery of urban foot traffic whether the patterns are driven by renewed demand for amenities or by increased commuter presence as on-site work partially resumed.

This empirical challenge arises because U.S. urban centers disproportionately host *both* clusters of office job sites that are highly remote-compatible *and* dense concentrations of popular urban amenities. Table 1 illustrates this overlap: office clusters with high shares of remote-adopting jobs are typically located in neighborhoods closer to city centers with higher population density, and amenity clusters are also much more likely to be concentrated in these same urban locations.

Drawing on insights from the model, we propose empirical tests at finer geographic resolution to disentangle the drivers of changing foot traffic and residential patterns.

4.2.1 Spatial Patterns in Foot Traffic

To separate amenity visits chained to commuting trips (e.g., lunch breaks) from leisure-driven visits anchored by high-value urban amenities, we disaggregate cities into fine neighborhoods and analyze foot traffic at the Census tract level.

Commute-Chained Amenity Foot Traffic To assess whether remote work lowers urban foot traffic by reducing commute-chained amenity visits, we examine foot traffic around large employment centers such as Central Business Districts (CBDs), where the decline in on-site commuters is expected to be most pronounced. During the height of the pandemic, these tracts should experience sharper drops in amenity visits relative to other areas. If remote work remains persistent after the pandemic subsides, foot traffic to amenities in these tracts should remain subdued.

Anchoring Effect of Urban Amenity Premium On the other hand, if the premium value of urban amenities anchors foot traffic under remote work, then neighborhoods with very high amenity value—such as popular recreational or commercial streets with dense retail—should exhibit a rapid rebound after the initial pandemic-era decline and should not experience a permanent reduction once the pandemic subsides.

Moreover, if remote work relaxes workers' time budgets sufficiently, foot traffic in these high-amenity neighborhoods should more than fully recover, ultimately surpassing the pre-pandemic baseline.

Rising Non-Local Foot Traffic to Urban Amenities In the model, a key mechanism enabling a strong recovery of urban foot traffic despite residential suburbanization is the ability of residents to *travel* for amenities. Thus, if urban amenity visits rebound while the residential population remains suburbanized, an increasing share of urban foot traffic should originate from residents living farther away from these amenity clusters.

Therefore, empirically, while the temporary surge in amenity aversion during the height of the pandemic should reduce the share of non-local inbound trips to high-amenity census tracts, once the pandemic subsides, an increasing fraction of visits to these urban locations should originate from *non*-local residents of lower-amenity suburban neighborhoods.

Remote Work's Effect on Workers' Demand for Urban Amenities Finally, the crucial countervailing force that allows remote work to raise urban foot traffic is its ability to relax workers' leisure time, thereby increasing their demand for amenities, particularly high-value urban amenities. If this channel is operative, then empirically, workers who frequently work remotely should be more likely to visit amenities in general, and more likely to patronize high-value amenities specifically, compared to workers who primarily work on-site.

4.2.2 Spatial Patterns in Residential Housing Demand

To validate Propositions 1 and 5 regarding the effects on residential population, we examine the trajectory of housing demand at the census tract level.

Reduced Housing Demand Near Remote-Compatible Job Centers Based on Proposition 1, the rise of remote work erodes the commuting-time advantage of residing in urban centers, leading to out-migration from these areas. To test this channel, we examine changes in housing demand in neighborhoods around major job centers such as CBDs, where the reduction in commuting needs should be most pronounced. These neighborhoods are expected to experience disproportionately large declines in housing demand, reflected in lower rent and housing value growth relative to other locations.

Amenities' Mitigated Effects on Housing Demand Based on Proposition 5, neighborhoods with high amenity value should experience a population decline—and hence in housing demand—during the peak of the pandemic. However, once the pandemic subsides, this demand is expected to recover. That said, the fluctuation should be relatively moderate, since the value of amenity access remains steady if the cost of leisure travel θ_a is not too high.

Similarly, the rise of remote work, while it affects amenity foot traffic, is expected to also have moderate effects on residential location choices, particularly if individuals are willing to travel for amenities. Therefore, rent and housing value growth around high-amenity hot spots should differ moderately, if any, from that in other neighborhoods.

4.2.3 Identifying Local Commuter Shocks vs. Amenity Hot Spots

4.2.4 Local Commuter Shocks – RS_j

To identify neighborhoods expected to experience larger reductions in workers' physical presence due to remote work, we measure the fraction of nearby jobs that are remote-adoptive based on the industrial composition of pre-pandemic commuters to surrounding job sites. Specifically, we use pre-pandemic SafeGraph foot traffic data to calculate the number of commuting trips to each location by industry and then estimate how many of those trips would have disappeared under remote work adoption.[8]

Using this approach, we first compute the number of commuters in each census tract likely to adopt remote work, relative to the total number of commuters to that tract. We then aggregate within a 3-mile radius to construct the fraction of commuters likely to go remote after 2020, denoted as RS_j. This variable captures the spatial variation in the expected reduction in commuting trips.

4.2.5 Local Consumption Amenity Provision – Am_j

Next, we calculate the value of local amenity provision. A natural starting point is to measure amenity establishment density at a highly localized level. However, relying on the raw count of establishments poses

[8]As an alternative, one could use the Zip Code Business Patterns (ZCBP), which report establishment counts by industry and size. However, small ZIP code-industry-size cells are masked in the ZCBP, which could introduce bias into such measurements.

an obvious drawback: amenities differ substantially in quality, capacity to serve customers (i.e., size), and the diversity of services offered. Ignoring these variations risks serious measurement error, particularly because establishments in large amenity hot spots are often designed to accommodate far larger volumes of customers than their suburban counterparts.

To account for variation in amenity quality and service capacity, we measure amenity provision using the pre-pandemic density of recorded foot traffic to amenity establishments. For each census tract, we calculate the total foot traffic to establishments in the designated NAICS categories (as defined in Section 4.1) and divide by the tract's land area. We denote this measure of local amenity provision by Am_j. [9]

4.3 Regression Analysis

We use a regression model to separate the effect of reduced commuting vs. the anchoring effect of high-value amenities. The regression is specified as follows:

$$\ln M_{jt} = \gamma_t^{RS} RS_j + \gamma_t^{Am} Am_j + \delta_j + \delta_t + \mathbf{X}_j \Pi_t + \varepsilon_{jt}. \tag{6}$$

M_{jt} is the outcome variable, which is the foot traffic at amenities at census tract j at time (year-quarter) t. 2019 Q1 is treated as the omitted time category for the time effect coefficients γ_t^{RS} and γ_t^{Am}. δ_j is the census tract fixed effects, which accounts for cross-sectional variation in foot traffic across neighborhoods. δ_t is the time fixed effects, which accounts for the nationwide ups and downs in foot traffic throughout the pandemic. We also use a number of tract-level characteristics as controls, including MSA indicators, log median income, the share of Black and Hispanic residents, the share of college graduates, the share of renters, and pre-pandemic population density, and allow their coefficients to vary by time so that any of fluctuations in $\ln M_{jt}$ led by time-varying factors related to these local characteristics will be accounted for. The goal of the specification is to isolate the spatial variation in the change in local commuters, captured by RS_j, and in the existing value of local amenities, captured by Am_j. To facilitate the interpretation of the results, we standardize RS_j and Am_j such that each of the regressors has a mean of 0 and a standard deviation of 1.

The key coefficients of interest are γ_t^{RS} and γ_t^{Am}. The coefficients represent the trajectories of foot

[9] As an alternative, we can construct an amenity density measure using Zip Code Business Patterns (ZCBP). Specifically, we count the total number of establishments in the designated NAICS codes, assign them to the census tract corresponding to the nearest ZIP Code, and divide by the land area of that ZIP Code. This measure of nearby amenity density can serve as an additional proxy for the spatial variation in initial amenity provision.

traffic normalized to 2019 Q1 in neighborhoods with a large decrease in commuters and in neighborhoods with very high amenity value relative to the average neighborhood.

Figure 5a plots estimates of γ_t^{RS} and γ_t^{Am}, respectively. Based on the trajectory of γ_t^{RS}, after the start of the pandemic, tracts that experienced a larger loss of commuters due to the remote work shock saw a larger drop in foot traffic to nearby amenities, and such a disproportionate drop in amenity foot traffic to these neighborhoods never fully recovered back to the pre-pandemic level, even by mid-2024. This result is consistent with the prediction that a permanent loss of commuters permanently reduces the amenity foot traffic associated with commuting.

In contrast, the trajectory of γ_t^{Am} implies that while the high-value amenity hot spots saw a disproportionate loss of foot traffic during the peak of the pandemic, foot traffic to these locations was quickly regained by the end of 2020. Starting in 2021, these neighborhoods even started to attract disproportionately more foot traffic relative to the average neighborhood. The quick recovery of foot traffic to neighborhoods with high amenity value, despite the depressed amenity traffic in neighborhoods with sustained shortfalls in commuters, demonstrates that urban amenities with high value premium produce a powerful anchoring effect for urban foot traffic. Not only that, the fact that the high-value amenity hot spots saw higher-than-average growth in foot traffic after 2021 suggests that the amenity hot spots have increasingly attracted a larger proportion of foot traffic.[10]

To validate the findings from the foot traffic analysis, we also analyze the log of total consumer transactions at the census tract level, recorded in the SafeGraph Spend data, as the outcome variable. The specification follows equation 6. Figure 5b reports the estimates of γ_t^{RS} and γ_t^{Am} based on the spending data. The results closely mirror those obtained from the foot traffic analysis. Both γ_t^{RS} and γ_t^{Am} declined sharply in 2020, consistent with the pandemic shock: neighborhoods with large commuter losses and those with high amenity value both experienced disproportionate drops in consumer transaction volume relative to other neighborhoods.

After the pandemic peak, however, the trajectories diverged in the same way as in the foot traffic results. Neighborhoods near office clusters with a large and persistent decline in commuting continued to show depressed transaction volumes through mid-2024. In contrast, amenity hot spots began to see disproportionately higher consumer transaction volumes starting in 2021, surpassing their pre-pandemic baseline. This

[10]This could mean that these high-amenity neighborhoods lost less foot traffic than the average neighborhood since 2019 Q1 or that these neighborhoods gained more foot traffic than the average neighborhood.

elevated level of spending in amenity-dense neighborhoods persisted and did not revert as of mid-2024.

Furthermore, to examine whether amenity hot spots disproportionately attract non-local inbound visitors, Figure 5c plots the estimated time effects using visitors' log distance to home as the outcome variable. The results show that neighborhoods experiencing commuter losses did not exhibit a statistically significant change in the average distance to visitors' homes. In contrast, amenity hot spots saw a statistically significant increase in the average home-to-visit distance. This pattern suggests that the spatial concentration of visits in amenity clusters is driven by residents traveling farther for leisure.

Because the key to the empirical test is whether neighborhoods with strong initial amenity value experience a rebound in traffic, it is important to ensure that our measurement of amenity clusters is accurate. As a robustness check, we replace our foot traffic–based measure of amenity value with two alternatives: (1) the density of amenity business establishments, and (2) the density of consumer transactions recorded in the Spend data. The count of amenity establishments is taken from the 2019 ZIP-code-level County Business Patterns.[11]

Table 2 reports the regression results at a year-to-year frequency. The findings are consistent across specifications: while foot traffic and spending activity remain persistently low in neighborhoods where commuter presence is expected to stay depressed, amenity-rich areas show a strong rebound, regardless of whether amenity value is measured through establishments, transactions, or foot traffic.

4.4 Spatial Changes in Population and Housing Prices and Rents

Next, we examine the spatial changes in housing demand. Because no publicly available data provides neighborhood-level population changes at fine geographic detail, we are in the process of constructing a panel of neighborhood population change. In the meantime, we analyze local housing markets using data on rents and home values.

Figures 6a and 6b plot the time effects with log housing rent and listed home value as the outcome variables, respectively. The patterns mirror those from the foot traffic analysis: during the peak of the pandemic, both rents and home values declined in neighborhoods exposed to negative commuting shocks and in neighborhoods with high amenity value. After 2021, however, the trajectories diverged. In neighborhoods affected by commuting shocks, rents and home values remained below pre-pandemic levels, whereas in

[11] We compute amenity establishment density at the ZIP code level and then assign values to census tracts based on the proximity between ZIP codes and tracts.

neighborhoods near large amenity clusters, both measures rose above their pre-pandemic baselines.

It is important to note, however, that the magnitude of the positive amenity effects on rents and home values is much smaller than the surges observed in foot traffic and consumer spending. Moreover, these positive amenity effects are smaller than the negative effects of remote work. This pattern reinforces the model's insight: because residents can *travel* to high-value amenity clusters, the premium associated with living near such amenities diminishes, making the residential housing demand around them less responsive than foot traffic or spending.

4.4.1 Discussion

The empirical analysis thus far validates the model's prediction that urban amenity value acts as a powerful anchoring force, sustaining foot traffic even amid the permanent decline in commuter presence and the associated loss of commute-linked amenity visits. Moreover, amenity hot spots have attracted relatively more traffic in the era of remote work, suggesting that remote work may have increased demand for premium amenities.

That said, while remote work is a plausible driver, alternative explanations, such as pandemic-induced preference shifts, cannot be ruled out. To directly test whether remote work increases individuals' propensity to visit amenity hot spots, we next turn to individual-level mobility data.

4.5 Remote Work and Demand for Urban Amenities — Microdata Analysis

We use the Global Wireless Solutions (GWS) consumer panel data to examine how remote work influences travel behavior. The real-time mobility records are aggregated into an individual-by-day panel, from which we construct key variables such as whether the individual commuted to their usual workplace and the share of non-work time spent in high-amenity locations. Because the data identify each person's usual home and work locations, we can incorporate these characteristics directly as controls.

The following is the specification of our regression model:

$$y_{ijnt} = \beta_R Remote_{it} + \delta_i + \iota_t + \mathbf{X}_j \mathbf{\Pi}_{res,t} + \mathbf{X}_n \mathbf{\Pi}_{work,t} + \varepsilon_{ijnt}.$$

In the above equation, i indexes an individual; j indexes the residential location of the individual; n indexes the location of the usual workplace; t indexes the day of the observation. y_{ijnt} is the daily visiting outcomes — i.e., fraction of time away from workplace spent in high-value amenity hot spots on day t by individual i. $Remote_{it}$ is an indicator equal to one if individual i is absent from their usual workplace on a non-holiday workday t. δ_i and ι_t denote individual and day fixed effects. The individual fixed effects can absorb all the variation in the change in foot traffic due to the spatial sorting of residents based on their taste for amenities and remote work. The time (day) fixed effects capture time-specific variation in remote work prevalence and amenities' overall popularity. We also control for characteristics of the residential and workplace locations, with coefficients allowed to vary over time.

To ensure that $Remote_{it}$ does not capture variation arising from transitions in and out of employment, we restrict the sample to observations where individuals have an identifiable workplace within a given month. This restriction implies that our analysis focuses on the impact of hybrid remote work on travel behavior, rather than the effect of *full* remote work.

4.5.1 Baseline Regression — Effect of Working Remotely on Visits to Amenity Hot Spots

In our first regression, we examine the effect of remote work on the share of time away from the workplace that individuals spend in high-value amenity hot spots. We define high-value hot spots as census block groups in the top decile of foot traffic density (per square mile) in 2019. Column 1 of Table 4 reports the baseline estimate. Controlling for individuals' residential and workplace characteristics (distance to downtown and whether the block group itself is a high-value amenity location), we find that remote work increases the same-day daily time (not at the workplace) spent in high-value amenity block groups by 0.12 percentage points. Given that the average share of time spent in such locations is about 1 percent, this effect corresponds to a 12 percent increase relative to the mean.

Column 3 of Table 4 replaces the outcome variable with the share of daily non-workplace time spent in city-center locations, defined as block groups within a five-mile radius of downtowns. The estimated same-day effect of remote work is negative and statistically significant, though modest in magnitude at roughly -2 percent relative to the mean. This result is consistent with the model's prediction that remote work has offsetting effects on urban amenity foot traffic: a negative effect from the loss of commute-chained visits, and a positive effect from increased leisure-driven visits. In Column 4, we instead use as the outcome the share of non-workplace time spent in block groups in the top quartile of expected commuter losses, areas disproportionately hosting worksites where employees are more likely to work remotely. Unsurprisingly, the estimated same-day effect of remote work is negative and statistically significant.

A key concern with the above regressions is that remote work days are identified solely by workers' physical absence from their usual workplace. Although our sample only includes individuals with a routine workplace, it may also capture vacation days. If a nontrivial share of vacation days is misclassified as remote work, and if individuals visit high-amenity locations more frequently while on vacation, the resulting estimates may conflate vacation-related travel behavior with the effects of remote work.

4.5.2 The Effects of Remote Work Routines

To overcome the challenge of distinguishing between remote workdays and vacations, we identify each worker's routine weekly absences from the workplace and use these recurring absences as a proxy for remote workdays. The rationale is that vacation days are typically sporadic and unlikely to generate consistent weekly patterns of absence. By focusing on these systematic absences, we isolate differences in travel behavior that are more plausibly attributable to remote work rather than vacation-related activities.

We measure routine absences using a rolling window. For each individual-day observation, we compute the fraction of days on which the individual commutes to their usual workplace for each day of the week, within the nearest four-week period (two weeks before and two weeks after the observation). For example, for a Tuesday observation, we calculate the share of days in which the worker commutes to the workplace out of the two preceding and two subsequent Tuesdays. The day of the observation itself is excluded from this calculation to avoid conflating measurement error with vacation-related absences.

In the following regressions, the indicator variable $Remote_{it}$ in Equation 4.5 is defined using this rolling-window measure rather than the current-day workplace attendance. Specifically, $Remote_{it} = 1$ if the individual is absent from the workplace on all corresponding days within the rolling window, and $Remote_{it} = 0$ otherwise.

Column 1 of Table 5 shows that a routine absence leads to a 0.02 percentage point increase in the probability of visiting amenity hot spots, which is around 2 percent relative to the outcome mean. This estimate is much smaller than the baseline estimate, suggesting that the same-day effect of a routine remote day may not be economically large in magnitude. That said, if we restrict the sample to individuals who live and work away from urban centers, the space where high-amenity hot spots are disproportionately clustered, the effect is much larger. In percentage terms, the same-day effect of routine remote day on visits to amenity hot spots is around 10 percent in Column 2 of Table 5.

Although the results are robust to potential conflation with one-off vacation days, two concerns remain.

The first relates to intertemporal substitution between leisure and work across remote and on-site days. Remote work may simply reallocate amenity visits from on-site days to remote days, without changing the overall volume of amenity travel. In this case, a higher frequency of remote work days would not necessarily translate into greater total demand for amenities.

A second, related concern is that the effect of routine remote work may not be confined to the same day. If remote work alters schedules beyond the immediate day, for instance, if working remotely on a Tuesday enables individuals to plan more leisure activities on Monday evening, our regression framework, which restricts effects to the same day, could understate the true impact. This possibility may help explain why the estimated effects appear relatively modest.

4.5.3 Intertemporal Effects of Remote Work

To capture a broader range of intertemporal reallocation of amenity visits, we extend the analysis to examine how remote workdays affect travel patterns on the days immediately preceding and following routine remote workdays. These regressions exploit the cross-week difference in remote work intensity as the source of identifying variation.

Column 3 of Table 5 shows that once we include two backward and two forward lags of the routine remote work indicator, the same-day effect disappears, while the backward two-day lag and the forward one- and two-day lags are positive and statistically significant. This pattern suggests that having worked remotely two days earlier, or anticipating remote work in the next one to two days, raises the likelihood of visiting high-value amenity hot spots. Summing across these intertemporal effects yields a total impact of about 9 percent of the outcome mean, which is economically meaningful. Notably, the anticipation of an upcoming remote work day exerts the strongest effect on current-day amenity visits, consistent with the intuition presented earlier.

Moreover, in Column 4, where the sample is restricted to workers who both live and work in suburban neighborhoods, the same-day effect becomes positive and statistically significant, and the effects of expected remote work one and two days ahead also remain positive and statistically significant. The combined impact across adjacent days amounts to 15 percent of the outcome mean, which is even larger in economic magnitude than the baseline effect.

Furthermore, Column 5 replaces the outcome variable with the share of time spent in city centers and restricts the sample to suburban residents and workers — i.e., those whose primary activities are located outside city centers. In this specification, both the same-day effect and the anticipation effects are positive, indicating that remote work encourages suburban-based individuals to travel into city centers for leisure. Although the two-day lag effect is negative, its magnitude is small relative to the same-day and one-day-ahead effects. Overall, the impact of remote work across these adjacent days corresponds to about 13 percent of the outcome mean, representing a quantitatively large economic effect.

4.5.4 Discussion

So far, we have shown that remote work days, both same-day and anticipated, have statistically and economically significant effects on time spent in amenity hot spots.

That being said, one remaining concern, however, is that the intensity of remote work observed at the individual level may still be endogenous to unobserved time-varying lifestyle characteristics and the changing preferences for remote work. If so, the association between the change in remote work take-up and the change in visits to high-value amenity locations could reflect omitted variable bias rather than a causal effect. To address this concern, our ongoing work leverages spatial variation in workplace adoptiveness to remote work as a source of identification for the causal impact of remote work on travel behavior. In addition, we incorporate variation in timing and geographic detail to improve measurement and strengthen identification.

Further results along these lines will be reported soon!

5 Conclusion

Following the surge in remote work adoption after 2020, many researchers and commentators have predicted that the permanent reduction in commuting to urban centers could set off a self-reinforcing cycle of urban decline. In this paper, however, we present a more optimistic view of remote work's impact on cities. We emphasize that cities serve not only as centers of production but also as centers of consumption.

We argue that the prediction that remote work necessarily depresses foot traffic and economic activity in urban centers rests on three implicit assumptions. First, that urban centers derive their appeal fundamentally as commuting destinations, with other economic activities arising only as endogenous byproducts of commuter flows. Second, that demand for urban amenities originates solely from local residents. Third, that remote work does not affect individuals' leisure time budgets. Once these assumptions are relaxed, the impact of remote work on urban amenity foot traffic becomes theoretically ambiguous. In particular, if urban amenities provide sufficiently large value premiums and leisure travel costs are low, an increase in remote work adoption may, in fact, generate an *increase* in visits to urban centers.

We provide empirical evidence consistent with these theoretical predictions. After an initial decline in foot traffic, high-value amenity hot spots in urban areas experienced a disproportionately strong recovery in both visits and consumer spending, even as commuting trips remained below pre-pandemic levels. Using fine-grained geographic data, we show that while neighborhoods with large expected commuter losses faced persistent reductions in amenity foot traffic, neighborhoods with high amenity value experienced a post-pandemic surge, ultimately capturing a larger share of overall amenity visits than before the pandemic. Moreover, individual-level mobile device data reveal that holding workplace and residence characteristics constant, remote work days increase the likelihood of visiting amenity hot spots, with particularly strong effects for workers who live and work in suburban areas.

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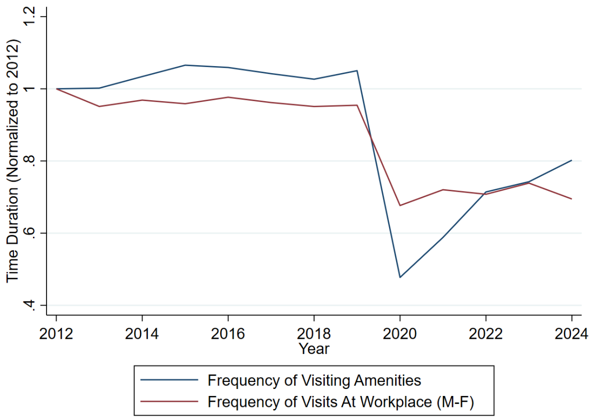
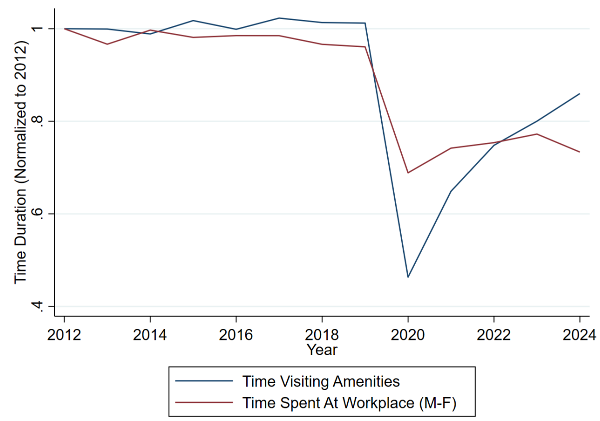
Figure 1: Commuting vs. Visiting Amenities From Time-Use Data



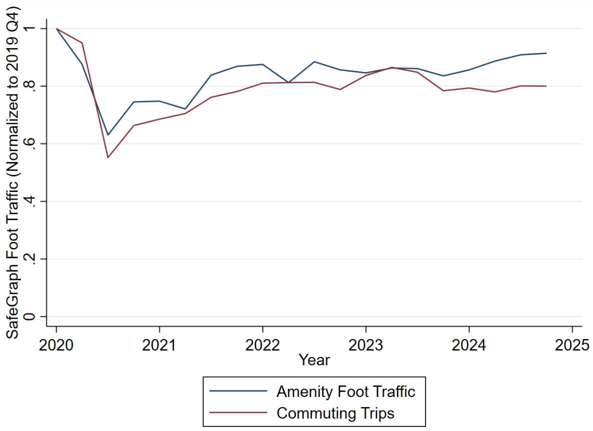
(a) Number of Distinct Activities (Work or Amenity-Related)



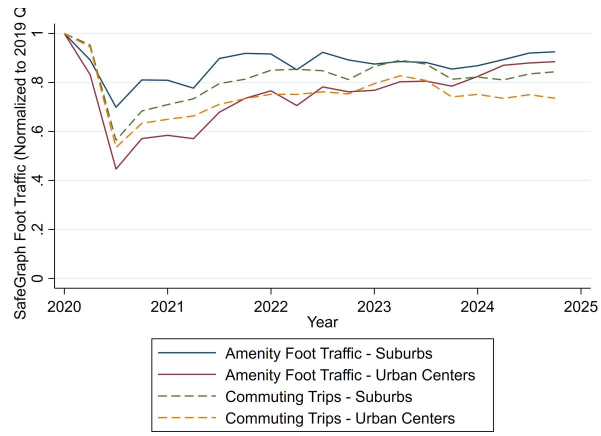
(b) Time Spent at Destinations

Note: Figure 1a plots the normalized frequency of working at the workplace and visiting amenities. The frequency is calculated as the number of distinct ATUS activities that are categorized as working at workplaces or amenity activities. Figure 1b plots the normalized total duration of time used either working at the workplace or in amenity activities. We restrict the sample between the ages of 25 and 65 and working at least part-time. Amenity trips activities related to eating and drinking, grocery shopping, shopping for food, other non-grocery shopping, personal care, participating in or attending sporting and recreational events, and socializing and communicating with destinations other than one's home. Visiting one's workplace is defined as work activities taking place at the place of work.

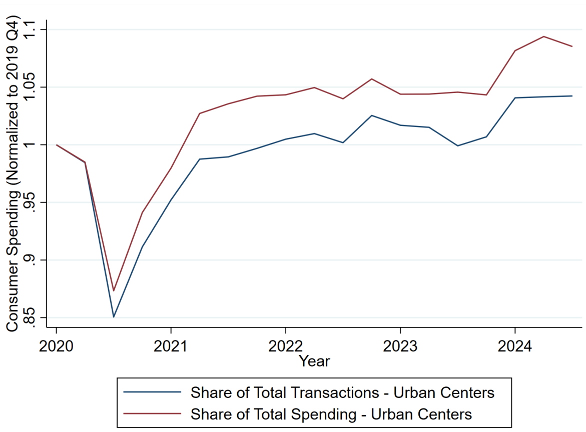
Figure 2: Amenity Visits and Commuting Trips



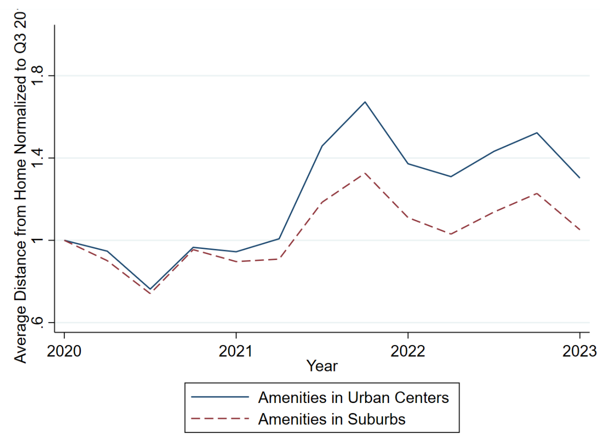
(a) National



(b) Urban Centers vs. Suburbs



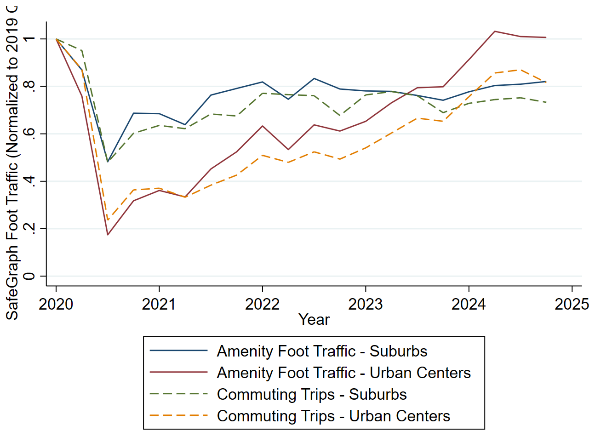
(c) Payments Recorded at Amenity Establishments



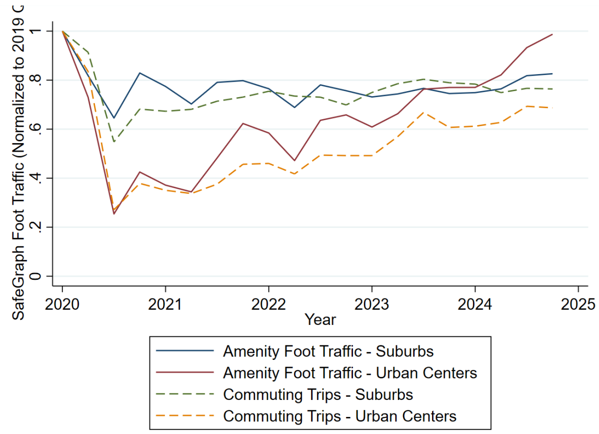
(d) Distance to Home

Note: These figures summarize the amenity and commuting trip patterns over time since the outbreak of the pandemic. Figure 2a presents the normalized amenity trips and commuting trips recorded nationally in the SafeGraph Foot Traffic data. Amenity foot traffic is the sum of trips that last less than one hour and at establishments that fall in the amenity categories defined in the manuscript. Commuting trips are defined as the sum of trips that last at least one hour and at establishments not categorized as amenities. Figure 2b presents the summary of trip patterns for urban centers and suburbs, separately, using the SafeGraph Foot Traffic data. Urban centers are defined as census tracts within 5 miles of the downtowns of the respective MSAs. Figure 2c presents the share of total consumer spending transactions and total consumer spending amount recorded in the SafeGraph Spend data that occurred in establishments located in urban centers. Figure 2d presents the average distance to visitors' homes for trips to amenities in urban centers and amenities in the suburbs. The foot traffic data plotted after the end of 2022, shown in Figures 2 and 2b are subject to the adjustment procedure outlined in section 3.1 and Appendix section A4.

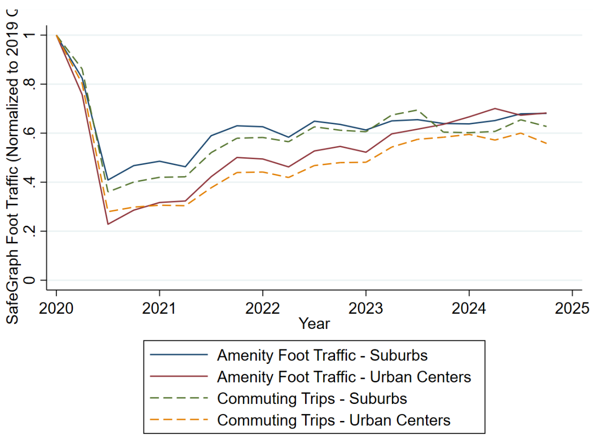
Figure 3: Foot Traffic Patterns by MSA



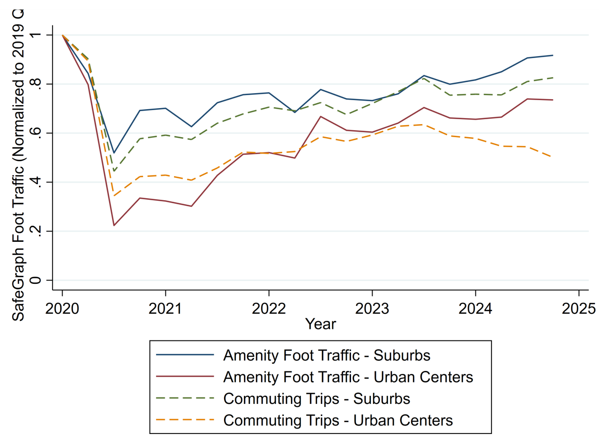
(a) New York MSA



(b) Chicago MSA



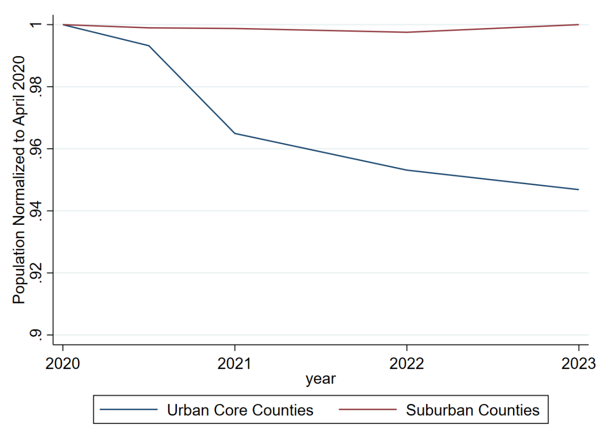
(c) San Francisco MSA



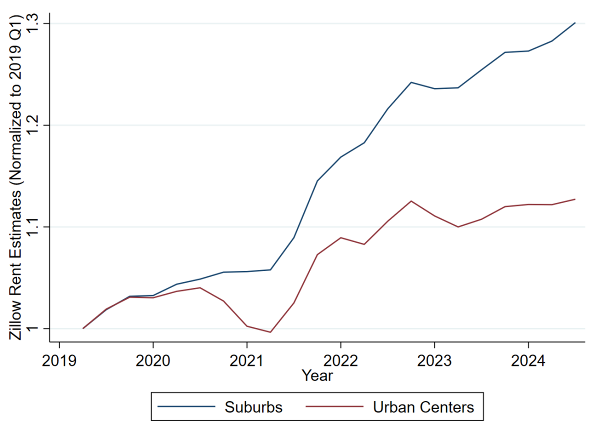
(d) Washington MSA

Note: These figures present the summaries of trip patterns for urban centers and suburbs, separately, using the SafeGraph Foot Traffic data, for four selected MSAs (New York, Chicago, San Francisco, and Washington). Urban centers are defined as census tracts within 5 miles of the downtowns of the respective MSAs. The foot traffic data plotted after the end of 2022 are subject to the adjustment procedure outlined in section 3.1 and Appendix section A4.

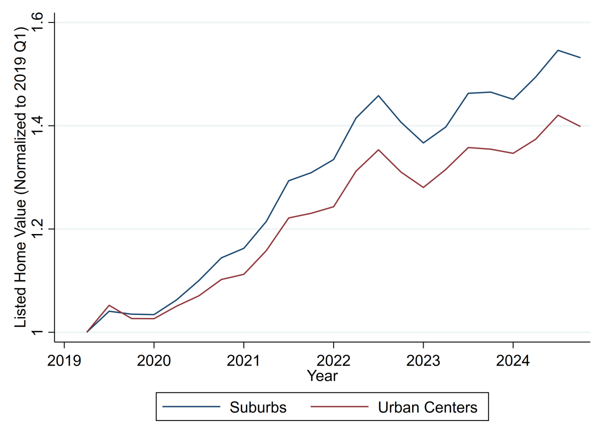
Figure 4: Suburbanization of Residents Since 2020



(a) Population Changes in Core Urban Counties vs. Suburban Counties in Select Metros



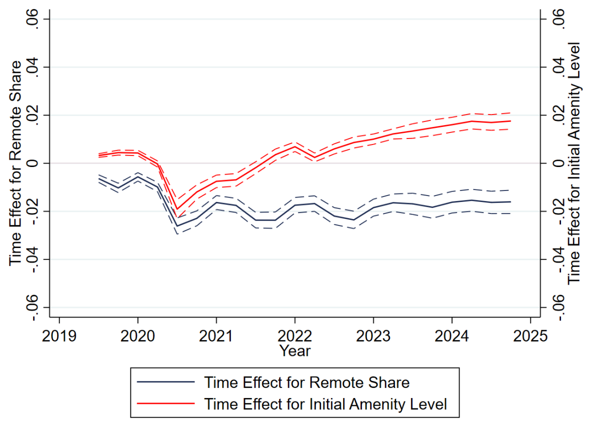
(b) Rent Growth in Urban Neighborhoods vs. Suburban Neighborhoods



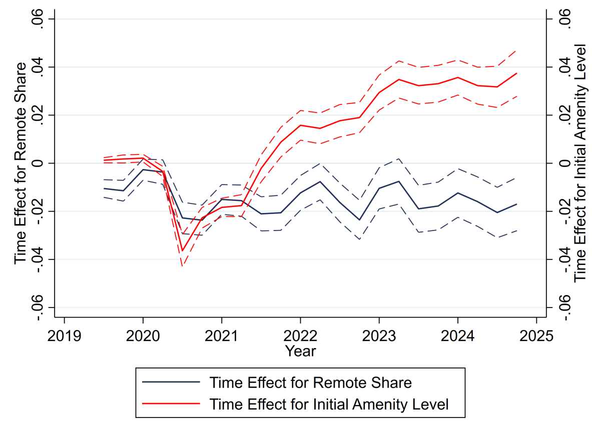
(c) Home Value Growth in Urban Neighborhoods vs. Suburban Neighborhoods

Note: The figures present measures of spatial allocation of in urban centers versus the suburban locations over time. Figure 4a presents the change in population in the urban core counties in select MSAs (New York City, excluding Staten Island (New York MSA), San Francisco County (San Francisco MSA), Denver County (Denver MSA), Baltimore City (Baltimore MSA), Suffolk County (Boston MSA), Philadephia County (Philadelphia MSA), District of Columbia (Washington MSA) where county division is fine enough to designate some counties as distinctly urban and other counties as distinctly suburban. The county-level population estimates are from the U.S. Census Bureau's annual population estimates. Figure 4b plots the average rent for neighborhoods in the suburbs and urban centers, respectively, normalized to the levels of 2019 Q1. Figure 4c plots the average listed home value for neighborhoods in the suburbs and urban centers, respectively, normalized to the levels of 2019 Q1. We define urban centers are census tracts that fall within 5 miles of the downtown of any MSAs in the US. Suburbs are census tracts that fall outside 5 miles of downtown but within some MSAs.

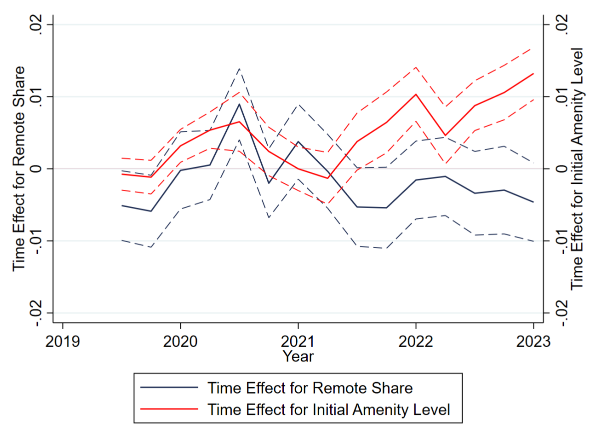
Figure 5: The Spatial Time Effects on Foot Traffic and Consumer Spending Activities By Remote Work Shock and Local Amenity Provision



(a) Foot Traffic



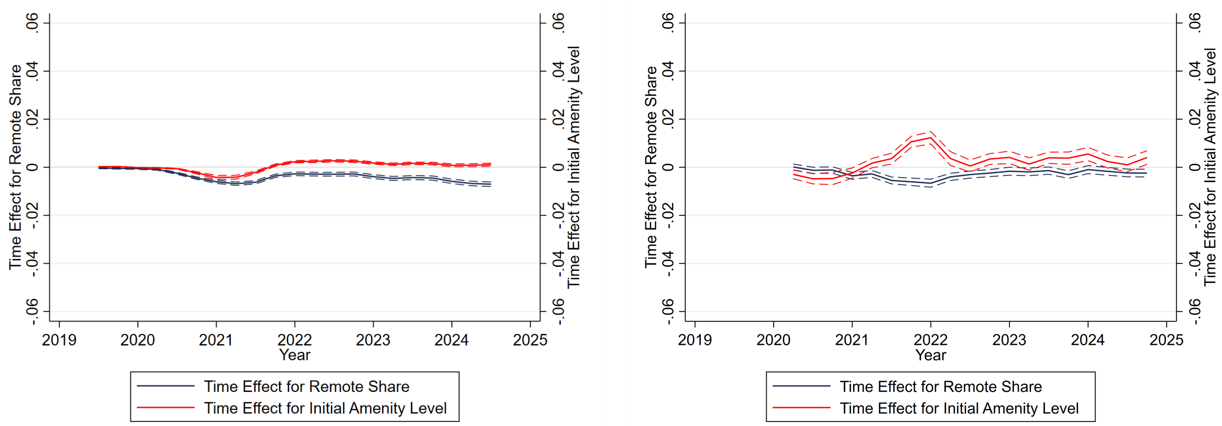
(b) Consumer Spending Transactions



(c) Visitors' Distance from Home

Note: The graphs plot time effects for remote work shock and amenity cluster size, γ_t^{RS} and γ_t^{Am}, in the regression model specified in equation 6. The frequency of time is a quarter. 2019 Q4 is the omitted base time period. The dashed lines are the upper and lower bounds of the 95% confidence interval. Figure 5a plots the effects where the tract-level log visits to amenities are the outcome variable. The foot traffic data used after the end of 2022 are subject to the adjustment procedure outlined in section 3.1 and Appendix section A4. Figure 5b plots the effects where the tract-level log transaction volume is the outcome variable. Figure 5c plots the effects where the tract-level log average distance to home of the visitors is the outcome variable.

Figure 6: The Spatial Time Effects on Rent and Home Prices



(a) Rent

(b) Listed Home Value

Note: The graphs plot time effects for remote work shock and amenity cluster size, γ_t^{RS} and γ_t^{Am}, in the regression model specified in equation 6. The frequency of time is a quarter. 2019 Q4 is the omitted base time period. The dashed lines are the upper and lower bounds of the 95% confidence interval. Figure 6a plots the effects where the tract-level log rent is the outcome variable. Figure 6b plots the effects where the tract-level log listed home value is the outcome variable. Both rent and listed home value are provided at the ZIP code level. We assign each census tract the rent or home value of the ZIP Code whose geographic centroid is closest to the centroid of the census tract.

Table 1: Local Amenities, Remote Work Share, Distance to Downtown, and Population Density

	(1) Standardized Amenity level	(2) Fraction of Remote Jobs (Stand.)	(3) Fraction of Remote Jobs	(4) Standardized Amenity level
Standardized Pop Den	0.496***	0.0498***	0.00227***	
	(0.0350)	(0.00786)	(0.000359)	
Distance to Downtown (Mile)	-0.00360***	-0.0152***	-0.000695***	
	(0.000802)	(0.000525)	(2.39e-05)	
Fraction of WFH-Adopting Jobs				4.748***
				(0.253)
Constant	0.0575***	0.263***	0.0674***	-0.261***
	(0.0123)	(0.00930)	(0.000424)	(0.0101)
Observations	60,647	60,647	60,647	61,532
R-squared	0.278	0.136	0.136	0.136

Note: This table presents the results from regressions designed to demonstrate the spatial relationship between distance to urban centers, population density, amenity levels, and the local fraction of remote-adopting jobs. Column 1 presents results from regressing the standardized amenity level (pre-pandemic foot traffic density to amenity establishments) on standardized population density and distance to downtown (miles). Column 2 presents results from regressing the standardized fraction of remote-adopting jobs on standardized population density and distance to downtown (miles). Column 3 replaces the standardized fraction of remote-adopting jobs with a non-standardized version of the same variable as the outcome variable. Column 4 presents the results from regressing the standardized amenity level on the local fraction of remote-adopting jobs. *** $p < 0.01$, ** $p < 0.05$, *$p < 0.1$.

Table 2: Regression Results with Alternative Initial Amenity Measurements

	Ln Amenity Foot Traffic		Ln Transaction Volume	
Initial Amenity	Estab. Density	Transaction Density	Estab. Density	Transaction Density
	(1)	(2)	(3)	(4)
Remote Job Share × (Standardized)				
2020	-0.0118***	-0.0132***	-0.0112***	-0.0139***
	(0.00100)	(0.000839)	(0.00250)	(0.00236)
2021	-0.0145***	-0.0161***	-0.0119***	-0.0117***
	(0.00132)	(0.00113)	(0.00331)	(0.00318)
2022	-0.0144***	-0.0156***	-0.00959**	-0.00754*
	(0.00152)	(0.00131)	(0.00405)	(0.00390)
2023	-0.0110***	-0.0108***	-0.00920*	-0.00550
	(0.00205)	(0.00171)	(0.00518)	(0.00506)
2024	-0.00926***	-0.0101***	-0.0106*	-0.00726
	(0.00234)	(0.00202)	(0.00566)	(0.00549)
Initial Amen. Level × (Standardized)				
2020	-0.0202***	-0.00675***	-0.0263***	-0.0254***
	(0.00183)	(0.000908)	(0.00296)	(0.00218)
2021	-0.00843***	0.00167	-0.0112***	-0.0232***
	(0.00154)	(0.00121)	(0.00393)	(0.00313)
2022	0.000308	0.00708***	0.0177***	-0.0171***
	(0.00134)	(0.00128)	(0.00498)	(0.00398)
2023	0.00663***	0.0193***	0.0272***	-0.0140***
	(0.00180)	(0.00187)	(0.00607)	(0.00487)
2024	0.00728***	0.0236***	0.0249***	-0.0171***
	(0.00216)	(0.00214)	(0.00614)	(0.00546)
Observations	328,781	323,014	312,586	328,500
R-Squared	0.988	0.988	0.945	0.944

Note: This table presents the regression coefficients for the regression model specified in equation 6. The time frequency is annual. Columns 1 and 3 use the amenity establishment density (standardized) sourced from the County Business Patterns in 2019 as the initial amenity level measurement. Columns 2 and 4 use the consumer transaction density (number of transactions divided by the land area) reported at the census tract-year level, sourced from the SafeGraph Spend data, as the initial amenity level measurement. Columns 1 and 2 report regression results where the outcome variable is the log amenity foot traffic at the census tract-year level. Columns 3 and 4 report regression results where the outcome variable is the log transaction volume at amenity establishments reported at the census tract-year level. The foot traffic data used after the end of 2022 are subject to the adjustment procedure outlined in section 3.1 and Appendix section A4. *** $p < 0.01$, ** $p < 0.05$, *$p < 0.1$.

Table 3: Commuters are Less Likely to Make Amenity Trips

	(1)	(2)	(3)
Dep Var	Visit Amenities	Duration of Amenity Travel	Duration of Amenity Travel
Commute Indicator	-0.0327***	-5.621***	-8.318***
	(0.00924)	(0.606)	(0.915)
Constant	0.523***	21.73***	41.30***
	(0.00789)	(0.545)	(0.827)
Sample	Work Days	Work Days	Work Days Reporting Amenity Travels
Observations	25,842	25,842	13,076
R-squared	0.076	0.068	0.119

Note: The table reports coefficient estimates for regressions in which we regress amenity travel choice during the 24 hours on the indicator variable of whether an individual commutes over the same period. We use data from the American Time Use Survey over the period from 2012 to 2023. We restrict the sampled individuals to be aged 25 to 65 and fully employed. We also restrict the 24 hours to weekdays and during which at least one leg of the activity during the day is for work. The commute indicator is defined as one is the individual reports work-related travel immediately before or after working at the workplace. Column 1 uses the indicator variable of whether the individual visits amenities altogether as the outcome variable. Column 2 uses the total duration of travel time related to amenity visits as the outcome variable. Column 3 uses the same outcome variable but restricts the sample to days in which amenity travel time is nonzero. *** $p < 0.01$, ** $p < 0.05$, *$p < 0.1$.

Table 4: Workers Visit High-Value Amenity Hot Spots More on Remote Work Days

	(1)	(2)	(3)
Dep Var	Amenity Spots	City Centers	Large Commuter Shocks
Remote	0.00123***	-0.00200***	-0.00599***
	(8.08e-05)	(0.000237)	(0.000325)
Dep Var Mean	0.00964	0.0941	0.177
Observations	17,464,351	17,464,351	17,464,351
R-squared	0.513	0.674	0.544

Notes: The table reports coefficient estimates of β_R from the regression specified in equation 4.5. The variable Remote equals 0 if the individual spent at least three hours at their usual workplace during the 24-hour period, and 1 otherwise. In Columns 1, the outcome variable is the fraction of the day spent in high-value amenity hot spots, defined as census block groups in the top 15th percentiles of foot traffic density. In Column 2, the outcome variable is the fraction of the day spent in city centers, defined as census block groups located within five miles of downtowns. In Column 3, the outcome variable is the fraction of the day spent in census block groups with an industry mix corresponding to the top 50 percent of expected commuter losses. *** $p < 0.01$, ** $p < 0.05$, *$p < 0.1$.

Table 5: Workers Visit High-Value Amenity Hot Spots More on Days Before Routine Remote Work Days

Dep Var	(1) Amenity Spots	(2) Amenity Spots	(3) Amenity Spots	(4) Amenity Spots	(5) City Centers
Remote	0.000207***	0.000657***	-3.77e-05	0.000508***	0.00155***
	(6.61e-05)	(6.13e-05)	(6.31e-05)	(6.00e-05)	(9.67e-05)
Remote$_{t-1}$			-6.77e-05	-4.44e-05	6.08e-05
			(4.81e-05)	(4.92e-05)	(8.24e-05)
Remote$_{t-2}$			0.000120**	-2.34e-05	-0.000290***
			(4.95e-05)	(4.79e-05)	(8.09e-05)
Remote$_{t+1}$			0.000414***	0.000338***	0.00122***
			(5.18e-05)	(5.36e-05)	(8.49e-05)
Remote$_{t+2}$			0.000347***	0.000160***	0.000154*
			(4.82e-05)	(4.63e-05)	(8.13e-05)
Dep Var Mean	0.00964	0.00666	0.00964	0.00666	0.0196
Sample	Full	Suburb. Residents + Workers	Full	Suburb. Residents + Workers	Suburb. Residents + Workers
Observations	17,464,351	11,856,721	17,464,351	11,856,721	11,856,721
R-squared	0.513	0.404	0.513	0.404	0.137

Note: The table reports coefficient estimates of β_R from the regression specified in equation 4.5. Unlike Table 4, here the regressor Remote is constructed based on physical attendance at the usual workplace on the same weekdays in the two preceding weeks and the two subsequent weeks. The regressor equals 1 only if the individual worked remotely on all of the corresponding weekdays in these surrounding weeks. Importantly, the remote status on the observation day itself is excluded from this calculation. Columns 1 and 3 use the full sample, while Columns 2, 4, and 5 restrict the sample to individuals living and working in the suburbs (census block groups outside a five-mile radius of downtowns). Remote$_{t-x}$ and Remote$_{t+x}$ denote the individual's remote work status x days before and x days after the observation day, respectively. *** $p < 0.01$, ** $p < 0.05$, *$p < 0.1$.

Appendix

A1 Comparative Statics of the Model

Below, we provide proofs for the Propositions that pertain to the comparative statistics of the model's spatial equilibrium.

A1.1 Proofs of Propositions 1-3

Propositions 1 to 3 govern the comparative statics of a change (decrease) in ω_c. Since the effects of ω_c are jointly determined, we first derive the expressions of comparative statics before proceeding to the proofs.

We substitute the amenity provision (equation 4) and the inverse housing supply (equation 5) into the population (equation 1) and foot traffic (equations 2 and 3) so that the only three endogenous variables in the system are population in location u (N_u) and foot traffic to amenities in location u and s (M_u and M_s), respectively. The population in location s is $N - N_u$ and therefore does not need to be included as a separate endogenous variable. Then, we totally differentiate N_u (equation 1) and M_u and M_s (equations 2 and 3) with respect to the exogenous changes in ω_c.

First, we totally differentiate population of u (N_u) (equation 1) with respect to ω_c:

$$\left(-1 - \frac{NP_u\left(1-P_u\right)\kappa}{\sigma}\right)\left(\frac{\rho_u}{N_u} + \frac{\rho_s}{N_s}\right)\frac{\partial N_u}{\partial \omega_c} + \frac{NP_u\left(1-P_u\right)\beta_a}{\sigma\sigma_a}\left(x_{u|u} - x_{u|s}\right)\frac{\partial M_u}{\partial \omega_c}$$
$$+\frac{NP_u\left(1-P_u\right)\beta_a}{\sigma\sigma_a}\left(x_{s|u} - x_{s|s}\right)\frac{\partial M_s}{\partial \omega_c} + \frac{NP_u\left(1-P_u\right)\theta\alpha_L}{\sigma\sigma_a}\left(\tau^c_{u|s}MU_s - \tau^c_{u|u}MU_u\right) = 0$$

, where $MU_s = \frac{x_{u|s}}{\tau_{net,u|s}} + \frac{x_{s|s}}{\tau_{net,s|s}} + \frac{x_{0|s}}{\tau_{net,0|s}}$ and $MU_u = \frac{x_{u|u}}{\tau_{net,u|u}} + \frac{x_{s|u}}{\tau_{net,s|u}} + \frac{x_{0|u}}{\tau_{net,0|u}}$, which are the expected marginal utility of net leisure time for residents in u and s.

Next, we totally differentiate foot traffic in u and s (M_u and M_s) (equations 2 and 3):

$$\left(x_{u|u}-x_{u|s}-\omega_c\phi\right)\frac{\partial N_u}{\partial \omega_c}-\underbrace{\left(1-\frac{\beta_a}{\sigma_a}\left(N_u x_{u|u}\left(1-x_{u|u}\right)+N_s x_{u|s}\left(1-x_{u|s}\right)\right)\right)}_{\Phi_{uu}}\frac{\partial M_u}{\partial \omega_c}$$
$$-\underbrace{\frac{\beta_a}{\sigma_a}\left(N_u x_{u|u}x_{s|u}+N_s x_{u|s}x_{s|s}\right)}_{\Phi_{us}}\frac{\partial M_s}{\partial \omega_c}+N_s\phi$$
$$\underbrace{-N_s x_{u|s}\frac{\theta_c\tau^c_{u|s}\alpha_L}{\sigma_a}\left(MU_{u|s}-MU_s\right)-N_u x_{u|u}\frac{\theta_c\tau^c_{u|u}\alpha_L}{\sigma_a}\left(MU_{u|u}-MU_u\right)}_{\Phi^\omega_u}=0$$

$$\left(x_{s|u}-x_{s|s}\right)\frac{\partial N_u}{\partial \omega_c}-\underbrace{\left(1-\frac{\beta_a}{\sigma_a}\left(N_u x_{s|u}\left(1-x_{s|u}\right)+N_s x_{s|s}\left(1-x_{s|s}\right)\right)\right)}_{\Phi_{ss}}\frac{\partial M_s}{\partial \omega_c}$$
$$-\underbrace{\frac{\beta_a}{\sigma_a}\left(N_u x_{s|u}x_{u|u}+N_s x_{s|s}x_{u|s}\right)}_{\Phi_{us}}\frac{\partial M_u}{\partial \omega_c}$$
$$\underbrace{-N_s x_{s|s}\frac{\theta_c\tau^c_{u|s}\alpha_L}{\sigma_a}\left(MU_{s|s}-MU_s\right)-N_u x_{s|u}\frac{\theta_c\tau^c_{u|u}\alpha_L}{\sigma_a}\left(MU_{s|u}-MU_u\right)}_{\Phi^\omega_s}=0$$

Combining the last two equations, we get to solve for $\frac{\partial M_u}{\partial \omega_c}$ and $\frac{\partial M_s}{\partial \omega_c}$ in terms of $\frac{\partial N_u}{\partial \omega_c}$:

$$\frac{\partial M_u}{\partial \omega_c}=\Lambda^N_u\frac{\partial N_u}{\partial \omega_c}+\Lambda^0_u,$$

where

$$\Lambda^N_u=\frac{\Phi_{us}}{\Phi_{ss}\Phi_{uu}-\Phi^2_{us}}\left(\frac{\Phi_{ss}}{\Phi_{us}}\left(x_{u|u}-x_{u|s}-\omega_c\phi\right)+\left(x_{s|s}-x_{s|u}\right)\right),$$

and,

$$\Lambda^0_u=\frac{\Phi_{ss}\left(\Phi^\omega_u+N_s\phi\right)-\Phi_{us}\Phi^\omega_s}{\Phi_{ss}\Phi_{uu}-\Phi^2_{us}},$$

$$\frac{\partial M_s}{\partial \omega_c}=\Lambda^N_s\frac{\partial N_u}{\partial \omega_c}+\Lambda^0_s,$$

where

$$\Lambda^N_s=-\frac{\Phi_{uu}}{\Phi_{ss}\Phi_{uu}-\Phi^2_{us}}\left(\frac{\Phi_{us}}{\Phi_{uu}}\left(x_{u|u}-x_{u|s}-\omega_c\phi\right)+\left(x_{s|s}-x_{s|u}\right)\right),$$

and,

$$\Lambda_s^0 = -\frac{\Phi_{us}\left(\Phi_u^{\omega} + N_s\phi\right) - \Phi_{uu}\Phi_s^{\omega}}{\Phi_{ss}\Phi_{uu} - \Phi_{us}^2}.$$

Finally, we can plug in $\frac{\partial M_u}{\partial \omega_c}$ and $\frac{\partial M_s}{\partial \omega_c}$ into the population comparative static and express the effect of reducing ω_c on the equilibrium population of u as follows:

$$-\frac{\partial N_u}{\partial \omega_c} = -\frac{\frac{NP_u(1-P_u)}{\sigma}\left(\overbrace{\frac{\theta_c\alpha_L}{\sigma_a}\left(\tau_{u|s}MU_s - \tau_{u|u}MU_u\right)}^{\text{Commuting Effect}} + \overbrace{\frac{\beta_a}{\sigma_a}\left(x_{u|u} - x_{u|s}\right)\Lambda_u^0 + \frac{\beta_a}{\sigma_a}\left(x_{s|u} - x_{s|s}\right)\Lambda_s^0}^{\text{Amenity Value Effects}}\right)}{1 + \frac{NP_u(1-P_u)}{\sigma}\underbrace{\left(\kappa\left(\frac{\rho_u}{N_u} + \frac{\rho_s}{N_s}\right) - \frac{\beta_a}{\sigma_a}\left(x_{u|u} - x_{u|s}\right)\Lambda_u^N - \frac{\beta_a}{\sigma_a}\left(x_{s|u} - x_{s|s}\right)\Lambda_s^N\right)}_{\text{Endogenous Factors}}}$$

The numerator includes the two exogenous effects on population:

In the first component (named as the "commuting effect"), the decrease in ω_c exogenously reduces the relative desirability of the urban location vis-a-vis the suburban location because the commuting time saving provided by the urban location becomes less relevant. Such reduction in urban desirability is stronger if the typical commuting time saving of an urban residence, $\tau_{u|u}$ vs. $\tau_{u|s}$, is bigger, and commuting disutility θ_c is larger, and leisure time utility weight α_L is larger.

In the second component (named as the "amenity value effect"), the change in foot traffic led by the decrease in ω_c endogenously affects the value of amenity access by residents in the two locations, which is captured by $\frac{\beta_a}{\sigma_a}\left(x_{u|u} - x_{u|s}\right)\Lambda_u^0 + \frac{\beta_a}{\sigma_a}\left(x_{s|u} - x_{s|s}\right)\Lambda_s^0$ in the numerator. The amenity effects, however, are ambiguous, depending on the signs of Λ_u^0 and Λ_s^0, which represent the change in foot traffic in u and s and will be discussed in a few paragraphs. The effect on amenity value in u and s on population depends on $x_{u|u} - x_{u|s}$ and $x_{s|u} - x_{s|s}$, which represent how much amenity visit choice varies with where people live. If $x_{u|u} - x_{u|s} = 0$ and $x_{s|u} - x_{s|s} = 0$, which means that their choice of amenities stays the same wherever they live, their residential location choice should be independent of their valuation of amenities.

The denominator captures the endogenous factors for population change in equilibrium. First of all, because rent increases with population growth and decreases with population loss, the population will be mitigated with the endogenous housing supply responses in both locations, which are captured in $\kappa\left(\frac{\rho_u}{N_u} + \frac{\rho_s}{N_s}\right)$ in the denominator. The intuition is that if the housing supply is inelastic in either location, the sharp rent responses will deter some people from moving and offset some of the exogenous changes in location demand.

Second, the endogenous amenity change led by population change will magnify the exogenous population shock. The magnifying effects are captured by $-\frac{\beta_a}{\sigma_a}\left(x_{u|u}-x_{u|s}\right)\Lambda_u^N-\frac{\beta_a}{\sigma_a}\left(x_{s|u}-x_{s|s}\right)\Lambda_s^N$.

Proposition 1. *If the commuting time saving $\tau_{u|s}-\tau_{u|u}$ is sufficiently large and the leisure travel cost θ_a is sufficiently small, an increase in remote work (i.e., $\omega_c \downarrow$) leads to net migration from the urban to the suburban location—i.e., a reduction in population N_u in the urban location u and an increase in population N_s in the suburban location.*

Proof. To show the sufficient condition in which $-\frac{\partial N_u}{\partial \omega_c}<0$, we identify the conditions that ensure the numerator and the denominators are both positive. Namely, the sum of the "commuting effect" and the "amenity value effects" must be positive, and the "endogenous factors" must be positive.

First, for the "commuting effect" to be positive, the commuting time differential $\tau_{u|s}-\tau_{u|u}$ must be sufficiently large. In other words, urban locations must provide a large enough commuting time saving.

Second, "amenity value effects" the amenity value effects have ambiguous signs because of the ambiguity in Λ_u^0 and Λ_s^0. Thus, the sum of the commuting effect and the amenity value effects could, in principle, be negative even if the commuting effect is positive. However, if the marginal leisure travel cost θ_a is sufficiently small, the amenity choice differences $x_{u|u}-x_{u|s}$ and $x_{s|u}-x_{s|s}$ converge to zero. Therefore, there must exist a value θ_a low enough such that the sum of the commuting effect and amenity value effect is strictly positive.

For the endogenous factors in the denominator, the first term (endogenous rent factor) $\kappa\left(\frac{\rho_u}{N_u}+\frac{\rho_s}{N_s}\right)$ is always positive. The concern is that the two endogenous amenity change terms are negative and could be large enough in magnitude to render the denominator negative.

Yet, if θ_a is sufficiently small, the amenity choice differences $x_{u|u}-x_{u|s}$ and $x_{s|u}-x_{s|s}$ again converge to zero, which ensures the endogenous amenity terms are small enough that the denominator remains positive.

In summary, if the commuting time saving $\tau_{u|s}-\tau_{u|u}$ is sufficiently large and the leisure travel cost θ_a is sufficiently small, then $-\frac{\partial N_u}{\partial \omega_c}<0$. That is, an increase in remote work will lead to net migration from the urban to the suburban location.

□

Proposition 2. *The increase in remote work (i.e., $\omega_c \downarrow$) reduces urban amenity foot traffic M_u if ϕ is sufficiently large. But, if ϕ is small and cross-location commuting time $\tau_{u|s}^c$ sufficiently long and urban* *amenity premium $a_{u0} - a_{s0}$ sufficiently high, an increase in remote work could raise urban amenity foot traffic M_u.*

Proof. We show the sufficient condition such that $-\frac{\partial M_u}{\partial \omega_c} = -\Lambda_u^N \frac{\partial N_u}{\partial \omega_c} - \Lambda_u^0 > 0$ and the sufficient condition such that $-\frac{\partial M_u}{\partial \omega_c} = -\Lambda_u^N \frac{\partial N_u}{\partial \omega_c} - \Lambda_u^0 < 0$.

Let's first show the condition that leads to $-\frac{\partial M_u}{\partial \omega_c} > 0$.

First, we can show that Λ_u^N is positive if $\Phi_{ss}\Phi_{uu} - \Phi_{us}^2 > 0$, which would be held true if the endogeneity of amenity provision β_a is sufficiently small such that the equilibrium amenity provision becomes unstable. To ensure the stability of the amenity provision, we make this assumption in the model setup.

If $\Lambda_u^N > 0$ and that $-\frac{\partial N_u}{\partial \omega_c} < 0$, then to bring the whole term positive, $-\Lambda_u^0$ must be positive and sufficiently large in magnitude.

$-\Lambda_u^0$ captures the effect of ω_c on urban amenity foot traffic:

$$-\Lambda_u^0 = \frac{-\Phi_{ss}\left(\Phi_u^\omega + N_s\phi\right) + \Phi_{us}\Phi_s^\omega}{\Phi_{ss}\Phi_{uu} - \Phi_{us}^2},$$

Since it is assumed that $\Phi_{ss}\Phi_{uu} - \Phi_{us}^2 > 0$, for $-\Lambda_u^0$ to be positive, the numerator of the above expression must be positive. For the numerator to be positive, Φ_u^ω must be sufficiently negative or Φ_s^ω must be sufficiently positive. Φ_u^ω and Φ_s^ω capture the effects of restricting time budgets on the foot traffic in u and s, respectively.

Based on the results from the total differentiations, Φ_s^ω is potentially negative because restricting the time budget can reduce the foot traffic in all amenity locations. Therefore, for the numerator to be positive, Φ_u^ω must be sufficiently *more* negative than Φ_s^ω, i.e., $\Phi_u^\omega - \Phi_s^\omega$ must be negative and large enough in magnitude.

We know that if the cross-location commuting time $\tau_{u|s}^c$ and the urban amenity premium $a_{u0} - a_{s0}$ both go to ∞, then

$$\Phi_u^\omega \to \infty \quad \text{and} \quad \Phi_s^\omega \to 0.$$

This implies that for any negative value V, there must exist a cross-location commuting time $\tau_{u|s}^c$ sufficiently large and an urban amenity premium $a_{u0} - a_{s0}$ sufficiently high such that $\Phi_u^\omega - \Phi_s^\omega$ is less than V.

This means if the cross-location commuting time $\tau_{u|s}^c$ sufficiently large and an urban amenity premium $a_{u0} - a_{s0}$ sufficiently high, the effect of remote work on urban foot traffic will be positive — i.e., $-\frac{\partial M_u}{\partial \omega_c} > 0$.

For the effect of remote work on urban foot traffic to be negative — i.e., $-\frac{\partial M_u}{\partial \omega_c} < 0$, we just need to show that $-\Lambda_u^0 = -\Phi_{ss}\left(\Phi_u^\omega + N_s\phi\right) + \Phi_{us}\Phi_s^\omega$ is negative.

For that to be true, we just need the amount of amenity foot traffic chained with commuting trips (ϕ) to be sufficiently large. $\square$

Proposition 3. *The increase in remote work (i.e., $\omega_c \downarrow$) raises suburban amenity foot traffic M_s when the urban amenity premium $a_{u0} - a_{s0}$ is not too large or when ϕ is sufficiently large. Conversely, if the urban amenity premium $a_{u0} - a_{s0}$ is large enough and ϕ is small, then an increase in remote work could instead reduce suburban amenity foot traffic M_s.*

Proof. To show the condition in which a decrease in ω_c increases suburban foot traffic M_s, we need to show $-\frac{\partial M_s}{\partial \omega_c} = -\Lambda_s^N \frac{\partial N_u}{\partial \omega_c} - \Lambda_s^0 > 0$.

First of all we know that $\Lambda_s^N \leq 0$ and $-\frac{\partial N_u}{\partial \omega_c} < 0$ if the conditions stipulated in Proposition 1 holds. This means that as long as rising remote work leads to residential suburbanization, foot traffic due to residential shift must work in favor of suburban amenities — i.e., $-\Lambda_s^N \frac{\partial N_u}{\partial \omega_c} > 0$.

Given that, to ensure that the total foot traffic effect is positive, we need to make sure that $-\Lambda_s^0$ is either positive or not too negative such that it overwhelms the first term. $-\Lambda_s^0$ is specified below:

$$-\Lambda_s^0 = \frac{\Phi_{us}\left(\Phi_u^\omega + N_s\phi\right) - \Phi_{uu}\Phi_s^\omega}{\Phi_{ss}\Phi_{uu} - \Phi_{us}^2}.$$

If Φ_u^ω and $N_s\phi$ are large enough and Φ_s^ω is small enough, $-\Lambda_s^0 < 0$. As we mentioned earlier, Φ_u^ω and Φ_s^ω represent the changes in urban and suburban foot traffic caused by restricting the time budget, holding local population constant and amenity provision constant.

Since the larger the urban amenity premium $a_{u0} - a_{s0}$ is, the larger the difference $\Phi_u^\omega - \Phi_s^\omega$ is. Therefore, to ensure that $-\Lambda_s^0$ stays positive, ϕ must be sufficiently large or that the urban amenity premium $a_{u0} - a_{s0}$ must be small enough. $\square$

A1.2 Proof of Propositions 4-5

Propositions 4 and 5 characterize the comparative statics of an increase in τ_0. Because the effects of τ_0 are jointly determined, too, we first derive the relevant comparative static expressions before presenting the proofs of the propositions.

Analogous to the derivation of the comparative statics for Propositions 1–3, we totally differentiate the population equation with respect to τ_0:

$$\left(-1-\frac{NP_u\left(1-P_u\right)\kappa}{\sigma}\right)\left(\frac{\rho_u}{N_u}+\frac{\rho_s}{N_s}\right)\frac{\partial N_u}{\partial\tau_0}+\frac{NP_u\left(1-P_u\right)\beta_a}{\sigma\sigma_a}\left(x_{u|u}-x_{u|s}\right)\frac{\partial M_u}{\partial\tau_0}$$
$$+\frac{NP_u\left(1-P_u\right)\beta_a}{\sigma\sigma_a}\left(x_{s|u}-x_{s|s}\right)\frac{\partial M_s}{\partial\tau_0}+\frac{NP_u\left(1-P_u\right)\alpha_L}{\sigma\sigma_a}\left(x_sMU_{a,s}-x_uMU_{a,u}\right)=0$$

Next, we totally differentiate the foot traffic equations:

$$\left(x_{u|u}-x_{u|s}-\omega_c\phi\right)\frac{\partial N_u}{\partial\tau_0}-\underbrace{\left(1-\left(\frac{\beta_a}{\sigma_a}\left(N_ux_{u|u}\left(1-x_{u|u}\right)+N_sx_{u|s}\left(1-x_{u|s}\right)\right)\right)\right)}_{\Phi_{uu}}\frac{\partial M_u}{\partial\tau_0}$$
$$-\underbrace{\left(\frac{\beta_a}{\sigma_a}\left(N_ux_{u|u}x_{s|u}+N_sx_{u|s}x_{s|s}\right)\right)}_{\Phi_{us}}\frac{\partial M_s}{\partial\tau_0}$$
$$\underbrace{-\frac{1}{\sigma_a}\left(N_ux_{u|u}\left(MU_{a,u|u}-MU_{a,u}x_u\right)+N_sx_{u|s}\left(MU_{a,u|s}-MU_{a,s}x_s\right)\right)}_{\Phi_u^\tau}=0$$

$$\left(x_{s|u}-x_{s|s}\right)\frac{\partial N_u}{\partial\tau_0}-\underbrace{\left(1-\left(\frac{\beta_a}{\sigma_a}\left(N_ux_{s|u}\left(1-x_{s|u}\right)+N_sx_{s|s}\left(1-x_{s|s}\right)\right)\right)\right)}_{\Phi_{ss}}\frac{\partial M_s}{\partial\tau_0}$$
$$-\underbrace{\left(\frac{\beta_a}{\sigma_a}\left(N_ux_{u|u}x_{s|u}+N_sx_{u|s}x_{s|s}\right)\right)}_{\Phi_{us}}\frac{\partial M_u}{\partial\tau_0}$$
$$\underbrace{-\frac{1}{\sigma_a}\left(N_ux_{s|u}\left(MU_{a,s|u}-MU_{a,u}x_u\right)+N_sx_{s|s}\left(MU_{a,s|s}-MU_{a,s}x_s\right)\right)}_{\Phi_s^\tau}=0$$

Again, combining the last two equations, we get to solve for the derivatives of foot traffic in terms of the derivative of u's population:

$$\frac{\partial M_u}{\partial\tau_0}=\Gamma_u^N\frac{\partial N_u}{\partial\tau_0}+\Gamma_u^0,$$

where

$$\Gamma_u^N=\frac{\Phi_{us}}{\Phi_{ss}\Phi_{uu}-\Phi_{us}^2}\left(\frac{\Phi_{ss}}{\Phi_{us}}\left(x_{u|u}-x_{u|s}-\omega_c\phi\right)+\left(x_{s|s}-x_{s|u}\right)\right),$$

and,

$$\Gamma_u^0=\frac{\Phi_{ss}\Phi_u^\tau-\Phi_{us}\Phi_s^\tau}{\Phi_{ss}\Phi_{uu}-\Phi_{us}^2},$$

$$\frac{\partial M_s}{\partial \tau_0} = \Gamma_s^N \frac{\partial N_u}{\partial \tau_0} + \Gamma_s^0,$$

where

$$\Gamma_s^N = -\frac{\Phi_{uu}}{\Phi_{ss}\Phi_{uu} - \Phi_{us}^2} \left(\frac{\Phi_{us}}{\Phi_{uu}} \left(x_{u|u} - x_{u|s} - \omega_c \phi \right) + \left(x_{s|s} - x_{s|u} \right) \right),$$

and,

$$\Gamma_s^0 = -\frac{\Phi_{us}\Phi_u^\tau - \Phi_{uu}\Phi_s^\tau}{\Phi_{ss}\Phi_{uu} - \Phi_{us}^2},$$

Here is the equilibrium effect on population:

$$\frac{\partial N_u}{\partial \tau_0} = \frac{\frac{NP_u(1-P_u)}{\sigma}\left(\overbrace{\frac{\alpha_L}{\sigma_a}\left(x_s MU_{a,s} - x_u MU_{a,u} \right)}^{\text{Leisure Time Effect}} + \overbrace{\frac{\beta_a}{\sigma_a}\left(x_{u|u} - x_{u|s} \right)\Gamma_u^0 + \frac{\beta_a}{\sigma_a}\left(x_{s|u} - x_{s|s} \right)\Gamma_s^0}^{\text{Amenity Value Effect}} \right)}{1 + \frac{NP_u(1-P_u)}{\sigma}\underbrace{\left(\kappa\left(\frac{\rho_u}{N_u} + \frac{\rho_s}{N_s} \right) - \frac{\beta_a}{\sigma_a}\left(x_{u|u} - x_{u|s} \right)\Gamma_u^N - \frac{\beta_a}{\sigma_a}\left(x_{s|u} - x_{s|s} \right)\Gamma_s^N \right)}_{\text{Endogenous Factors}}}$$

Proposition 4. *An increase in amenity aversion ($\tau_0 \uparrow$) reduces amenity foot traffic in both urban and suburban locations (M_u and M_s), provided that the urban amenity premium $a_{u0} - a_{s0}$ is sufficiently large and the aversion shock is strong enough. In this case, the decline in M_u exceeds that in M_s — i.e., urban amenity foot traffic falls more sharply than suburban amenity foot traffic.*

Proof. First, to establish that amenity foot traffic declines in both locations in response to a rise in τ_0, it suffices to show that Γ_u^0 and Γ_s^0 are negative and sufficiently so to outweigh any migration effect.

Here, Γ_u^0 and Γ_s^0 capture each location's foot traffic response to an increase in τ_0, holding population migration to zero. Their values depend on the relative magnitudes of Φ_u^τ and Φ_s^τ. Moreover, note that as the urban amenity premium becomes large, we have $\Phi_{us} \to 0$, $\Phi_{ss} \to 1$, and $\Phi_{uu} \to 1$. In this case, $\Gamma_u^0 \to \Phi_u^\tau$ and $\Gamma_s^0 \to \Phi_s^\tau$.

For Φ_u^τ to be negative, it suffices that $MU_{a,u|u} - MU_{a,u}x_u > 0$ and $MU_{a,u|s} - MU_{a,s}x_s > 0$. The latter condition, $MU_{a,u|s} - MU_{a,s}x_s > 0$, always holds. The former, however, may fail if the amenity choice probability x_u is too high. As τ_0 increases, x_u declines, and eventually $MU_{a,u|u} - MU_{a,u}x_u > 0$ will be satisfied once τ_0 is sufficiently large. In that case, $\Phi_u^\tau < 0$.

For Φ_s^τ to be negative, it is sufficient that $MU_{a,s|u} - MU_{a,u}x_u > 0$ and $MU_{a,s|s} - MU_{a,s}x_s > 0$. The first condition, $MU_{a,s|u} - MU_{a,u}x_u > 0$, always holds. The second condition may fail if the amenity choice probability x_s is too high. However, as τ_0 increases, x_s decreases, and eventually $MU_{a,s|s} - MU_{a,s}x_s > 0$ will be satisfied once τ_0 is sufficiently large. In this case, $\Phi_s^\tau < 0$.

Moreover, because the marginal utility MU diverges as τ_0 approaches the total leisure endowment τ, both Φ_u^τ and Φ_s^τ can become arbitrarily negative, thereby dominating any migration effect. These results imply that, with a sufficiently large urban amenity premium and a sufficiently strong τ_0 shock, foot traffic declines in both u and s.

Next, we establish that if the urban amenity premium is large enough, the decline in foot traffic is greater in u than in s.

When the urban amenity premium is very large, we have $MU_{a,u|u} \to MU_{a,u}$ and $MU_{a,u|s} \to MU_{a,s}$, which implies $\Phi_u^\tau < 0$. Furthermore, if the τ_0 shock is large, then by the Inada condition of the log utility function, $MU_{a,s|u} \to \infty$ and $MU_{a,u|u} \to \infty$. Consequently, a sufficiently strong increase in τ_0 generates an arbitrarily large negative value of Φ_u^τ, implying that the loss of amenity foot traffic is more severe in u than in s.

Furthermore, if the urban amenity premium is very large, then $x_{s|u} \to 0$ and $x_{s|s} \to 0$, which implies that $\Phi_s^\tau \to 0$. This means that, for a given τ_0 shock, there exists an urban amenity premium sufficiently large such that $|\Phi_s^\tau|$ is small in magnitude while $|\Phi_u^\tau|$ is large in magnitude, with $\Phi_u^\tau < \Phi_s^\tau$.

□

Proposition 5. *An increase in amenity aversion (τ_0 ↑) induces net migration from the urban location (u) to the suburban location (s) — i.e., a decline in the urban population N_u and a corresponding rise in the suburban population N_s, provided that β_a is sufficiently small, the urban amenity premium $a_{u0} - a_{s0}$ is sufficiently large, and the aversion shock is strong enough.*

Proof. For an increase in amenity aversion to reduce the urban population N_u, two conditions must hold: the sum of the "leisure time effect" and the "amenity value effect" must be negative, and the "endogenous factors" must not be too negative such that the denominator dips below zero.

First, the leisure time effect has an ambiguous sign. Its direction depends on how the probability-weighted marginal utility of leisure time for residents in s compares with that for residents in u. If the urban amenity premium is positive, the probability that residents from both locations choose to visit u will be high. In this case, $MU_{a,s} > MU_{a,u}$. However, because the cost of accessing amenities is lower for urban residents, it follows that $x_u > x_s$. This leads to an ambiguous sign for the leisure time effect.

Therefore, for the numerator to be negative, the amenity value effect must itself be negative and sufficiently large in magnitude.

Since $x_{u|u} - x_{u|s} > 0$ and $x_{s|u} - x_{s|s} < 0$, the numerator will be negative if Γ_u^0 is sufficiently negative or if Γ_s^0 is sufficiently positive.

If the urban amenity premium is very large, it implies that the probability of visiting u over s becomes one, which ensures that $MU_{a,u|u} \to MU_{a,u}$ and $MU_{a,u|s} \to MU_{a,s}$, which in turn implies $\Phi_u^\tau < 0$. Moreover, if the τ_0 shock is large enough, then by the Inada condition of the log utility function, we have $MU_{a,s|u} \to \infty$ and $MU_{a,u|u} \to \infty$. This implies that a sufficiently strong increase in τ_0 will generate a very large magnitude of negative value for Φ_u^τ.

Furthermore, if the urban amenity premium is very large, then $x_{s|u} \to 0$ and $x_{s|s} \to 0$, which implies that $\Phi_s^\tau \to 0$.

This, in turn, implies that $\Gamma_u^0 < 0$, with its magnitude becoming arbitrarily large when both the urban amenity premium and the τ_0 shock are sufficiently strong. Taken together, a sufficiently large urban amenity premium and τ_0 shock ensure that the amenity value effect dominates the leisure time effect.

Finally, we must verify that the "endogenous factors" do not drive the denominator below zero, which would imply the absence of a stable equilibrium. This condition is satisfied if β_a is sufficiently small. $\square$

A2 Graphical analysis

We draw out a series of diagrams to intuitively illustrate the driving forces behind the changes in foot traffic activities in urban and suburban locations in response to each shock. In Figure A1, we highlight the very different mechanisms through which the increase in remote work adoption and change in aversion toward amenities affect urban foot traffic.

In these diagrams, amenity *supply* as a function of local foot traffic is represented by $a(M)$ curve. Since we assume that more foot traffic to each location endogenously leads to higher amenity value at that location, the amenity supply curve is upward-sloping. Since amenity supply is assumed to be exogenously more abundant (i.e., $a_{u0} > a_{s0}$) in the urban location, the $a_u(M)$ curve is above $a_s(M)$.

Amenity *demand* is exhibited as the location's received amenity visits made by residents living in all locations. Because amenity choice probability and each location's population are both increasing functions of local amenity value, the aggregate amenity visit should also be an increasing function of the local amenity value - $M_j(a)$ is upward sloping. The amenity demand curves for u and s are represented by $M_u(a)$ and $M_s(a)$, respectively. Since the urban location receives exogenously large amenity visits due to the associated commuting trips (captured by ϕ), the amenity demand in the urban location is higher than the amenity demand in the suburban location - $M_u(a) > M_s(a)$. Hence, in Figure A1a, the initial amenity demand in u is to the right of the initial amenity demand in s. The equilibrium foot traffic and the amenity value are represented by the cross point between the amenity demand and supply curves of the corresponding locations.

Note that amenity value and foot traffic are both higher in the urban than in the suburban locations: $a_u > a_s$ and $M_u > M_s$. The urban premia in amenity value and foot traffic reflect both the exogenously abundant amenity supply component in the urban location *and* the endogenously higher amenity demand due to the commuting crowd.

A2.1 Changes in Commuting Patterns

During the pandemic, because of the rise in remote work adoption, work presence downtown is sharply reduced, and the work-related amenity visits in u locations further diminish. In addition, the population relocates from u to s location due to the lessened commuting need. The combination of these factors pulls the amenity demand for u inward while pushing the amenity demand for s outward. Such pull and push forces lead to *parallel* and converging shifts in the two amenity demand curves, leading to the narrowing of the gap between amenity value and visits between the urban and suburban locations, as shown in Figure A1a.

A2.2 Changes in Amenity Preference

In addition to the direct impact of reduced commuting traffic and the suburbanization of population, the substantially reduced commuting time reduces the disutility of making amenity trips, especially trips with long travel costs. The reduction in the disutility of amenity travel should enable stronger demand for amenities in general, and, thereby, increase the slope/sensitivity to amenity difference between locations, lowering the slope of the $M_u(a)$ and $M_s(a)$ curves.

On the other hand, the pandemic simultaneously led to an abrupt and temporary increase in the aversion to going outside the home and risking infection. The disutility of using amenities reduces people's sensitivity to the difference in amenity value, vastly increasing the steepness of the $M_u(a)$ and $M_s(a)$ curves and temporarily overwhelming the opposing effect coming from the reduced commuting time.

Consistent with that intuition, Figure A1b presents the scenario in which the reduction of residents' overall demand for amenities and thereby their responsiveness to local differences in amenity value would lower their marginal demand (foot traffic) for amenities, effectively making the amenity demand curves steeper (less steep with respect to a). The changed slope of the demand curves lowers the equilibrium foot traffic and amenity value in both u and s locations because workers in both locations value amenities less. But the diagram shows that the drop in foot traffic and thereby amenity value is much larger in the u location because u starts with a higher level of amenity value compared with s, consistent with the result in the comparative statics.

A2.3 Combined Pandemic Effects

Combining the effects of both the shifts and the tilts in the demand curves (as represented by the shifts from $M_u(a)$ and $M_s(a)$ to $M'_u(a)$ and $M'_s(a)$ in Figure A2a), we can see that the dual shocks during the pandemic would strongly reduce the amenity value and foot traffic in the urban location as both the remote work shock and the amenity preference shock reduce foot traffic there. On the other hand, for the suburban location, while a parallel outward shift would bring more foot traffic, the counterclockwise tilt of the demand curve would lower traffic. So the effect of the pandemic on suburban locations' amenity value and foot traffic is indeterminate.

A2.4 Post-Pandemic Effect

Lifting of the pandemic-related aversion to amenities After the pandemic ends, since the concerns of COVID-19 transmission have been removed, an increase in τ_0, the temporary disutility of visiting amenities due to disease concerns is lifted, and the demand for amenities likely has bounced back. This means that, to some extent, the population will shift back from the suburb to the urban location, which means that the $M_u(a)$ curve will shift back outward, and the $M_s(a)$ curve will shift back inward, to some degree. In addition, the steepness of both $M_u(a)$ and $M_s(a)$ will recover and be reduced back to their original levels.

In Figure A2a $M''_j(a)$ represents the effect of the recovery of amenity aversion in equilibrium. We can see that amenity value in the urban location would bounce back strongly from the low level during the pandemic, while the suburban location would see a more moderate increase in amenity value and foot traffic. Hence, while the long-term reduction in commuting frequency would still lead to a net loss in urban amenity foot traffic, a full recovery in amenity aversion would ensure that urban amenities reclaim much of the loss of traffic seen during the pandemic.

Persistent prevalence of remote work After the pandemic ends, research has demonstrated that remote work is very likely here to stay (Barrero et al., 2021; Gupta et al., 2021). This means that the parallel shifts in the amenity demand curves that occurred during the pandemic will likely not fully recover due to the sustained popularity of remote work. Moreover, the sustained prevalence of remote work implies that commuting time stays permanently reduced, which raises the total amount of leisure time at workers' disposal and, thereby, reduces the disutility of amenity travel. The reduced disutility of travel costs for amenities implies that the demand for amenities should increase. During the pandemic, the increased demand for amenities was overwhelmed by the temporary aversion to amenities. Once the temporary aversion is lifted after the pandemic ends, the increased demand for amenities should bring up the general sensitivity toward amenity value across locations, which will make the amenity demand curve even less steep than before the pandemic. In other words, the curve $M_j''(a)$ would further tilt clockwise to $M_j'''(a)$, as shown in Figure A2b.

If the preference for amenities increases sufficiently due to the permanent increase in remote work adoption and if the urban location carries sufficiently high amenity value premium, it is possible that urban amenities gain so much more foot traffic that they overshoot the pre-pandemic benchmark. In contrast, the increase in amenity demand would not produce as big an overshoot of amenity foot traffic in the suburban location, resulting in a disproportionate concentration of foot traffic in the urban location.

A3 Data Validations

A3.1 SafeGraph Foot Traffic validation

SafeGraph foot traffic data provides us with information on amenity and commuting trip patterns at a highly geographically detailed level. To make sure that we can reliably use it for analysis, we validate it with Google Mobility data, a publicly available data source that tracks mobility patterns at the county level for several different categories of destinations during the COVID-19 pandemic.

The Google Mobility data reports how much the number of visits changes in each month during the pandemic relative to the baseline period, which is the 5 weeks Jan 3–Feb 6, 2020. They calculate these mobility numbers based on data from users who have opted in to Location History for their Google Account, which is a subsample of all users and of the underlying population. We use the county-level Google Mobility index to places of retail and recreation in July, August, and September of 2022 as the ending period (2022 Q3). The index would represent the percentage change in mobility between the beginning of 2020 and Q3 of 2022. Then, we take the SafeGraph Foot Traffic data and calculate the percent change in county-level short visits to amenities (as defined in the paper) between 2019 Q4 and 2022 Q3.

Figure A3a presents the binned scatterplot between the SafeGraph county-level growth in amenity visits and the county-level Google Mobility index to retail and recreation places. We can see that the relationship between the two variables is strong and the magnitude lines up reasonably well.

A3.2 SafeGraph Spend Data Validation

Next, we provide external validation for the SafeGraph Spend data. SafeGraph Spend data covers a subset of the merchants across the U.S. Therefore, to rely on the data for spatial analysis, we need to ensure that the spending patterns observed in the Spend data indeed track the spatial patterns of consumer spending. Spending data at a detailed geographic level is hard to come by with publicly available resources. The lowest level of geography available is at the state level for the Monthly State Retail Sales (MSRS) data reported by the U.S. Census Bureau. The dataset is constructed with both the national Monthly Retail Trade Survey (MRTS) brick and mortar sales and the state- and NAICS-level payroll data. The retail sale growth (12-month) is reported each month for NAICS codes 441, 442, 443, 444, 445, 446, 447, 448, 451, 452, 453, representing sub-industries of the retail trade sector.

To mimic the MSRS data, we construct the 12-month growth measure for the selected NAICS code separately for each state and month. We remove the 12-month periods ending in March and April of 2021 because the baseline time over those periods is at the depth of the pandemic level, during which the sales and spending numbers were exceedingly low, leading to explosively large growth rate numbers. We then generate a residualized binned scatterplot, after controlling for the year dummies, the NAICS industry dummies, and their interaction terms, as shown in Figure A3b. We can see that the state-time variation in spending growth tracks the Census-reported sales growth reasonably well, except that the spending growth has a slight positive level bias. In other words, SafeGraph spending growth appears to be positive in data points where Census sales growth is zero. Nevertheless, since our analysis relies on time-varying spatial variation in spending and transactions, instead of the level variation over time, the positive level bias is unlikely to create bias for our empirical analysis, so long as the spatial variation does not exhibit systematic bias in measurement.

A3.3 SafeGraph Home Panel Data Validation

To track population change at the highly detailed census tract level, we use SafeGraph's Home Panel Summary data. Home Panel Summary Monthly patterns provide the number of devices by census tract based on the devices' primary nighttime geohash with a high degree of confidence. The included devices are those that have made at least one visit during the referenced month. The device count based on place of residence is used for approximating the number of residents over time by location.

Publicly available population at the census tract only comes with pooled American Community Survey (ACS) data. Since our goal is to study population change since the start of 2020 and track the precise trajectory over the years during and after the peak of the pandemic, the slow-moving time frame of the ACS is inadequate for our purpose. That being said, the county-level population estimates are released annually by the U.S. Census Bureau. This allows us to produce cross-validation between the SafeGraph device count growth and the population growth at the county level.

To do so, we aggregate the SafeGraph Home Panel Summary device count up to the county level at two points in time: 2019 Q4 and 2022 Q4, and calculate the device count growth. Since the national device count changes over time, we normalize the county-level device count by multiplying the county-level share of the national devices by the national population count at the corresponding points in time. We also calculate the county-level population growth from the Census Bureau between April 2020 and July 2022. Figure A3c presents the binned scatterplot between the county-level device count growth and the county-level population growth. We can see that they line up reasonably well. However, we can clearly see that device count growth swings much more widely than population growth. Namely, while counties with high population growth over the period also tend to see stronger device count growth, the magnitude of the device count growth tends to be much larger.

A3.4 Remote Work Shocks

The spatial remote work shocks are constructed using the NAICS industry mix profile of pre-pandemic foot traffic (and employment data) combined with the measurement of remote work adoption at the industry or industry-MSA level. In this section, we validate that the remote work shock indeed predicts a large drop in commuting trips.

First, we divide census tracts into three categories: those with high remote work shock, moderate remote work shock, and low remote work shock. The census tracts with high remote work shock are those with industry mixes within a 3-mile radius that give rise to a level of shock in the top 10 percent of all census tracts. Census tracts with moderate and low remote work shocks are those in the 46th-90th percentiles and the 1st-45th percentiles. Then, we plot the normalized commuting trips to each of the census tract categories, recorded in the SafeGraph Foot Traffic data. Commuting trips are defined as the trips that last at least one hour and go to destinations that are not considered amenities.

Figure A4 plots the normalized numbers of commuting trips by categories. We can see that census tracts that saw the highest remote work shock indeed experience the sharpest decline in commuting trips during the pandemic and remain the lowest in terms of the number of commuting trips by the end of 2022. Census tracts with a moderate level of remote work shock are stuck in the middle of the pandemic, and the census tracts with a low level of remote work shock saw the least decline in commuting trips, though all census tracts saw a considerable decline during the pandemic and a lack of full recovery by the end of 2022.

A4 Smoothing Adjustment for Foot Traffic

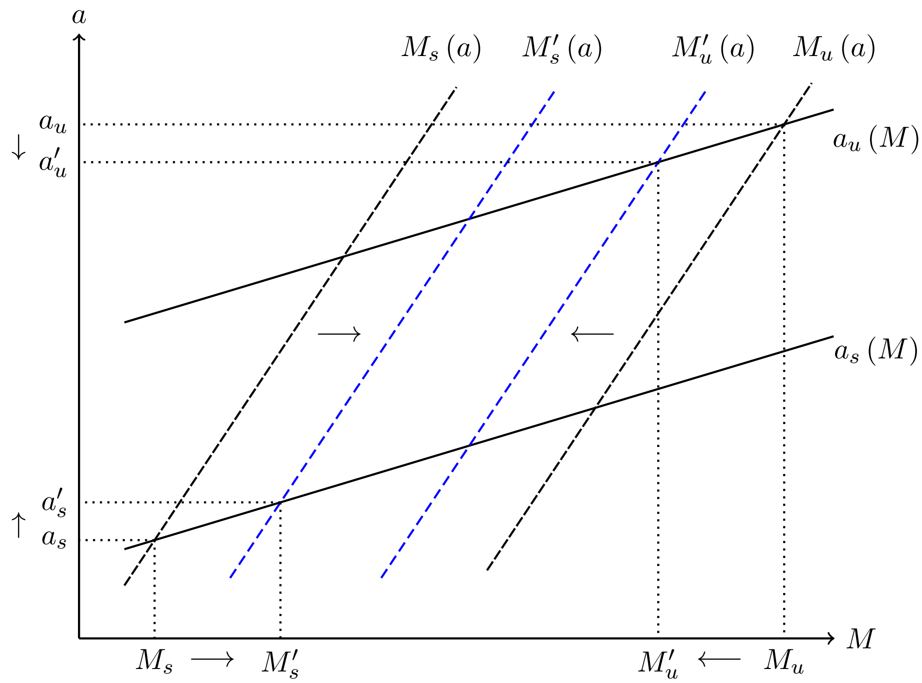
To accommodate and smooth over the arbitrary structural breaks discussed in section 3.1 in the manuscript, we introduce a simple imputation procedure on the tract-level foot traffic statistics. The idea is that we remove the foot traffic information that occurs over the months in which the structural breaks occur. To operationalize on that idea, over all the months where structural breaks occur nationally, we assume that the foot traffic sees no change over the said months.

Let M_{jt} be the raw foot traffic in census tract j and during time (month) t, as measured by Advan/SafeGraph. Let $\mathbf{S}$ be the set of months over which there are structural breaks in the data. We construct the imputed foot traffic at the census tract j as follows:

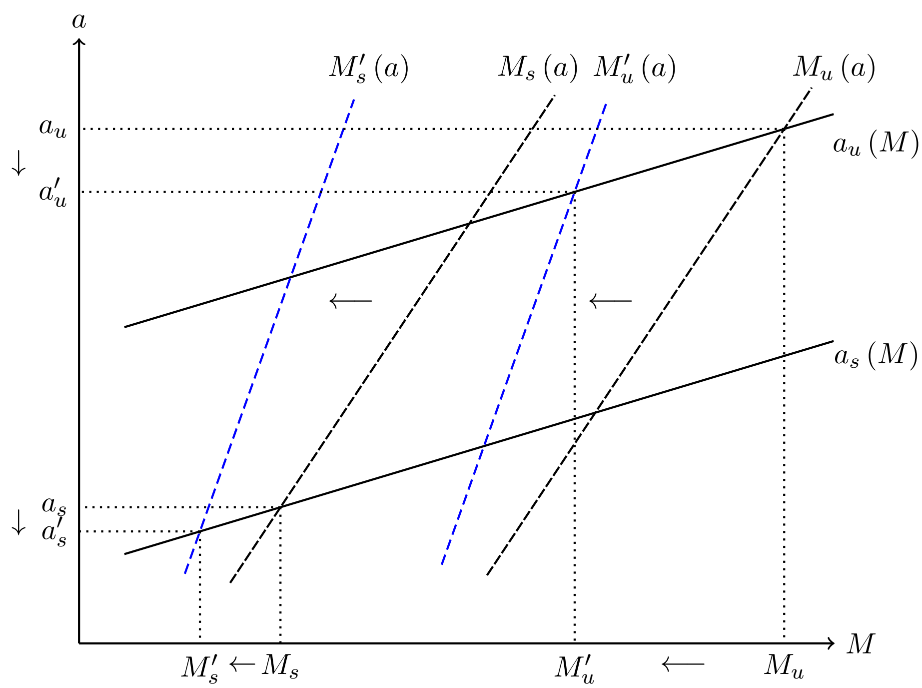
$$\tilde{M}_{jt} = \left(\prod_{t' \in \mathbf{S}, t' \leq t} \frac{M_{j,t'-1}}{M_{j,t'}} \right) M_{jt}$$

The set of months that saw structural breaks includes December 2022, June, September, October 2023, and January and May of 2024. Since S contains only time periods after the end of 2022, no adjustment is made for foot traffic before then: $\tilde{M}_{jt} = M_{jt}$ for t before 2022 December.

Figure A1: Population and Commuter Shock vs. Amenity Preference Shock in Equilibrium



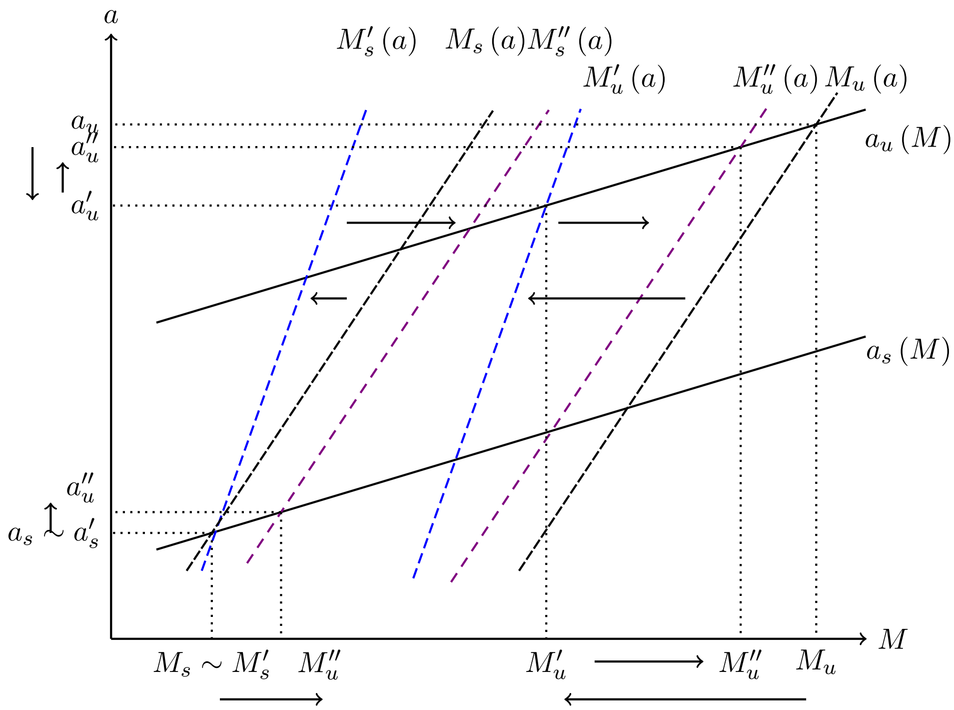
(a) Shifts in Amenity Demand due to Changes in Population and Commuter Traffic



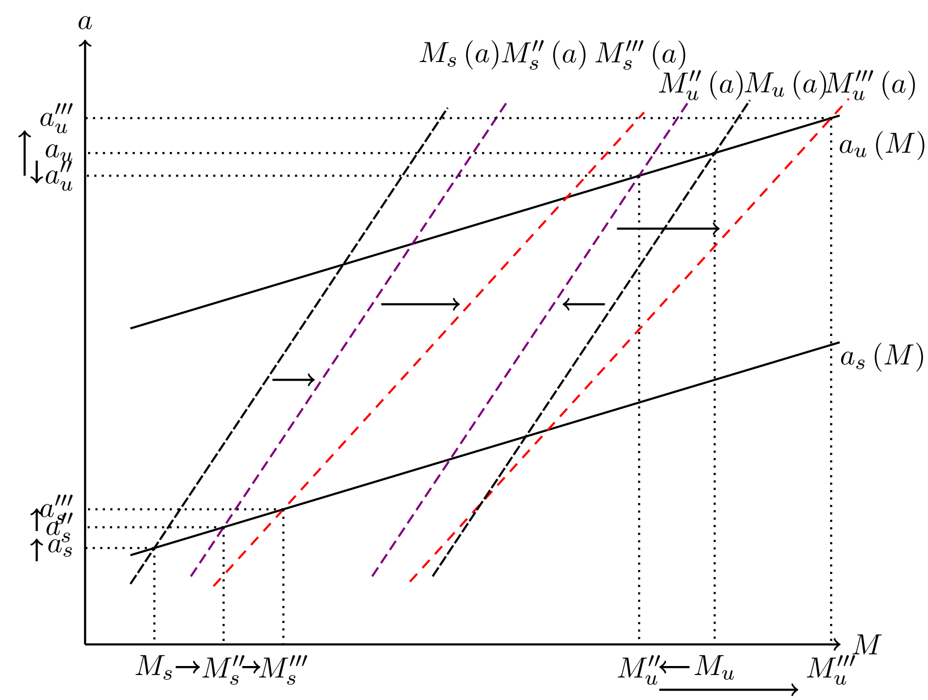
(b) Negative Shock to Preferences for Amenities

Note: The figures present graphical illustrations of how changes in commuting patterns and in the preferences for amenities over the pandemic can affect amenity visit foot traffic in equilibrium. In both subfigures, the solid upward-sloping curves are the amenity provision curves in the u and s locations, respectively. The slopes of the curves with respect to M reflect the endogeneity of amenity. The dashed lines represent the amenity demand curves. They are upward sloping because a higher amenity a leads to more visits. In Figure A1b, we illustrate commuting shocks (reduction in commuting time) as shifting the amenity demand curve inward in the u location and outward in the s location. Equilibrium amenity levels and foot traffic are given by the cross-points between the amenity demand curves and the respective amenity provision curves. In Figure A1b, we illustrate the negative shock to preferences for amenities as a reduction in the sensitivity of foot traffic with respect to amenity levels, which represents an increase in the slope of the amenity demand curves.

Figure A2: Recovery of Amenity Preference Post-COVID



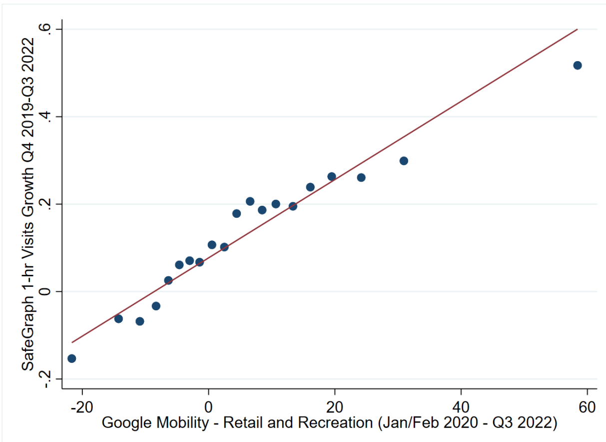
(a) During and After the Pandemic: Lifting of Pandemic Aversion to Amenities



(b) Accounting for the Full Change in Amenity Preference

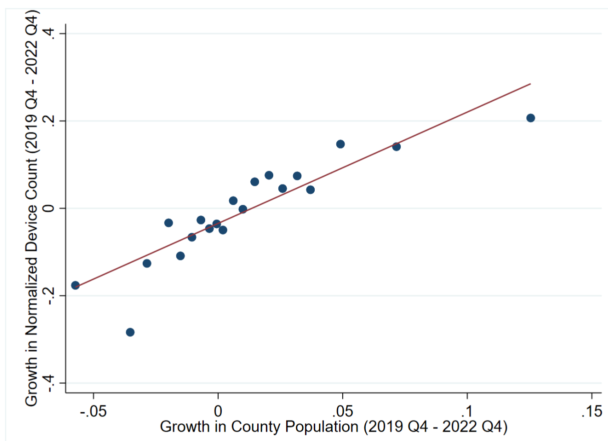
Note: The figure presents a graphical illustration of the simultaneous changes in commuting patterns and in the preferences for amenities that can jointly affect amenity visit foot traffic in equilibrium during the pandemic, and how the recovery of preference for local amenities can partially reverse the amenity foot traffic.

Figure A3: Cross-Validation for SafeGraph Foot Traffic, Spend, and Device Count Data



(a) SafeGraph Foot Traffic vs. Google Mobility

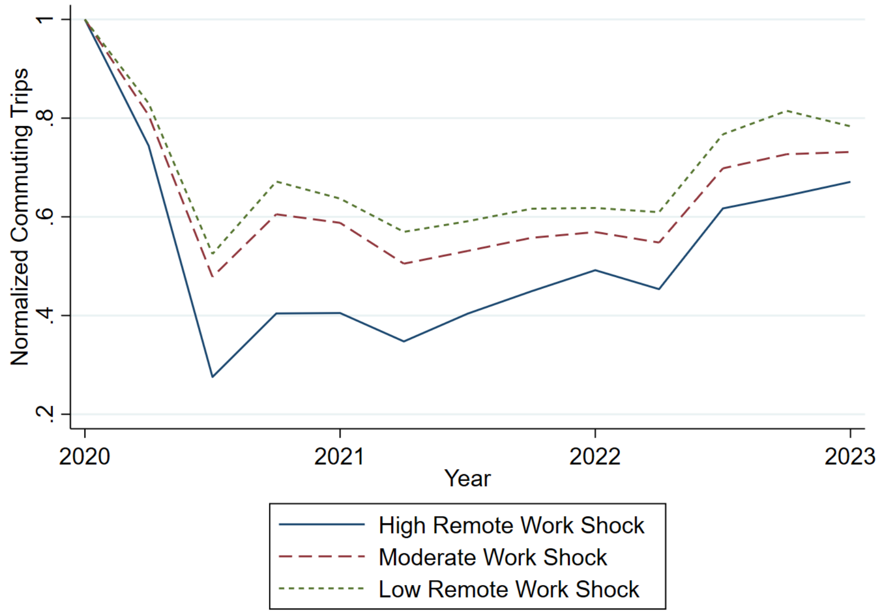
(b) Spending vs. Retail Sales



(c) Device Count vs. Population Count

Note: These figures show the results of the cross-validation checks for the geographically detailed foot traffic and device count data. For each of the data, we aggregate the data to the county level and compare the county-level changes against publicly available external datasets at the county level. In Figure A3a, we plot the growth of short visits to amenities (trips that last less than one hour) between 2019 Q4 and 2022 Q3 in the SafeGraph data against the Google Mobility Index tracking changes in mobility to retail and recreational facilities between Jan 3–Feb 6 of 2022, and 2022 Q3. In Figure A3b, we present the residual binned scatterplot after controlling for year dummies, NAICS dummies, and the interaction between the two sets of dummies. For this graph alone, we remove the 12-month periods ending in March and April of 2021. The vertical axis represents the monthly total spending growth over a 12-month horizon from the SafeGraph Spend data, and the horizontal axis represents the monthly retail sales over a 12-month horizon reported from the Monthly State Retail Sales (MSRS) provided by the U.S. Census Bureau. Figure A3c presents the binned scatterplot between the growth of normalized device count between 2019 Q4 and 2022 Q4 at the county level against the growth in county population estimated by the U.S. Census Bureau between April 2020 and July 2022.

Figure A4: Cross-Validation for Spatial Remote Work Shock



Note: This figure plots the normalized commuting trips to census tracts with high remote work shock, moderate remote work shock, and low remote work shock, recorded in the SafeGraph Foot Traffic data. Commuting trips are defined as the trips that last at least one hour and go to destinations that are not considered amenities. The census tracts with high remote work shock are those with industry mixes within a 3-mile radius that give rise to a level of shock in the top 10 percent of all census tracts. Census tracts with moderate and low remote work shocks are those in the 46th-90th percentiles and the 1st-45th percentiles.

Table A1: Hotels are Likely to Locate at Amenity Clusters

	(1)	(2)	(3)	(4)
Dep Var	Log Visits to Hotel	Visits to Hotel	Log Visits to Hotel	Visits to Hotel
Ln Amenity Density	0.645***		0.669***	
	(0.0119)		(0.0134)	
Ln Pop Density	0.347***		0.386***	
	(0.0165)		(0.0189)	
Ln Distance to Downtown	-0.0831***		-0.115***	
	(0.0135)		(0.0206)	
Amenity Density		1.45e-07***		1.46e-07***
		(2.37e-08)		(2.38e-08)
Pop Density		-5.837***		-6.048***
		(1.686)		(1.989)
Distance to Downtown		-6.39e-08***		-1.98e-07***
		(1.77e-08)		(7.63e-08)
Constant	-10.03***	0.00760***	-9.680***	0.0117***
	(0.269)	(0.00224)	(0.329)	(0.00450)
MSA FE	No	No	Yes	Yes
Observations	21,914	68,165	21,055	64,197
R-squared	0.509	0.130	0.522	0.131

Note: This table reports the results of regressing census tract-level hotel foot traffic in 2019 on the 2019 amenity foot traffic measure, controlling for population density and the distance to downtown. Columns 1 and 2 report results where we do not include the MSA fixed effects, while columns 3 and 4 report results where we do include them. Columns 1 and 3 report results of regressions in which all variables are log transformed, while columns 2 and 4 report results of regressions in which variables in levels are used. *** $p < 0.01$, ** $p < 0.05$, *$p < 0.1$.