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Uneven Home-to-Work Geographies during COVID-19: Evidence from U.S. LODES

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Uneven Home-to-Work Geographies during COVID-19: Evidence from U.S. LODES

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Abstract

Changes in aggregate employment counts do not fully describe the geography of linked home and workplace locations during COVID-19. We use U.S. Census Bureau Longitudinal Employer–Household Dynamics Origin–Destination Employment Statistics (LODES) for 2019–2021 to compare employment-linkage volume and distance dispersion across illustrative states and industry categories. Block-level records are aggregated to a 1-km grid and reciprocal directions are combined. Grid cells are organized into ten ordinal linkage-intensity groups, and job-weighted distance dispersion is calculated for each group pair. Across five illustrative states, linked-job counts fell by 1.2%–9.5% in 2020 relative to 2019. Arizona was 0.6% above its 2019 level in 2021, whereas Alabama, Colorado, Connecticut, and New York remained 1.3%–9.5% below their pre-pandemic levels. Occupied-cell counts changed much less than linked-job totals. The normalized dispersion matrices also differed: Connecticut and New Jersey retained higher displayed values toward high-intensity group pairs, while Montana and Oklahoma showed different arrangements across the group indices. Iowa's three broad industry categories exhibited distinct group-pair dispersion configurations. These descriptive comparisons show why employment volume, spatial coverage, and distance dispersion should be examined separately. The framework makes sector and geographical differences visible while distinguishing administrative employment linkages from observed daily commuting trips.

Keywords: employment geography, home-to-work linkages, COVID-19, LODES, spatial interaction, commuting potential

1 Introduction

The geography connecting homes and workplaces shapes access to employment and the spatial demands placed on transport systems. Research on jobs–housing relationships has examined these connections through the separation of residential and employment locations (Cervero 1989; Horner and Schleith 2012). During COVID-19, workplace disruption and changes in travel made this relationship particularly difficult to interpret. Studies documented reductions in movement and wider socioeconomic disruption (Kraemer et al. 2020; Nicola et al. 2020), but a reduction in journeys need not imply an equivalent change in recorded home-to-work employment links. A job can remain associated with the same home and workplace while travel frequency changes; employment can also contract while those locations remain occupied. Understanding the geography of disruption and recovery therefore requires examining how many jobs link places, which locations remain represented, and how the distances between linked locations are distributed.

We examine these dimensions using the U.S. Census Bureau Longitudinal Employer–Household Dynamics Origin–Destination Employment Statistics (LODES) for 2019–2021. As shown in Figure 1(a), the task is to compare annual home-to-work employment geography before and during the pandemic. LODES links residence and workplace census blocks for covered jobs, providing administrative employment associations rather than observations of daily trips. Figure 1(b) identifies three obstacles to this comparison. First, the many fine-scale origin–destination records require a spatial representation that makes their configurations manageable to examine. Second, linked-job totals contain no information about the variation in distance between linked locations: similar totals can accompany different distance distributions. Third, an all-jobs or geographically aggregated view can conceal differences between places and industries. These challenges lead to two questions: how did employment-linkage volume, spatial coverage, and distance-dispersion patterns differ over 2019–2021, and what additional contrasts emerge when the analysis distinguishes states and broad industry categories?

Existing research provides a basis for addressing each challenge. Spatial-network and trip-distribution studies organize large collections of interactions into interpretable representations (Barthélemy 2011; Lenormand et al. 2016); the present task applies a compact representation to annual administrative job links. Jobs–housing research establishes the importance of residential and employment locations and their fit (Cervero 1989; Blumenberg and Siddiq 2023), but a job total or mean separation alone cannot describe variation around the mean within different sets of links. Pandemic travel studies and work-from-home research, in turn, identify substantial socioeconomic and industry differences (Brough et al. 2021; Dingel and Neiman 2020). Their findings make disaggregation important without establishing what happened to the annual geography of recorded job links in each place. We therefore bring together a common spatial representation, distance-dispersion summaries alongside counts, and comparisons that retain geographical and industry distinctions.

We address these needs through the grid-based analysis in Figure 1(c), whose three components follow the challenge order in panel (b). Grid aggregation assigns residence and workplace locations to 1-km cells and combines reciprocal links, reducing the block-level records to a symmetric representation of linked-job weights. The maps in Figure 2 provide geographical context for this representation. Distance statistics then retain information absent from totals. Cells are organized into ten ordinal linkage-intensity groups, and the job-weighted mean separation and standard deviation of separation are calculated for each group pair. The groups classify cells by linked-job intensity; geographical distance is the measured quantity within a pair, not the criterion defining the groups. Finally, comparisons distinguish states, years, and the three broad LODES industry categories. Linked-job totals and occupied-cell counts establish volume and coverage, while normalized group-pair matrices show the relative arrangement of distance dispersion within each displayed analysis.

The paper contributes an integrated description of employment-linkage volume, spatial coverage, and within-group-pair distance dispersion, and uses it to identify contrasts in the existing state and industry examples. The evidence follows the same progression as Figure 1. Table 1 shows that linked-job counts in five illustrative states fell by 1.2%–9.5% in 2020, while occupied-cell counts changed much less. The state matrices in Figure 3 add information about configuration: Connecticut retains a recognizable ordinal dispersion pattern alongside its declining linked-job total, and the arrangements across intensity-group pairs differ among Connecticut, New Jersey, Montana, and Oklahoma. Figure 4 then shows distinct dispersion configurations for Iowa's three broad industry categories. Together, these comparisons explain why an employment total alone gives an incomplete account of home-to-work geography. They connect the observed volume changes to a separate examination of coverage and dispersion, preserving geographical and sector contrasts without equating normalized matrix values with absolute cross-state distances.

The remainder of the paper is organized as follows. Section 2 relates the study to spatial-interaction, commuting, and pandemic work-geography research. Section 3 introduces the data,

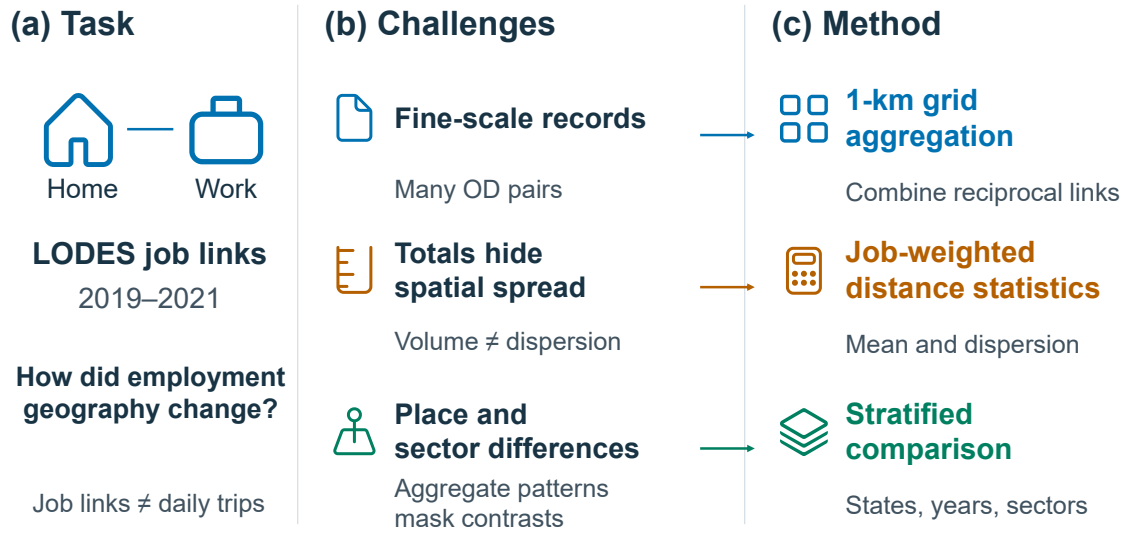


Fig. 1: Task, challenges, and analytical approach. (a) The study compares annual LODES home-to-work employment links in 2019–2021. (b) Fine-scale origin–destination (OD) records, the distinction between volume and spatial spread, and place–sector differences motivate the analysis. (c) Grid aggregation, job-weighted distance statistics, and stratified comparisons address these challenges in the same row order. Arrows connect each challenge to its analytical response. The diagram is conceptual and contains no measured values; empirical evidence appears in Table 1 and the subsequent figures.

grid representation, and dispersion measures. Section 4 reports changes in volume and coverage, state-level dispersion patterns, and industry differences in Iowa. Section 5 interprets their geographical implications and the study boundaries. Section 6 concludes.

2 Related work

2.1 Representing spatial interactions

Spatial-interaction research offers several ways to turn numerous origin–destination links into an interpretable account of movement. The gravity tradition relates flows to the sizes and separation of places (Zipf 1946), while the radiation model derives aggregate mobility flows from the distribution of population and intervening opportunities (Simini et al. 2012). Comparisons of trip-distribution models show why their assumptions and empirical performance must be examined across settings (Lenormand et al. 2016). These are principally models of how much movement occurs between locations. Our dispersion matrix addresses a different descriptive question: how variable are the lengths of recorded employment links between groups of cells with different linkage intensities? It summarizes observed weights rather than estimating a gravity or radiation model.

Individual-mobility studies add information about recurrence and scale that aggregate flow totals do not retain. González et al. (2008) identify regularities in individual trajectories, and Song et al. (2010) develop a model incorporating exploration and preferential return. Daily mobility motifs describe repeated sequences of visited locations (Schneider et al. 2013); work on mobility scales and visitation laws further distinguishes the spatial organization and frequency of movement (Alessandretti et al. 2020; Schläpfer et al. 2021). Reviews place these findings within a broader account of mobility models and geographically embedded networks (Barbosa et al. 2018; Barthélemy 2011). Their relevance here is conceptual: link weight, geographical separation, and recurrence are different properties. An annual count of jobs connecting two cells supplies a weight, but not the number or sequence of journeys made by the associated workers.

Administrative data therefore require a representation suited to their observational unit. The Census Bureau's comparison of LODES and American Community Survey commuting products documents differences in their design, coverage, and reference periods (Graham et al. 2014). Such differences preclude treating all home–work data as interchangeable measures of travel. The present grid representation retains the endpoints and weights of annual job links and then summarizes their distance dispersion. It does not reconstruct trajectories or infer daily travel frequency from those weights.

2.2 Jobs–housing relationships and distance measures

The jobs–housing literature examines how the spatial organization of employment and residence relates to commuting. Cervero (1989) connects regional mobility with jobs–housing balance, while Giuliano and Small (1993) show why spatial balance alone does not determine actual journeys to work. In the San Francisco Bay Area, Cervero and Duncan (2006) compare the travel associations of jobs–housing balance and retail–housing mixing. These studies motivate attention to the locations and types of opportunities, rather than treating employment totals as a sufficient description of transport demand. More recently, Blumenberg and Siddiq (2023) use LODES and housing data to relate jobs–housing fit to commute distance in Los Angeles, bringing housing affordability into the interpretation of residential–employment separation.

Distance also enters the excess-commuting literature through comparisons between observed journeys and a feasible or model-based benchmark. The debate between Hamilton and Röell (1982) and White (1988), and subsequent extensions by Horner (2002), make the benchmark central to interpreting commuting efficiency. A large separation cannot simply be labelled wasteful without specifying the alternatives available to workers and the spatial constraints of the comparison. Similarly, accessibility encompasses opportunities and transport, temporal, and individual constraints, not distance alone (Geurs and van Wee 2004). The statistic used here is neither an excess-commuting index nor an accessibility score: it measures the weighted variation in link lengths within an intensity-group pair.

Temporal analysis provides a direct bridge to the present study. Horner and Schleith (2012) demonstrate how LEHD records can be used to examine changes in land-use–transportation relationships over successive years. Our 2019–2021 comparison follows this administrative-data perspective but separates three descriptive dimensions: linked-job volume, occupied-cell coverage, and distance dispersion conditional on linkage-intensity groups. This separation matters because two collections of links can have similar totals or means while differing in their spread. Group-pair summaries retain some of that heterogeneity while remaining compact enough to compare across annual and sector panels.

2.3 Pandemic travel and unequal scope for adjustment

COVID-19 research initially emphasized restrictions, rapid changes in activity, and the relationship between mobility and infection. Kraemer et al. (2020) examine mobility and epidemic control in China, while Nicola et al. (2020) review disruption across economic sectors. At another scale, Martin and Bergmann (2021) consider international mobility, migration, and involuntary immobility. These contributions describe distinct processes; none makes a change in daily travel equivalent to a change in an annual residence–workplace link. For everyday activity, De Vos (2020) sets out potential consequences of distancing for travel, and survey studies document household travel and activity changes in Australia and Chicago (Beck and Hensher 2020; Shamshiripour et al. 2020). Their behavioural information is particularly valuable for understanding responses that an annual administrative record cannot observe.

Subsequent evidence shows that aggregate travel reductions concealed unequal capacities to adjust. Weill et al. (2020) document differences in distancing responses across areas with different incomes. Jay et al. (2020) link neighbourhood-income differences in staying home to work outside the home, and Brough et al. (2021) examine socioeconomic differences in travel in King County, Washington. Occupational evidence complements these observations: Dingel and Neiman (2020) classify the feasibility of working from

home, while Mongey et al. (2021) relate work-from-home feasibility and physical proximity to workers' economic vulnerability. Together, these studies support distinguishing industries and populations instead of assuming a uniform pandemic response. They do not, however, allow a broad LODES industry category to be treated as a direct indicator of teleworking or essential-worker status.

This distinction guides the Iowa comparison. The three LODES categories preserve broad industry differences in employment-linkage weights, but each category combines occupations and establishments with different work arrangements. Comparing their dispersion surfaces asks whether their recorded home–work geographies look alike. Attributing any contrast to telework, restrictions, or worker disadvantage would require additional occupational, behavioural, or policy information. Sector disaggregation is thus an informative first step rather than a substitute for measuring those mechanisms.

2.4 Remote work and the geography of home and employment

Research extending beyond the initial restrictions documents a substantial and uneven shift toward working from home. Bick et al. (2023) combine survey evidence with a model of work arrangements, and Barrero et al. (2023) review differences in adoption across workers, industries, and places. Althoff et al. (2022) examine how remote-work geography connects business-service employment and local consumer-service activity. European regional evidence likewise shows an uneven geography of remote jobs (Luca et al. 2025). These studies provide context for interpreting sector and place differences, rather than evidence that the particular patterns in our matrices were caused by remote work.

The distinction between travel frequency and home–work separation predates the pandemic. Using Dutch panel data, de Vos et al. (2018) study working from home and the willingness to accept longer commute times. Swiss evidence distinguishes fewer commuting trips from greater residence–workplace distances (Ravalet and Rérat 2019). A review of rebound effects explains why daily travel, residential relocation, and non-work journeys must be considered separately (Hostettler Macias et al. 2022); recent Swiss research further examines the connections between telework and daily and residential mobility (Macias et al. 2025). Reduced commuting frequency therefore need not imply a contraction of the spatial separation recorded in employment-linkage data.

The geographical consequences are also uneven. Drawing on UK case studies, McCollum (2025) questions whether the spread of remote and hybrid working necessarily reduces regional inequalities. This reinforces the need to distinguish an aggregate change in work arrangements from the opportunities available in particular places. Our contribution sits at the descriptive junction of these literatures: it examines annual employment-linkage volume, coverage, and dispersion together while retaining state and industry contrasts. It supplies a view of recorded home–work geography that can later be connected to travel and accessibility evidence, rather than an estimate of remote-work adoption or its causal effects.

3 Data and methods

3.1 LODES employment-linkage data

The analysis uses the Origin–Destination component of LODES for 2019, 2020, and 2021. Each record links a workplace census block to a residence census block and supplies the number of jobs associated with that pair. LODES is derived from administrative records and covers most wage and salary employment in participating U.S. states. It is particularly useful for spatial employment analysis because workplace and residence locations are provided within a consistent national data system. The distinction between its design and survey-based commuting products is described by Graham et al. (2014). The records identify linked home and work locations for jobs, but do not report trip frequency, travel mode, route, or whether work was performed remotely on a particular day.

We use the three broad LODES industry groups: SI01 (goods-producing industries), SI02 (trade, transportation, and utilities), and SI03 (all other services). The all-jobs analysis combines these groups. The period begins in 2019, which provides a pre-pandemic reference, and covers 2020 and 2021, capturing the initial disruption

Table 1: Occupied 1-km grid cells and linked-job counts in five illustrative states, 2019–2021.

State	Year	Occupied grid cells	Linked jobs
Alabama	2019	46,501	13,323,226
	2020	46,389	12,869,788
	2021	46,384	13,149,582
Arizona	2019	19,353	20,548,647
	2020	19,209	20,302,748
	2021	19,145	20,675,754
Colorado	2019	23,578	18,927,448
	2020	23,566	18,135,560
	2021	23,568	18,151,270
Connecticut	2019	10,526	10,846,070
	2020	10,546	10,052,502
	2021	10,564	10,263,076
New York	2019	64,330	61,585,141
	2020	64,709	55,716,924
	2021	64,702	55,733,943

and the first subsequent year available in the assembled data. The design is descriptive and comparative. It identifies differences in the annual geography of employment linkages but does not estimate a causal treatment effect of lockdown orders, remote work, or any single policy.

Table 1 reports the linked-job counts and occupied grid cells for five states used to illustrate changes in scale. The states span different regional and urban contexts and reveal that cell coverage was comparatively stable even when linked-job counts shifted substantially. These examples are not intended to constitute a statistically representative sample of all states; the spatial panels later in the paper are selected comparisons that expose contrasting configurations.

3.2 A common spatial grid

Residence and workplace block centroids are assigned to a regular grid with a nominal cell size of 1 km. The grid reduces the computational and visual complexity of block-level records while preserving the approximate separation between origins and destinations. Let i and j denote grid cells. The directed job count from residence cell i to workplace cell j is $T_{i\to j}$. For the comparative matrices, reciprocal directions are combined as

$$T_{ij} = T_{i\to j} + T_{j\to i}. \tag{1}$$

This produces a symmetric measure of the strength of the employment linkage between two cells. In the retained implementation, diagonal entries are constructed by applying the same reciprocal sum, so within-cell counts are doubled. The diagonal is therefore interpreted consistently across years as a relative within-cell component rather than as an unduplicated count of trips.

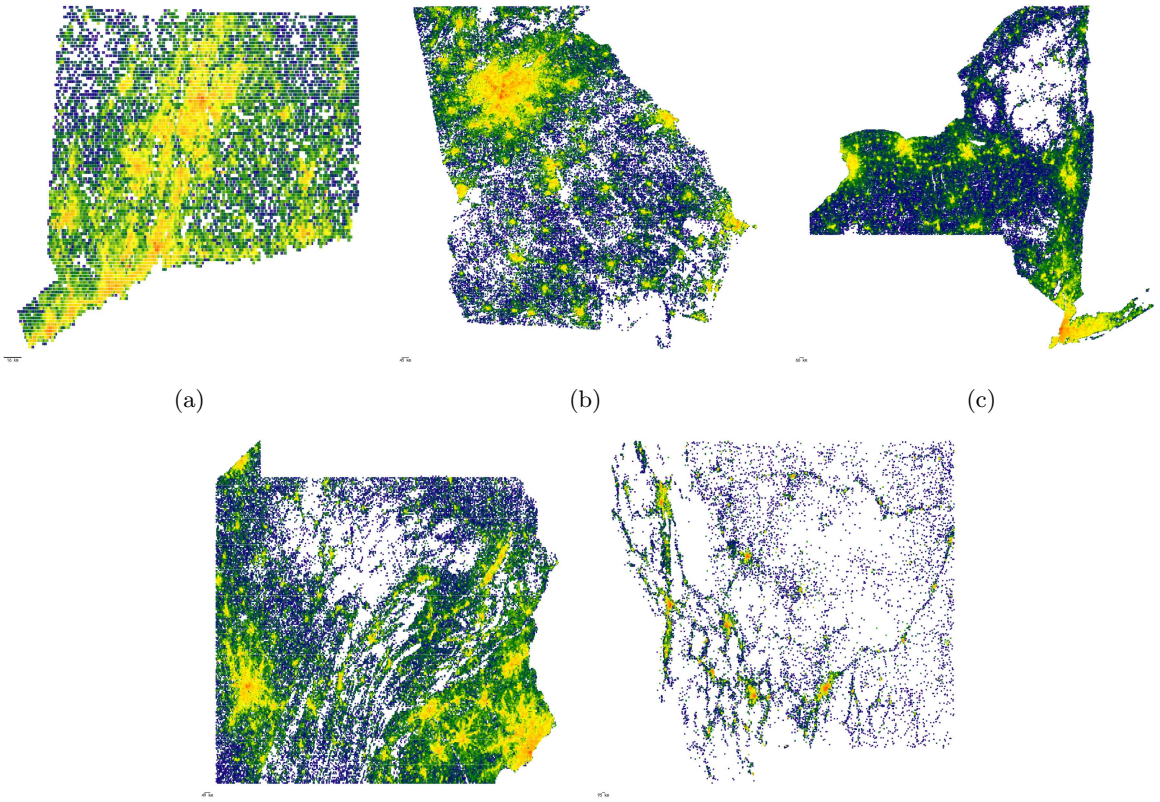
The linkage intensity of cell i is its total linked-job weight, $T_i = \sum_{j=1}^{N} T_{ij}$, where N is the number of grid cells in the study area. The common grid supports two views of the data. Geographical maps show the spatial distribution of linked-job counts. Group-pair matrices summarize distance dispersion between sets of cells ordered by linkage intensity. Figure 2 presents five geographical examples. These maps provide spatial context; their colours and mapped extents are interpreted within each panel rather than as a common national numerical scale.

3.3 Linkage-intensity groups and weighted distance dispersion

Grid cells are organized into ten ordinal linkage-intensity groups, denoted by G_k with $k = 1, \ldots, 10$. Larger group indices indicate higher cell-level linked-job intensity. The two matrix axes identify pairs of these groups; they are not intervals of geographical distance. Group indices are interpreted ordinally within each displayed analysis, without assuming identical absolute flow ranges across states, years, or sectors.

Let r_{ij} be the Euclidean separation between grid cells i and j, and let T_{ij} be the symmetric linked-job weight defined in Equation 1. For cells belonging to groups G_k and $G_{k'}$, the job-weighted mean separation is

$$\bar{r}_{kk'} = \frac{\sum_{i\in G_k,\, j\in G_{k'}} T_{ij} r_{ij}}{\sum_{i\in G_k,\, j\in G_{k'}} T_{ij}}, \tag{2}$$



(a) (b) (c)

(d) (e)

Fig. 2: Illustrative grid-based maps of home-to-work employment linkages. Each panel shows the spatial concentration of occupied cells and their aggregated linkages in one study area. The panels are used to display contrasting configurations; comparisons of absolute colour intensity across panels are not made.

and the corresponding weighted standard deviation is

$$\sigma_{kk'} = \left[\frac{\sum_{i \in G_k,\, j \in G_{k'}} T_{ij} (r_{ij} - \bar{r}_{kk'})^2}{\sum_{i \in G_k,\, j \in G_{k'}} T_{ij}} \right]^{1/2}. \quad (3)$$

These quantities are defined for group pairs with positive total linked-job weight. Each matrix entry summarizes a collection of cell-to-cell links. Its value describes how widely their separations vary around the group-pair mean, giving greater weight to links associated with more jobs. A higher $\sigma_{kk'}$ indicates greater within-pair distance dispersion; it does not by itself establish a longer mean separation or a larger job total.

The displayed matrices use normalized values. Their shapes show which linkage-intensity group pairs have relatively higher or lower distance dispersion within a panel. A peak locates a group pair with high displayed dispersion, while a band identifies several such pairs. Neither the position of a peak nor its extent along an axis locates a geographical area or a distance interval. We compare panel configurations without treating normalized colour values as raw distances or assuming a common absolute scale across panels.

For industry s (SI01, SI02, or SI03), the calculation uses the sector-specific linked-job weights T^s_{ij} and the corresponding group assignments. The weighted mean is

$$\bar{r}^s_{kk'} = \frac{\sum_{i \in G_k,\, j \in G_{k'}} T^s_{ij} r_{ij}}{\sum_{i \in G_k,\, j \in G_{k'}} T^s_{ij}}. \quad (4)$$

The weighted sum of squared deviations and total weight are

$$S^s_{kk'} = \sum_{i \in G_k,\, j \in G_{k'}} T^s_{ij}(r_{ij} - \bar{r}^s_{kk'})^2, \qquad (5)$$

$$W^s_{kk'} = \sum_{i \in G_k,\, j \in G_{k'}} T^s_{ij}, \qquad (6)$$

giving

$$\sigma^s_{kk'} = \left(\frac{S^s_{kk'}}{W^s_{kk'}} \right)^{1/2}. \qquad (7)$$

The statistic retains the same definition across sectors, while the linked-job weights can differ. The group indices identify intensity categories, and s identifies an industry category; these are separate dimensions. The annual comparisons describe aggregate employment links and do not follow the same workers through time.

3.4 Comparative strategy

The empirical analysis has three stages. First, linked-job totals and occupied cells establish the scale of annual change. Second, state-year matrices compare the normalized dispersion structure for Connecticut, New Jersey, Montana, and Oklahoma. These cases contrast compact northeastern settlement systems with lower-density interior states. Third, Iowa provides a sectoral comparison across the three broad industry groups. The interpretation is based on recurring spatial features—concentration, gradient, broadening, and persistence—rather than on a claim that one scalar index captures every geographical change.

This strategy deliberately keeps volume and configuration separate. A fall in linked jobs can occur without a major change in the set of occupied cells, while a similar total can conceal a redistribution across distances or sectors. Reading the table, maps, and matrices together therefore provides a more informative account than any one component alone.

The temporal comparison uses 2019 as the reference rather than assuming that 2020 defines a new equilibrium. For each example, we first compare 2020 with 2019 to identify the immediate annual displacement, and then compare 2021 with both years to distinguish partial recovery, persistence, and further reconfiguration. This three-point design cannot identify a long-run trend, but it prevents the recovery year from being interpreted without its pre-pandemic baseline. Likewise, state and sector panels are interpreted through repeated features across all three years instead of isolated colour differences in one panel.

4 Results

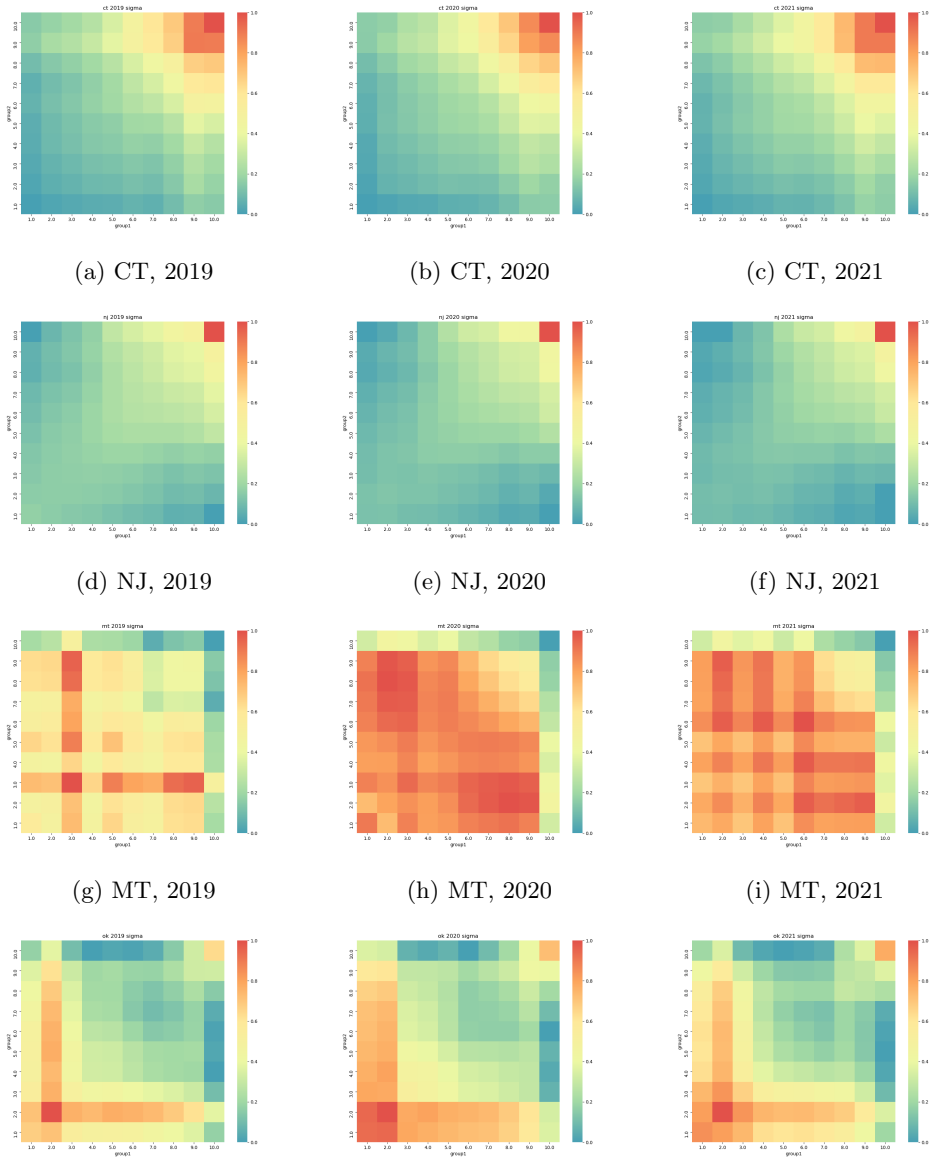
4.1 Employment-linkage volume and spatial coverage

The first pandemic year was associated with a contraction in linked-job counts in all five examples, with different magnitudes. Relative to 2019, the 2020 total fell by 3.4% in Alabama, 1.2% in Arizona, 4.2% in Colorado, 7.3% in Connecticut, and 9.5% in New York (Table 1). New York had the largest decline among these examples and Arizona the smallest.

The 2021 counts reveal equally uneven trajectories. Arizona stood 0.6% above its 2019 level, suggesting recovery in the volume of recorded linkages. Alabama remained 1.3% below 2019, Colorado 4.1% below, Connecticut 5.4% below, and New York 9.5% below. New York's 2021 count was almost unchanged from 2020, while Alabama and Connecticut recovered part, but not all, of their initial decline. These are changes in linked jobs, not estimates of daily commuting frequency. They indicate that the recorded employment-linkage totals did not return to their baselines at the same pace.

Occupied-cell counts were much more stable than linked-job totals. Alabama's occupied cells declined by only 0.3% from 2019 to 2021, while Connecticut's increased by 0.4% and New York's by 0.6%. Arizona showed the largest reduction among the examples, at approximately 1.1%. Thus, the pandemic-era contraction was expressed mainly through the strength of employment linkages within an enduring spatial footprint, rather than through wholesale disappearance of the grid cells containing home or workplace activity. This separation between spatial extent and linkage volume is important: a nearly unchanged footprint can coexist with a substantial reduction in the number of jobs connecting its parts.

The geographical examples in Figure 2 add a second dimension to this result. Employment linkages cluster around major urban concentrations,



(a) CT, 2019 (b) CT, 2020 (c) CT, 2021

(d) NJ, 2019 (e) NJ, 2020 (f) NJ, 2021

(g) MT, 2019 (h) MT, 2020 (i) MT, 2021

(j) OK, 2019 (k) OK, 2020 (l) OK, 2021

Fig. 3: Normalized group-pair distance-dispersion matrices for Connecticut (CT), New Jersey (NJ), Montana (MT), and Oklahoma (OK). Columns show 2019, 2020, and 2021. Each axis indexes ten ordinal linkage-intensity groups; larger indices indicate higher cell-level linked-job intensity, not longer distance. Each entry summarizes $\sigma_{kk'}$ from Equation 3. Colours show normalized within-panel values, not raw distances or job counts.

but their visible reach and density differ across settings. Some panels are dominated by dense cores and short connecting structures; others include broader networks spanning multiple centres or large low-density areas. The maps therefore motivate the matrix analysis: the relevant contrast is not simply whether linkages exist, but how their weights are distributed across spatial separation.

4.2 State-specific dispersion patterns

Figure 3 compares normalized group-pair distance-dispersion matrices for Connecticut, New Jersey, Montana, and Oklahoma. Both axes index the ten linkage-intensity groups, ordered from lower to higher cell-level linked-job intensity. Colours represent the displayed values of $\sigma_{kk'}$ after normalization. The comparison concerns the arrangement of higher and lower dispersion across intensity-group pairs, not a distribution of jobs among short- and long-distance intervals.

Connecticut displays a comparatively smooth gradient in all three years (Figure 3a–c). Higher displayed dispersion occurs toward pairs of higher-intensity groups, while pairs of lower-intensity groups have lower displayed values. This pattern remains recognizable across 2019–2021. Read alongside Connecticut's falling linked-job counts and comparatively stable occupied-cell count in Table 1, it shows that changes in employment volume can coexist with a persistent ordinal dispersion pattern.

New Jersey also retains a recognizable structure across the three years (Figure 3d–f). Higher displayed values occur toward the high-intensity end of both axes, with sharper local contrasts than in the Connecticut panels. These contrasts distinguish the within-panel dispersion configuration. Their location on the matrix identifies intensity-group pairs, rather than neighbourhoods, employment centres, or geographical directions.

Montana shows a different arrangement (Figure 3g–i). In 2019, high displayed values form localized bands among the intensity-group pairs. In 2020 and 2021, elevated values extend across a broader portion of the group-index matrix, with local variation still visible. This change concerns which intensity-group pairs have relatively high distance dispersion. It does not quantify an increase in mean separation or the number of long-distance employment links.

Oklahoma exhibits recurring bands of higher displayed dispersion near the lower-intensity ends of the group axes (Figure 3j–l), alongside lower-valued regions elsewhere in the matrix. The columns show 2019, 2020, and 2021. This arrangement differs from the high-intensity-corner pattern in Connecticut and New Jersey. Together, the four cases show that the association between ordinal linkage intensity and within-pair distance dispersion is not visually uniform across the illustrated states.

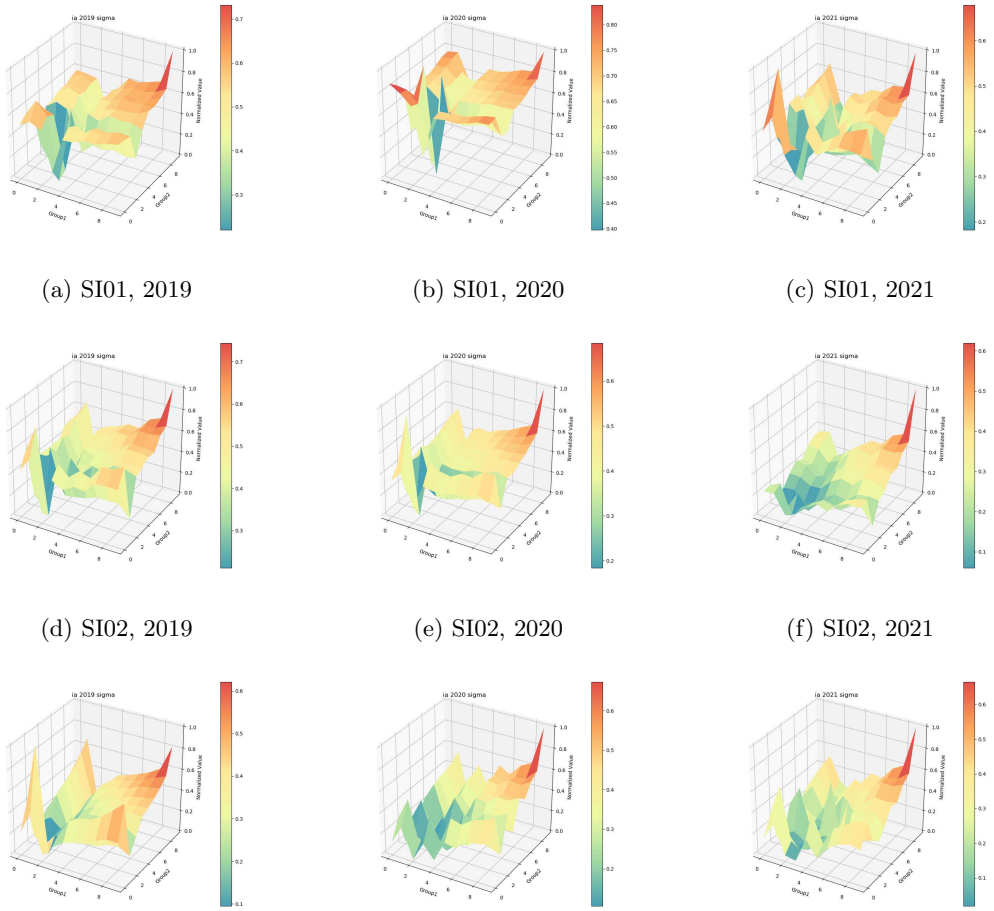
4.3 Industry differences in Iowa

The industry comparison examines whether broad sectors have similar group-pair dispersion patterns within Iowa. Figure 4 reports goods-producing industries (SI01), trade, transportation, and utilities (SI02), and all other services (SI03) in 2019–2021. Each surface represents the sector-specific weighted distance dispersion $\sigma^{s}_{kk'}$ across linkage-intensity group pairs. The two horizontal axes are group indices; surface height and colour represent displayed dispersion.

The three sectors do not share an identical surface. Goods-producing employment has pronounced local peaks and troughs across intensity-group pairs. The trade–transportation–utilities panels retain a high-valued corner, while the arrangement of lower-valued pairs varies across years. The other-services panels also show local contrasts whose positions and shapes differ among the annual views. These observations describe differences in the displayed dispersion patterns without assigning them to particular occupations or work arrangements.

The sector partition reveals variation that an all-jobs summary can conceal. Even within one state, the three categories weight residence–workplace links differently and need not produce the same within-group-pair dispersion. The comparison retains this distinction without treating a common state boundary as control for establishment locations, residential distributions, or industry composition. Differences between surfaces therefore provide descriptive evidence of sector heterogeneity, rather than an isolated sector effect.

Several features remain recognizable across the annual panels, alongside local changes in the group-pair surfaces. Persistence here refers to the configuration of normalized dispersion values. It does not establish that the same jobs or workers remained linked, or that mean home-to-work separation was unchanged. The Iowa panels thus complement the state examples by showing how the dispersion comparison can retain industry distinctions within a geographical setting.



(a) SI01, 2019 (b) SI01, 2020 (c) SI01, 2021

(d) SI02, 2019 (e) SI02, 2020 (f) SI02, 2021

(g) SI03, 2019 (h) SI03, 2020 (i) SI03, 2021

Fig. 4: Industry-specific group-pair distance dispersion in Iowa, 2019–2021. Rows show SI01 (goods-producing industries), SI02 (trade, transportation, and utilities), and SI03 (all other services); columns show the three years. Both horizontal axes index ten ordinal linkage-intensity groups, not distance intervals. Surface height and colour show normalized values of $\sigma^s_{kk'}$ from Equation 7 within each panel.

5 Discussion

5.1 Employment volume and group-pair distance dispersion

The results distinguish three aspects of employment geography. Linked-job totals measure the amount of recorded association, occupied-cell counts describe its spatial coverage, and $\sigma_{kk'}$ summarizes variation in separation within a linkage-intensity group pair. New York combined a large decline in linked-job volume with comparatively stable occupied-cell coverage, whereas Arizona recovered its total by 2021. The state matrices add a different comparison: higher displayed dispersion occurs among different intensity-group pairs in Connecticut, New Jersey, Montana, and Oklahoma.

The group-pair representation complements an area-wide account of the jobs–housing relationship. A single mean separation cannot show whether distances within a given intensity-group pair cluster near their mean or span a wider range. The dispersion matrix retains that information, while the sector panels show that its configuration can differ between industry categories. Because

dispersion, mean separation, and job counts measure different properties, none can substitute for the others when interpreting geographical change.

The results also clarify how LODES should be used in pandemic research. They do not show that workers made a corresponding number of daily trips, nor do they directly identify telework. Instead, they describe the potential spatial demand embedded in the administrative connection between home and workplace. That potential remains relevant for transport and land-use planning because hybrid work does not eliminate the location of either end of the link. It changes how frequently the connection may be activated. A stable linkage geography alongside lower observed mobility would imply different infrastructure questions from a simultaneous relocation of homes, jobs, and establishments.

5.2 Implications for regional planning

The separation between spatial footprint and linkage strength has practical value. Where occupied cells remain stable but linkage counts fall, planners should not assume that employment has permanently withdrawn from those locations. The pattern may instead reflect fewer linked jobs within an enduring settlement system, an incomplete recovery, or a change in the organization of work. Such areas may still generate substantial peak or periodic travel even if average weekday flows decline. Flexible service planning and repeated observation are more appropriate than treating a one-year contraction as irreversible spatial abandonment.

The matrix comparison can guide further investigation of employment geography by identifying intensity-group pairs with contrasting distance dispersion. Translating those contrasts into transport priorities requires locating the contributing cells and examining their mean separations, job weights, and network connections. A broad high-valued region in a group-index matrix alone cannot identify a long-distance corridor or justify an investment at a particular location. Linking these summaries to accessibility measures would make their planning implications more specific.

Sectoral differences carry a parallel implication. Goods-producing employment, trade and transportation activities, and other services cannot be expected to respond identically to remote work or business disruption. Monitoring recovery by aggregate employment alone may therefore mix structural persistence in one sector with reorganization in another. The Iowa comparison shows how the same grid and distance framework can be used to identify these contrasts before a more detailed industry or policy analysis is undertaken.

5.3 Persistence, recovery, and spatial inequality

Recovery is often measured as a return of aggregate employment to a previous level. The state examples show why that definition is incomplete. Arizona's linked-job count exceeded its 2019 level in 2021, while the other four states remained below their baseline. Even where totals recover, however, the residence–workplace configuration may not return in the same way. Growth can be concentrated in different establishments, industries, or parts of a metropolitan area. Conversely, a state that remains below its earlier total may preserve much of its spatial structure. Volume recovery and geographical recovery are therefore related but distinct processes.

This distinction matters for spatial inequality. Workers do not encounter an aggregate state economy; they encounter accessible jobs from particular residential locations. If recovery occurs mainly in linkages that are difficult to reach without a car, concentrated in a limited set of centres, or associated with sectors unavailable to local residents, a rising total may coexist with worsening access for some communities. The current matrices do not identify those distributional outcomes directly, but they locate the geographical question that an equity analysis must answer. Combining the framework with worker characteristics, earnings categories, and transport accessibility would reveal whether a restored employment total also restores opportunity across neighbourhoods.

Temporal persistence also deserves attention. Recognizable features across the annual group-pair matrices indicate persistence in the displayed dispersion configuration. Such persistence is compatible with several underlying changes: job weights may shift, the mean separation within a group pair may change, or different cells may occupy the same ordinal group. The aggregate

panels do not distinguish these possibilities. Following cell membership and reporting group-pair weights alongside distances would clarify which aspects of the employment geography persist.

At the same time, persistence should not be mistaken for inevitability. A stable matrix over a short period may reflect durable assets, but it can also conceal adjustment costs and unequal capacity to relocate. Some workers and firms can respond to disruption through remote work, schedule changes, or residential choice; others remain tied to fixed sites and transport options. Sector-specific analysis is one route to making these differences visible. More detailed occupational and earnings disaggregation would be the next step toward connecting the aggregate geography to lived access and resilience.

5.4 Relationship to mobility research

Human-mobility research has established regularities in travel distance, visitation, and flow networks (González et al. 2008; Song et al. 2010; Barbosa et al. 2018; Alessandretti et al. 2020; Schläpfer et al. 2021). Pandemic studies show how travel responses varied across socioeconomic groups and places (Brough et al. 2021; Weill et al. 2020; Jay et al. 2020). Our analysis complements these studies by examining employment-linked locations. Annual administrative records and high-frequency mobility observations resolve different temporal scales and different objects: the former connect homes to recorded workplaces, while the latter can record changes in movement. Their rates of change need not coincide.

The grid approach is useful precisely because it does not force these layers into a single measure. Device traces can reveal rapid behavioural change but may have uneven population coverage and limited occupational information. LODES offers broad administrative coverage and industry categories but only annual linkage counts and no travel frequency. Used together in future research, these sources could distinguish short-run suppression of movement from longer-run reorganization of employment geography. The present paper establishes the employment-linkage side of that comparison.

The approach also connects network and regional perspectives. In the grid network, cells are nodes and linked jobs are edge weights. Grouping cells by their total linkage intensity then summarizes variation in the geographical lengths of links between group pairs. This reduces the representation to an intensity-indexed distance-dispersion matrix. The reduction does not retain individual routes or the directional imbalance removed by symmetrization, but it offers a compact description to examine alongside maps, totals, and sector-specific results.

The distinction between index space and geographical space is important for regional comparisons. Adjacent entries in the matrix refer to neighbouring intensity categories, not neighbouring places. A wider band of high displayed values therefore describes dispersion across more group pairs, rather than a wider geographical footprint. Reading the matrices together with the count table and maps keeps these interpretations separate. It also avoids ranking states by absolute distances from independently scaled visual summaries.

5.5 Limitations and research agenda

Several boundaries are necessary for interpreting the findings. LODES connects home and workplace census blocks for jobs; it does not observe daily commuting, trip frequency, mode, route, or remote-work days. The results should therefore be read as changes in employment linkage geography and potential commuting demand. The annual data also cannot isolate the timing of short-lived restrictions or distinguish the effects of individual policies from broader economic and behavioural change.

The figures show normalized group-pair dispersion. Absolute linkage-intensity thresholds and a common normalization rule are not specified, so the comparisons are confined to ordinal within-panel configurations and their visible differences. They do not establish changes in raw mean separation, a common cross-state effect size, or population-wide representativeness. The selected examples do not form a probability sample. Aggregation to a 1-km grid also suppresses within-cell variation, while symmetrization removes directional imbalance. Further analysis should report group boundaries and membership, retain raw

group-pair statistics, test grid-resolution sensitivity, and preserve direction when it is substantively important.

The analysis is descriptive. Settlement form and sector composition are possible explanations for the observed differences, but the figures alone do not identify a causal mechanism. Future research could combine the linkage matrices with telework feasibility, establishment openings and closures, metropolitan classification, local restrictions, and independent mobility data. A broader state panel could examine national timing together with state and sector variation. Releasing processed matrices and code would enable sensitivity checks of the normalization, grid resolution, and linkage-intensity grouping.

6 Conclusion

The illustrated states showed uneven changes in home-to-work employment linkages during 2019–2021. Linked-job counts fell by 1.2%–9.5% in 2020, and only Arizona exceeded its 2019 level by 2021. Occupied-cell counts changed much less, separating changes in employment volume from changes in spatial coverage. The state matrices showed different configurations of weighted distance dispersion across linkage-intensity group pairs, and the Iowa comparison retained further distinctions between broad industry categories.

The grid-based analysis combines linked-job totals with group-pair distance statistics to describe employment geography at more than one level of aggregation. Its contribution is the joint examination of volume, coverage, and within-group-pair dispersion across annual and sector views. These dimensions reveal differences that a single employment total would conceal, while keeping the interpretation tied to administrative residence–workplace links. Further connections to observed travel and accessibility would be needed to translate the descriptive patterns into specific transport or land-use decisions.

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