

When Is a Commute “Reverse”? Network Centrality and the Geography of Urban Labor Markets

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Abstract

Reverse commuting has a familiar monocentric meaning: travel from a central residential area toward suburban employment. Yet an origin–destination matrix does not identify a commute as reverse without first specifying the metropolitan hierarchy relative to which its direction is judged. We develop a network-based measure that uses the stationary structure of the full tract-to-tract commuting system to identify counter-directional flows. Under a conventional near-monocentric configuration with predominantly inward commuting, the measure recovers the familiar classification of outward trips as reverse. In polycentric systems, the same rule remains operational without requiring a unique CBD or a predetermined core–periphery boundary. Applying the method to U.S. Census LODES data, we show that network, distance-based, and local inflow–outflow classifications imply substantially different levels and geographies of reverse commuting across metropolitan areas. These differences demonstrate that empirical conclusions about commute direction depend materially on the urban hierarchy embedded in the measurement rule.

Keywords: Reverse commuting; polycentric cities; commuting networks; urban labor markets

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1. Why Reverse Commuting Needs Rethinking

Reverse commuting has a familiar intuitive meaning: it refers to travel that runs against the dominant metropolitan commute direction, typically understood as movement from a dense central area toward suburban employment locations. This intuition is clear in a stylized monocentric city. When the central business district (CBD) is the dominant employment center, density and employment concentration decline with distance from downtown, and most commuters travel inward, the concepts of “central,” “suburban,” “outward,” and “against the dominant flow” describe nearly the same empirical object. Under those assumptions, defining reverse commuting as movement away from the center is transparent.

The difficulty is that reverse commuting is not observed directly in an origin–destination matrix. It is a classification imposed on observed flows after the researcher specifies the spatial hierarchy relative to which movement is judged conventional or reverse. This makes the concept especially sensitive to assumptions about urban form. Applied spatial research often requires choices about areal units, boundary definitions, distance metrics, and spatial lag structures. In many spatial applications, such choices alter the specification of a broadly stable estimand and can be examined through sensitivity analysis. Reverse commuting is different because the assumed spatial hierarchy partly defines the estimand itself: without a hierarchy, an observed flow has no intrinsic conventional or reverse direction. A core-to-suburb rule therefore maps uniquely onto movement against the dominant metropolitan direction only under restrictive assumptions about urban structure.

Those assumptions are increasingly difficult to maintain. Employment and residential activity have decentralized substantially across metropolitan areas (Brueckner & Fansler, 1983; Brueckner, 2000; Nechyba & Walsh, 2002; Liotta et al., 2022). Contemporary cities often contain multiple employment clusters, dispersed residential development, and complex cross-suburban commuting patterns (Giuliano & Small, 1991; Anas et al., 1998; McMillen, 2003; Duranton & Puga, 2015). Urban activity has also become increasingly consumption-

oriented, with employment, amenities, and residential demand jointly shaping metropolitan spatial structure (Glaeser et al., 2001; Glaeser & Gottlieb, 2006). As a result, commuting flows frequently connect residential neighborhoods to suburban office corridors, logistics centers, airports, industrial districts, medical complexes, and mixed-use subcenters rather than to a uniquely dominant urban core.

In such settings, conventional verbal definitions become under-specified. A commute from a dense inner-ring neighborhood to a suburban medical complex may be outward by distance but inward with respect to employment centrality. A suburb-to-suburb trip may appear lateral under a CBD-distance rule but may run against the dominant direction of labor-market connectivity. A flow away from one urban subcenter and toward another may be difficult to classify without first specifying which center defines the relevant hierarchy. The problem is not that conventional definitions of reverse commuting are meaningless; it is that they embed a simplified model of metropolitan structure. Once centrality is multi-dimensional, the empirical content of “reverse” depends on how the researcher defines the relevant center, the relevant periphery, and the dominant direction of commuting.

This measurement problem matters because reverse commuting is not simply a descriptive curiosity. It has been used to interpret central questions in urban economics, transportation planning, and metropolitan policy: whether employment decentralization reduces or reconfigures spatial mismatch; whether central-city residents can access suburban job growth; whether transit systems remain too strongly oriented around suburb-to-downtown peak flows; and whether the resurgence of central cities reflects employment access, consumption amenities, or both. In policy practice, the concept was institutionalized through the federal Job Access and Reverse Commute program, which funded transportation services intended to connect welfare recipients and low-income workers to employment opportunities.¹

¹The standalone Job Access and Reverse Commute program has been repealed, but JARC-type activities remain eligible under the Federal Transit Administration’s Urbanized Area Formula Grants and Formula Grants for Rural Areas programs. The program was designed to address transportation barriers faced by low-income workers, including limited access to suburban employment and work schedules poorly served by conventional transit. See <https://www.transit.dot.gov/funding/grants/grant-programs/job-access-and-reverse-commute-program-5316>.

In empirical research, reverse commuting has been used to study welfare-to-work transportation barriers, transit-service gaps, socioeconomic disparity between home and work locations, suburban employment access, and the changing role of central cities as places of residence rather than only places of production (Cervero et al., 2002; Cervero & Tsai, 2003; Aguiléra et al., 2009; Davidson & Ryerson, 2018, 2021; Davidson et al., 2023).

Reverse commuting also plays a specific role in urban economics through the consumer-city literature. In the traditional production-centered view of urban form, central-city residence is valuable largely because it provides access to central-city employment. Glaeser, Kolko, and Saiz’s consumer-city argument shifts attention toward the consumption value of urban density: restaurants, entertainment, cultural variety, social interaction, aesthetic amenities, and other goods that make cities attractive places to live even when productive activity decentralizes (Glaeser et al., 2001). Reverse commuting provides one empirical signature of this mechanism. If a worker lives in the central city but works in a suburban location, then the worker’s residential choice cannot be explained solely by proximity to a central-city job. Instead, the outward commute suggests that the central city provides residential or consumption value large enough to offset the cost of traveling elsewhere for work. In this sense, reverse commuting is not incidental to the consumer-city hypothesis; it is one of the behavioral patterns that helps distinguish a city valued for production access from a city valued for consumption, amenities, and interaction. Later work on urban resurgence similarly emphasizes the role of dense cities in facilitating social interaction and renewed central-city living, reinforcing the idea that commuting direction can reveal how the economic function of cities changes over time (Glaeser & Gottlieb, 2006; Glaeser et al., 2008; Couture & Handbury, 2020).

The policy and theoretical importance of reverse commuting makes its measurement consequential. A policy aimed at “reverse commuters” implicitly assumes a model of who those commuters are and where they travel. If the measure identifies the wrong flows, corridors, or neighborhoods, then policy analysis may be organized around a salient but

incomplete geography of need. Similarly, if reverse commuting is used as evidence for spatial mismatch, consumer-city dynamics, or metropolitan restructuring, then the classification rule shapes the substantive interpretation of urban change. The goal is therefore not merely to propose another descriptive index, but to provide a theoretically consistent and empirically reproducible way to classify commute direction when the conventional monocentric hierarchy is no longer adequate.

Existing measures typically classify commuting direction using either an exogenously imposed spatial hierarchy or a local flow balance. Distance-based measures define direction relative to a CBD or metropolitan center, while in/out measures classify locations according to whether they primarily send workers elsewhere or receive workers from surrounding areas. These approaches are intuitive and transparent, but they rely on a center-based or locally bilateral view of urban structure. They are therefore less well suited to metropolitan systems in which employment access is mediated through multiple subcenters, corridor-based job clusters, and intermediary neighborhoods (Redfearn, 2007; Giuliano & Dargay, 2012; Manduca, 2021).

This paper treats reverse commuting as a measurement problem and develops a network-based approach for identifying counter-directional commuting in polycentric metropolitan systems. We represent each metropolitan commuting system as a directed weighted network in which neighborhoods are connected through observed residential-to-workplace flows. Each neighborhood’s position within that system is summarized by the stationary distribution of a stochastic process defined on the full commuting network. We then compare stationary, network-adjusted flows in reciprocal directions. An observed commute is classified as reverse when its direction is less prevalent than the reciprocal direction after accounting for each tract’s systemwide network exposure. Although the resulting comparison is bilateral in form, it is metropolitan in informational content because the stationary weights are jointly determined by the full origin–destination matrix.

The broader contribution is to show that reverse commuting is not a primitive feature of

origin–destination data, but a classification that depends on assumptions about metropolitan centrality, peripherality, and prevailing commute direction. The paper makes three specific contributions. First, it provides a theoretically explicit definition that reproduces the familiar outward–reverse classification when a dominant inward-oriented hierarchy is present, but remains applicable when urban structure is polycentric or non-radial. Second, it introduces a tractable network-adjusted directional measure that combines reciprocal flow asymmetry with each tract’s recursive position in the metropolitan commuting system. Third, it shows empirically that conventional and network-based classifications often identify different shares, geographies, and metropolitan rankings of reverse commuting, particularly where employment is spatially dispersed. Because the proposed framework requires only standard origin–destination commuting matrices, it can be applied consistently across metropolitan areas and over time as employment geography evolves.

2. Commuting as a Networked Process

A commute is not conventional or reverse in isolation; it becomes so only relative to a hierarchy of metropolitan places. Conventional measures impose this hierarchy in one of two ways. A CBD-distance rule assumes that centrality declines with distance from a selected center. In this framework, a reverse commute is typically defined as a trip from a designated core—identified, for example, by proximity to the CBD or by a central-city boundary—to a workplace outside that core. The hierarchy is therefore exogenous: places are ordered relative to a predetermined center, and movement outward across the resulting core–periphery boundary is classified as reverse.

An in/out rule instead defines hierarchy using local commuting balance. A tract is treated as workplace-oriented when it receives more inbound commuters than it sends out as resident workers, and as residence-oriented when the reverse is true. A reverse commute is then a trip from a net labor-importing or job-rich tract to a net labor-exporting or residential tract. This hierarchy is local: direction is determined by each tract’s own inflow–outflow balance

rather than by its position within the metropolitan system.

These measures are useful precisely because they are transparent. Their simplicity, however, comes from treating the relevant metropolitan hierarchy as either exogenous or local. A network approach starts from a different premise: the hierarchy of places is itself embedded in the full system of observed commuting relationships.

This perspective follows naturally from spatial equilibrium models in which residential locations, workplace locations, amenities, land costs, and commuting frictions are jointly determined (Roback, 1982; Redding & Rossi-Hansberg, 2017). Households choose where to live partly on the basis of housing costs, amenities, and access to employment opportunities, while firms choose locations partly on the basis of productivity, land costs, labor accessibility, and agglomeration advantages. The observed origin–destination matrix is therefore not simply a collection of unrelated bilateral trips. It is a reduced-form representation of how workers, firms, and places are connected across metropolitan space (Couture & Handbury, 2020; Redding, 2023). Two neighborhoods with similar direct inflow or outflow totals may consequently occupy very different positions within the broader labor-market system.

The relevant network structure is recursive. A neighborhood’s metropolitan position depends not only on the volume of its direct commuting ties, but also on where those ties lead. A mixed-use gateway tract, for example, may not be the largest employment center in a metropolitan area, but it may be closely connected to a major job hub and may link surrounding residential neighborhoods to a broader corridor of economic activity. Likewise, a residential tract may send relatively few commuters directly to the largest employment center while remaining strongly connected to places that are themselves integrated into that center. Local inflows, outflows, or distance from a selected CBD do not fully describe these mediated relationships.

This distinction is especially important in metropolitan areas with multiple employment clusters. Rather than a single dominant center, many cities contain job hubs connected through intermediary neighborhoods, corridor-based development, and mixed-use subcenters

(Redfearn, 2007; Giuliano & Dargay, 2012; Manduca, 2021). A neighborhood may therefore be strongly embedded in the metropolitan employment system even when it has weak direct commuting ties to the largest or most traditional center. Conversely, a neighborhood with substantial local inflows may occupy a relatively limited systemwide position if those inflows originate in places that are otherwise weakly connected to the metropolitan network.

Figure 1 illustrates this distinction. Tract A is primarily residential and sends many workers to nearby Tract B , a mixed-use gateway. Tract B , in turn, has strong commuting ties to Tract C , a major employment hub such as an airport zone, medical complex, industrial district, or suburban office corridor. Direct commuting from A to C may be limited. A local flow-balance measure or a distance-from-center rule may therefore treat A as peripheral to the employment system associated with C . A network measure can instead recognize that A 's metropolitan position is partly mediated through its connection to B , whose own position depends on its ties to C and to the rest of the commuting system.

The figure should not be interpreted as depicting a literal multi-stage journey by a single commuter. The $A \rightarrow B$ and $B \rightarrow C$ edges represent separate observed origin–destination trips. The recursive process instead asks how frequently a synthetic traveler encounters each tract when successive destinations are drawn from the observed commuting probabilities. This allows the position of A to reflect not only its direct ties, but also the systemwide relationships carried through B . Nor does the procedure identify the general-equilibrium effects connecting employment, housing, and local services causally. It summarizes the relational structure that jointly determined residential and workplace choices leave in the observed commuting matrix.

A network approach therefore asks where each neighborhood sits within the full system of commuting relationships. Neighborhoods are not central simply because they receive many commuters, nor peripheral simply because they are far from a CBD. Their position depends on how frequently they are encountered through the recursively connected metropolitan system. The same logic applies to commute direction: a flow becomes conventional or reverse

only relative to a hierarchy inferred from the full commuting network. The next section formalizes this hierarchy and defines the counter-directional member of each reciprocal commuting relationship.

3. A Network-Based Definition of Reverse Commuting

We define commute direction using the structure of the full metropolitan commuting network. Within a given metropolitan area and year, let $\mathbf{W} \in \mathbb{R}_+^{n \times n}$ denote the origin–destination commuting matrix, where W_{ij} is the number of commuters residing in neighborhood i and working in neighborhood j . Row-normalizing $\mathbf{W}$ gives a transition matrix $\mathbf{P}$ with elements

$$P_{ij} = \frac{W_{ij}}{\sum_k W_{ik}}, \quad (1)$$

where P_{ij} is the observed probability that a resident commuter from neighborhood i works in neighborhood j . The matrix $\mathbf{P}$ therefore summarizes the destination structure faced by residents of each origin neighborhood.

The key step is to use this transition matrix to summarize each neighborhood’s systemwide exposure within the metropolitan commuting network. Let $\boldsymbol{\pi}$ denote the stationary distribution satisfying

$$\boldsymbol{\pi}^\top = \boldsymbol{\pi}^\top \mathbf{P}, \quad \sum_i \pi_i = 1. \quad (2)$$

The component π_i measures the long-run exposure of neighborhood i under the commuting-induced stochastic process. Equivalently, $\boldsymbol{\pi}$ is a left-eigenvector centrality measure for the row-stochastic commuting matrix. A tract receives greater stationary exposure when it is reached with high probability from tracts that themselves carry substantial stationary mass, including through longer circulation and return paths in the commuting network. The transition probabilities are derived directly from observed residential-to-workplace commuting flows rather than from abstract network ties (Kane et al., 2024). Technical conditions for existence, uniqueness, and computation are provided in Appendix A.

A useful interpretation is provided by a taxi analogy. Imagine a fixed fleet of taxis circulating through the metropolitan labor market. After dropping a commuter at a workplace tract, each taxi immediately picks up a new commuter residing in that tract and travels to that commuter’s workplace, with destinations drawn according to the observed probabilities in $\mathbf{P}$. Over many transitions, taxis spend more time in tracts that are repeatedly encountered through the full commuting system. The stationary distribution $\boldsymbol{\pi}$ records this long-run exposure.

The analogy is not intended as a behavioral model of individual commuters or as a claim that workers make successive multi-stage journeys. The stationary process is a reduced-form device for summarizing the relational position of each tract within an origin–destination matrix generated by residential and workplace choices (Redding & Rossi-Hansberg, 2017). Its purpose is to infer a metropolitan hierarchy from observed commuting relationships without choosing a CBD or imposing a spatial ordering in advance.

We then define commute direction by comparing stationary edge frequencies in reciprocal directions. Let

$$F_{ij} = \pi_i P_{ij} \tag{3}$$

denote the long-run frequency with which the induced process traverses the directed edge from neighborhood i to neighborhood j . For each reciprocal tract pair, define the network-adjusted directional ratio

$$R_{ij} = \frac{F_{ij}}{F_{ji}} = \frac{\pi_i P_{ij}}{\pi_j P_{ji}}. \tag{4}$$

Although this comparison is bilateral in form, it is metropolitan in informational content: the stationary weights π_i and π_j are jointly determined by the full origin–destination network. Equivalently,

$$\log R_{ij} = \log \left(\frac{P_{ij}}{P_{ji}} \right) + \log \left(\frac{\pi_i}{\pi_j} \right), \tag{5}$$

so the classification combines reciprocal directional asymmetry with each tract’s systemwide network exposure.

For reciprocal positive flows, $R_{ji} = R_{ij}^{-1}$. Except in the directionally balanced case $R_{ij} = 1$, exactly one member of the reciprocal pair is therefore identified as counter-directional. An observed $i \rightarrow j$ commute is classified as reverse when

$$R_{ij} < 1, \tag{6}$$

meaning that its stationary network-adjusted frequency is lower than that of the reciprocal $j \rightarrow i$ direction. The measure therefore identifies the less prevalent direction of a commuting relationship after adjusting for the different positions of its endpoints in the metropolitan network.²

The network rule recovers the conventional interpretation under a natural near-monocentric configuration.³ In the canonical monocentric setting, employment is concentrated at a dominant CBD and workers residing outside the core ordinarily commute inward (Alonso, 1964; Muth, 1961; Mills, 1967). Strictly interpreted, that benchmark contains no outward employment trips to classify. Once a limited amount of employment decentralization is admitted, however, a core-to-periphery trip becomes an unusual outward movement within an otherwise inward-oriented commuting system.

Let i denote the more central location and j the more peripheral location. A sufficient condition for the observed outward commute $i \rightarrow j$ to be classified as reverse is

$$\pi_i P_{ij} < \pi_j P_{ji}, \tag{7}$$

²Empirically, we construct $\mathbf{W}$ from tract-to-tract LODES flows, restrict each MSA-year network to the largest closed strongly connected component after removing zero-outflow tracts, and compute $\boldsymbol{\pi}$ by power iteration using a lazy transition matrix to ensure aperiodic convergence. Appendix A provides details. When $P_{ji} = 0$, the observed $i \rightarrow j$ direction has no reciprocal observed flow and is not classified as reverse.

³The classic Alonso–Muth–Mills model does not express commuting patterns using the transition probabilities defined here. Its stronger spatial premise is that employment is concentrated at the CBD and that residential workers outside the core commute radially inward. Mills (1967), for example, allows some suburban workers to be employed locally while assuming that the remaining workers commute to the CBD. The relevant empirical special case is therefore a near-monocentric perturbation in which some employment has decentralized but the prevailing commute direction remains inward.

or equivalently,

$$\frac{P_{ji}}{P_{ij}} > \frac{\pi_i}{\pi_j}. \quad (8)$$

The right-hand side adjusts for the greater systemwide exposure of the central location. The condition therefore requires the ordinary inward direction to be sufficiently more prevalent that the outward movement remains atypical even after accounting for the core’s larger network position. This is the natural empirical analogue of conventional reverse commuting: centrality is concentrated near the core, prevailing movement is inward, and relatively unusual outward trips are classified as reverse.

The same criterion remains well-defined when metropolitan structure ceases to be radial. Unlike a distance-to-CBD rule, the network measure does not require a single center to be selected in advance. Unlike an in/out rule, it does not evaluate each tract using only its own local commuting balance. Direction is instead inferred from reciprocal flows after each endpoint has been positioned within the full metropolitan network. The measure consequently preserves the conventional interpretation when a dominant inward-oriented hierarchy is present while adapting to multiple employment centers, cross-suburban corridors, and other polycentric structures.

The resulting measure remains tractable because it requires only standard origin–destination commuting matrices. It can therefore be implemented consistently across metropolitan areas and over time as employment geography evolves. The next section compares its classifications with those produced by distance-based and local inflow–outflow rules.

4. What Changes When We Use Networks?

We implement the proposed framework using tract-level origin–destination commuting flows from the Longitudinal Employer–Household Dynamics Origin–Destination Employment Statistics (LODES). For each MSA–year, census tracts serve as nodes and observed residential-to-workplace commuting flows define directed edges. We classify each observed off-diagonal

tract-to-tract commute according to the network-based measure described above. Unless otherwise noted, reverse-commuting shares are commuter-weighted: they represent the share of commuters traveling on OD pairs classified as reverse under a given method. The empirical exercise is descriptive rather than causal. Its purpose is to show how measured reverse commuting changes when commute direction is defined relative to the endogenous structure of the commuting network rather than to a fixed center or local flow balance.

We compare the network classification to two conventional benchmarks. The in/out benchmark classifies each tract according to its local employment balance, identifying job-rich tracts as those receiving more workplace commuters than they send out as resident commuters. A commute is classified as reverse under this benchmark when it moves from a job-rich tract to a non-job-rich tract. The distance benchmark follows the logic of CBD-distance approaches that rank locations relative to a metropolitan center (Christopher et al., 1995; Berube & Forman, 2002) and of studies that frame reverse commuting as central-city-to-suburban or central-city-to-outskirts commuting (Glaeser et al., 2001; Aguilera et al., 2009). We define the metropolitan core as the closest quintile of tracts to a CBD proxy; a commute is classified as reverse when it moves from a core tract to a non-core tract. In both cases, the benchmark imposes a local or center-based hierarchy. The network measure instead infers direction from the full system of commuting relationships.

Figure 3 uses Houston and Raleigh to illustrate two distinct spatial forms of measurement disagreement observed in the metropolitan sample. The cases are not intended to be statistically representative. Rather, they show that alternative classification rules can disagree in different ways across urban space.

In Houston, the sign of the network-minus-benchmark gap changes across the metropolitan area. Conventional measures classify fewer commuters as reverse in some suburban corridors and intermediary locations but more commuters as reverse in others. This spatially uneven pattern is consistent with an urban structure in which different employment clusters and corridors generate locally distinct prevailing directions that cannot be summarized by

a single core–periphery boundary. Raleigh exhibits a different pattern. Positive gaps are distributed across a much broader set of origin tracts, meaning that both conventional rules classify smaller reverse-commuting shares across much of the metropolitan area rather than only around isolated employment clusters. The contrast matters because it shows that definitional disagreement is not merely an aggregate discrepancy. Depending on metropolitan structure, the choice of measure can either reclassify particular corridors or alter the inferred geography of reverse commuting across much of the urban region.

The disagreement between network-based and conventional classifications is not unique to the mapped examples. Figure 4 summarizes average commuter-weighted reverse-commuting shares across the 40 metropolitan areas in the analysis sample over the 2002–2021 period. In most metropolitan areas, the in/out and distance-based benchmarks produce lower reverse-commuting shares than the network framework, although the magnitude of the gap varies substantially across urban systems. This cross-metropolitan variation suggests that benchmark disagreement is not simply an artifact of a single city or year. Rather, it reflects broader differences in how metropolitan commuting systems are spatially organized.

Online Appendix C reports corresponding MSA-level time series, showing that network reverse-commuting shares and classification gaps also vary within metropolitan areas over time.

To examine whether these differences are systematically related to observable metropolitan characteristics, Table 1 reports descriptive MSA–year regressions for the 2009–2021 period. Column (1) examines the commuter-weighted reverse-commuting share implied by the network measure. Columns (2)–(3) examine the gap between the network measure and the in/out centrality and distance-based alternatives, respectively. Positive values in Columns (2)–(3) indicate that the alternative benchmark produces a lower reverse-commuting share than the network measure. All specifications include metropolitan and year fixed effects, so coefficients reflect within-metropolitan changes over time.

The clearest pattern is the relationship between metropolitan employment dispersion and

Table 1: Descriptive correlates of reverse-commuting shares and benchmark disagreement

Dependent Variables: Model:	Network reverse share (1)	In/Out bias (2)	Distance bias (3)
<i>Variables</i>			
Employment entropy	0.0226*** (0.0069)	-0.0075* (0.0042)	0.0143 (0.0124)
Log population	0.0003 (0.0200)	-0.0160 (0.0199)	-0.0242 (0.0360)
Log median wages	0.0850*** (0.0266)	0.0770*** (0.0255)	0.0961** (0.0464)
Unemployment rate	-0.0001 (0.0004)	-0.0003 (0.0004)	4.1×10^{-5} (0.0009)
Average commute time	-0.0008 (0.0010)	-0.0003 (0.0010)	-0.0002 (0.0017)
Vehicle access	0.0011 (0.0016)	0.0016 (0.0017)	0.0031 (0.0028)
Bachelor's+ share	-0.0015 (0.0010)	-0.0022** (0.0008)	-0.0012 (0.0021)
Housing price index change	2.73×10^{-5} (9×10^{-5})	-9.36×10^{-6} (8.17×10^{-5})	0.0003** (0.0001)
New construction permits per 100	0.0007* (0.0004)	0.0010*** (0.0003)	0.0011 (0.0007)
Amenity establishments per 100	-0.0003 (0.0031)	-0.0010 (0.0026)	-0.0028 (0.0072)
Amenity employment share	-0.0004 (0.0008)	-8.29×10^{-5} (0.0007)	-0.0008 (0.0014)
Professional services share	0.0003 (0.0010)	0.0006 (0.0008)	0.0010 (0.0016)
<i>Fixed-effects</i>			
Year	Yes	Yes	Yes
CBSA	Yes	Yes	Yes
<i>Fit statistics</i>			
Observations	520	520	520
R ²	0.99276	0.99212	0.98756
Within R ²	0.23729	0.17615	0.18322

This table reports descriptive associations between metropolitan characteristics and reverse-commuting outcomes using an annual balanced panel of 40 U.S. metropolitan statistical areas (MSAs) observed between 2009–2021. Column (1) examines the commuter-weighted reverse-commuting share implied by the network benchmark. Columns (2) and (3) examine benchmark gaps, defined as the network reverse-commuting share minus the reverse-commuting share implied by the corresponding alternative classification. The network benchmark classifies commute direction using tract-to-tract Longitudinal Employer–Household Dynamics Origin–Destination Employment Statistics (LODES) commuting flows. Employment entropy is constructed from tract-level workplace distributions within each metropolitan area as $H_m = -\frac{\sum_i s_{im} \ln(s_{im})}{\ln(N_m)}$, where s_{im} denotes tract i 's share of metropolitan workplace activity and N_m denotes the number of workplace tracts in metropolitan area m . Population, commuting characteristics, vehicle access, educational attainment, unemployment rates, and demographic measures are obtained from the American Community Survey (ACS). Median wages, professional-services employment shares, amenity employment shares, and amenity establishment measures are derived from Quarterly Census of Employment and Wages (QCEW) data. Housing price changes are constructed using Federal Housing Finance Agency (FHFA) metropolitan house price indexes, and residential development activity is measured using Census Building Permit Survey (BPS) data on newly authorized housing units. All specifications include metropolitan and year fixed effects. Standard errors are clustered at the CBSA level.

network-classified reverse commuting. Employment entropy—constructed from the distribution of workplace activity across tracts—is positively associated with the network reverse-commuting share. As workplace activity becomes less concentrated within a metropolitan area, a larger share of commuters therefore travels in directions classified as atypical by the recursively structured network measure. This result is consistent with the paper’s central argument that commute direction becomes less adequately summarized by a single center–periphery hierarchy as employment disperses. Wages, residential development, and the remaining metropolitan covariates exhibit some additional associations, but these are less directly tied to the paper’s measurement argument and are treated as ancillary. All estimates are descriptive: they document systematic covariation within metropolitan areas rather than the causal determinants of commuting structure.

5. Why the Measurement Choice Matters

The empirical patterns above point to a broader conceptual issue: commuting direction is not only a geographic fact, but also a measurement choice. A commute can appear conventional or reverse depending on whether metropolitan space is understood as a fixed center–periphery system, a collection of local inflow–outflow balances, or a relational network of labor-market connections. This distinction is especially important in polycentric regions, where employment access may be mediated through corridors, subcenters, and intermediary neighborhoods rather than through a single dominant downtown.

The network framework therefore reframes centrality and peripherality as relational positions within metropolitan labor-market systems. A neighborhood is not central simply because it is near a CBD or because it receives many direct inflows. It is central when it is repeatedly encountered through chains of commuting relationships. This perspective connects older concerns about spatial mismatch and employment suburbanization to newer questions about consumer-city dynamics, remote work, and the changing geography of metropolitan labor markets (Glaeser et al., 2001; Glaeser & Gottlieb, 2006; Aguiléra et al., 2009; Grengs,

2010; Monte et al., 2025). In each case, the relevant empirical question is not only whether workers move toward or away from downtown, but how employment access is organized across the full metropolitan commuting network.

These measurement choices matter because different literatures attach different substantive interpretations to reverse commuting. In the spatial-mismatch and transportation-equity literature, reverse commuting often indexes the ability of central-city or low-income residents to reach decentralized employment opportunities. In the consumer-city literature, it helps reveal whether central cities are valued as residential and consumption locations even when employment opportunities decentralize. In transportation planning, it identifies corridors and service patterns that may be poorly served by conventional radial transit networks. A measure of reverse commuting therefore does more than label flows; it shapes conclusions about job access, urban resurgence, metropolitan equity, and the changing economic role of central places.

A further advantage of the framework is that it produces tract-level measures, not only metropolitan aggregates. For each MSA-year, the procedure yields tract-specific centrality scores, origin-level reverse-commuting exposure, and tract-level disagreement between network and conventional classifications. Although the present paper uses these outputs primarily to illustrate how aggregate reverse-commuting shares differ across measurement approaches, the same tract-level panel can be linked to local housing, demographic, employment, amenity, and transportation data. This creates opportunities for future work examining which neighborhoods become more or less integrated into decentralized labor markets, how benchmark disagreement varies across different types of urban space, and whether changes in commuting structure align more closely with spatial-mismatch or consumer-city mechanisms.

6. Conclusion

This paper develops a network-based definition of reverse commuting for metropolitan systems that need not conform to a single core–periphery hierarchy. The measure uses the stationary structure of the full origin–destination network to compare reciprocal commuting directions after accounting for the systemwide exposure of their origin and destination tracts. In a conventional near-monocentric setting with predominantly inward commuting, it identifies relatively unusual outward trips as reverse. In polycentric settings, the same rule remains operational without requiring a predetermined downtown, local inflow–outflow classification, or one-dimensional spatial ordering.

The empirical illustration shows that network, in/out, and distance-based classifications produce different commuter-weighted reverse-commuting shares, with the magnitude and spatial pattern of disagreement varying substantially across metropolitan areas. Network-classified reverse commuting is also more prevalent as workplace activity becomes more spatially dispersed. Together, these results show that the hierarchy embedded in the classification rule affects not only the estimated prevalence of reverse commuting, but also its inferred geography across urban regions.

The goal is not to discard distance-based or local-balance measures. Those rules remain transparent, easy to implement, and closely connected to long-standing theories of monocentric urban form. They are most informative when the hierarchy they impose provides a reasonable description of the metropolitan labor market. As employment decentralization, hybrid work, suburban growth, and changing residential preferences produce more complex commuting systems, however, researchers also need measures that infer prevailing direction from the observed structure of metropolitan flows. More generally, the analysis shows that reverse commuting is not simply a geographic label: it is a theoretically consequential classification whose empirical meaning depends on the urban hierarchy used to define it.

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References

- Aguiléra, A., Wenglenski, S., & Proulhac, L. (2009). Employment suburbanisation, reverse commuting and travel behaviour by residents of the central city in the Paris metropolitan area. *Transportation Research Part A: Policy and Practice*, 43(7), 685–691. doi: 10.1016/j.tra.2009.06.004
- Alonso, W. (1964). Location and land use: Toward a general theory of land rent. In *Location and land use*. Harvard University press.
- Anas, A., Arnott, R., & Small, K. A. (1998). Urban spatial structure. *Journal of Economic Literature*, 36(3), 1426–1464.
- Berube, A., & Forman, B. (2002). *Living on the Edge: Decentralization Within Cities in the 1990s* (Tech. Rep.). Brookings Institution, Center on Urban and Metropolitan Policy.
- Brueckner, J. K. (2000). Urban sprawl: Diagnosis and remedies. *International Regional Science Review*, 23(2), 160–171.
- Brueckner, J. K., & Fansler, D. A. (1983). The economics of urban sprawl: Theory and evidence on the spatial sizes of cities. *The Review of Economics and Statistics*, 479–482.
- Cervero, R., & Tsai, Y.-H. (2003). Job access and reverse commuting initiatives in california: Review and assessment. *Transportation Research Record: Journal of the Transportation*

- Research Board*, 1859(1), 78–86. doi: 10.3141/1859-10
- Cervero, R., Tsai, Y.-H., Dibb, J., Kluter, A., Nuworsoo, C. K., Petrova, I., ... Deakin, E. (2002). *Reverse commuting and job access in california: Markets, needs and policy prospects* (Research Report No. UCB-ITS-RR-2002-7). Berkeley, CA: Institute of Transportation Studies, University of California, Berkeley. Retrieved from https://digitalcommons.calpoly.edu/crp_fac/17/
- Christopher, E. J., Rogus, M. J., & Soot, S. (1995). *Changes in the Direction of Urban Travel for the Chicago Area, 1970 to 1990* (Tech. Rep.). Chicago Area Transportation Study. (Paper submitted to the Transportation Research Board)
- Couture, V., & Handbury, J. (2020). Urban revival in america. *Journal of Urban Economics*, 119, 103267. Retrieved from <https://www.sciencedirect.com/science/article/pii/S0094119020300383> doi: <https://doi.org/10.1016/j.jue.2020.103267>
- Davidson, J. H., Feiglin, I., & Ryerson, M. S. (2023, jan). A one-seat ride coverage ratio using administrative origin destination data. *Findings*. Retrieved from <https://findingspress.org/article/57771-a-one-seat-ride-coverage-ratio-using-administrative-origin-destination-data> doi: 10.32866/001c.57771
- Davidson, J. H., & Ryerson, M. S. (2018). Building reverse commute typologies through urban and suburban socioeconomic characteristics. *Cities*, 81, 180–189. doi: 10.1016/j.cities.2018.04.007
- Davidson, J. H., & Ryerson, M. S. (2021). Modeling regional disparity and the reverse commute. *Transportation Research Part A: Policy and Practice*, 150, 124–139. doi: 10.1016/j.tra.2021.06.005
- Duranton, G., & Puga, D. (2015). Chapter 8 - Urban Land Use. In G. Duranton, J. V. Henderson, & W. C. Strange (Eds.), *Handbook of Regional and Urban Economics* (Vol. 5, p. 467-560). Elsevier. Retrieved from <https://www.sciencedirect.com/science/article/pii/B9780444595171000088> doi: <https://doi.org/10.1016/>

- Giuliano, G., & Dargay, J. (2012). Network Accessibility and Employment Centres. *Urban Studies*, 49(1), 77–95. doi: <https://doi.org/10.1177/0042098011411948>
- Giuliano, G., & Small, K. A. (1991). Subcenters in the Los Angeles region. *Regional Science and Urban Economics*, 21(2), 163–182.
- Glaeser, E. L., & Gottlieb, J. D. (2006). Urban resurgence and the consumer city. *Urban Studies*, 43(8), 1275–1299.
- Glaeser, E. L., Kahn, M. E., & Rappaport, J. (2008). Why do the poor live in cities? the role of public transportation. *Journal of Urban Economics*, 63(1), 1–24. doi: 10.1016/j.jue.2006.12.004
- Glaeser, E. L., Kolko, J., & Saiz, A. (2001). Consumer city. *Journal of Economic Geography*, 1(1), 27–50.
- Grengs, J. (2010). Job accessibility and the modal mismatch in Detroit. *Journal of Transport Geography*, 18(1), 42–54. doi: 10.1016/j.jtrangeo.2009.01.012
- Kane, M. J., Gilani, O., Khusainova, E., & Urbanek, S. (2024). Identifying loci in mobility networks with applications in New Zealand work commutes: a statistical test for identifying extreme stationary distribution values in Markov transition matrices. *Applied Network Science*, 9(1), 57. doi: 10.1007/s41109-024-00659-7
- Liotta, C., Viguié, V., & Lepetit, Q. (2022). Testing the monocentric standard urban model in a global sample of cities. *Regional Science and Urban Economics*, 97, 103832.
- Manduca, R. (2021). The spatial structure of US metropolitan employment: New insights from administrative data. *Environment and Planning B: Urban Analytics and City Science*, 48(5), 1357–1372. doi: <https://doi.org/10.1177/2399808320934821>
- McMillen, D. P. (2003). The return of centralization to Chicago: using repeat sales to identify changes in house price distance gradients. *Regional Science and Urban Economics*, 33(3), 287–304.
- Mills, E. S. (1967). An aggregative model of resource allocation in a metropolitan area. *The*

- American Economic Review*, 57(2), 197–210.
- Monte, F., Porcher, C., & Rossi-Hansberg, E. (2025). *Remote Work and City Structure* (Tech. Rep.). Working paper. (Latest version dated November 10, 2025)
- Muth, R. F. (1961). The spatial structure of the housing market. In *Papers of the regional science association* (Vol. 7, pp. 207–220).
- Nechyba, T. J., & Walsh, R. P. (2002). Urban sprawl. *Journal of Economic Perspectives*, 18(4), 177–200.
- Redding, S. J. (2023). Quantitative urban models: from theory to data. *Journal of Economic Perspectives*, 37(2), 75–98.
- Redding, S. J., & Rossi-Hansberg, E. (2017). Quantitative Spatial Economics. *Annual Review of Economics*, 9, 21–58. Retrieved from <https://www.annualreviews.org/content/journals/10.1146/annurev-economics-063016-103713> doi: <https://doi.org/10.1146/annurev-economics-063016-103713>
- Redfearn, C. L. (2007). The topography of metropolitan employment: Identifying centers of employment in a polycentric urban area. *Journal of Urban Economics*, 61(3), 519–541. doi: <https://doi.org/10.1016/j.jue.2006.08.009>
- Roback, J. (1982). Wages, rents, and the quality of life. *Journal of Political Economy*, 90(6), 1257–1278.

A. Existence, Uniqueness, and Computation of the Stationary Distribution

This appendix summarizes the Markov-chain conditions underlying the commuting-centrality measure used in Section 3 and describes how the measure is implemented empirically. The argument relies on standard results for finite-state Markov chains and nonnegative matrices commonly associated with the Perron–Frobenius theorem.

Setup

Let $\mathbf{W} \in \mathbb{R}_+^{n \times n}$ denote the nonnegative origin–destination commuting matrix, where $W_{ij} \geq 0$ is the number of commuters residing in neighborhood i and working in neighborhood j . In the empirical implementation, we first remove tracts with zero outbound commuting mass so that each retained row has positive total flow. Row-normalizing $\mathbf{W}$ then defines the transition matrix $\mathbf{P} \in \mathbb{R}^{n \times n}$:

$$P_{ij} = \frac{W_{ij}}{\sum_{k=1}^n W_{ik}}, \quad (9)$$

so that $\sum_{j=1}^n P_{ij} = 1$ for all retained neighborhoods i .

A stationary distribution is a probability vector $\boldsymbol{\pi} \in \mathbb{R}^n$ satisfying

$$\boldsymbol{\pi}^\top = \boldsymbol{\pi}^\top \mathbf{P}, \quad \pi_i \geq 0, \quad \sum_{i=1}^n \pi_i = 1. \quad (10)$$

Equivalently, $\boldsymbol{\pi}$ is a left eigenvector of $\mathbf{P}$ associated with eigenvalue 1.

Irreducibility, aperiodicity, and the lazy transition matrix

If the directed graph induced by positive entries of $\mathbf{P}$ is strongly connected, the corresponding Markov chain is irreducible. For a finite irreducible Markov chain, there exists a unique stationary distribution $\boldsymbol{\pi}$ with strictly positive entries. If the chain is also aperiodic, then

for any initial distribution $\mathbf{v}^{(0)}$,

$$\lim_{t \rightarrow \infty} \mathbf{v}^{(0)\top} \mathbf{P}^t = \boldsymbol{\pi}^\top. \quad (11)$$

Aperiodicity is therefore not required for uniqueness of the stationary distribution, but it ensures convergence of the power iteration used to compute it.

In tract-level commuting networks, irreducibility can fail if the directed commuting graph contains disconnected components or transient locations. To ensure that the stationary distribution is well-defined on the empirical state space, we restrict each MSA-year network to the largest closed strongly connected component of the directed commuting graph. This produces a recurrent state space in which every retained tract can be reached from every other retained tract and no retained tract has outgoing transitions to omitted tracts. In practice, this restriction removes only a small number of peripheral or disconnected tracts in each MSA-year and retains nearly all observed commuting mass; the stationary distribution should therefore be interpreted as centrality within the empirically connected metropolitan commuting network rather than as a substantively different sample definition.

To ensure aperiodicity without adding artificial cross-tract links, we use a lazy transition matrix:

$$\mathbf{P}^L = (1 - \lambda)\mathbf{P} + \lambda\mathbf{I}, \quad \lambda \in (0, 1), \quad (12)$$

where $\mathbf{I}$ is the identity matrix. In the empirical analysis, we set $\lambda = 0.10$. Because $\mathbf{P}^L$ assigns positive probability to remaining in the same tract, the resulting chain is aperiodic. Since the retained state space is strongly connected, $\mathbf{P}^L$ is primitive, and Perron–Frobenius implies that it has a unique strictly positive stationary distribution. Moreover, because

$$\boldsymbol{\pi}^\top \mathbf{P} = \boldsymbol{\pi}^\top \iff \boldsymbol{\pi}^\top \mathbf{P}^L = (1 - \lambda)\boldsymbol{\pi}^\top \mathbf{P} + \lambda\boldsymbol{\pi}^\top = \boldsymbol{\pi}^\top,$$

the lazy modification preserves the stationary distribution of $\mathbf{P}$ while improving convergence behavior.

Computation

The stationary distribution is computed by power iteration. Starting from an initial distribution $\mathbf{v}^{(0)}$, the algorithm repeatedly applies

$$\mathbf{v}^{(t+1)\top} = \mathbf{v}^{(t)\top} \mathbf{P}^L \quad (13)$$

until convergence. This approach is computationally efficient for tract-level commuting networks because the commuting matrix is sparse.

Implication for the reverse-commute odds ratio

Given a stationary distribution $\boldsymbol{\pi}$ and transition probabilities P_{ij} , the long-run frequency of transitions from i to j is

$$F_{ij} = \pi_i P_{ij}. \quad (14)$$

This motivates the directional odds ratio used in Section 3:

$$R_{ij} = \frac{\pi_i P_{ij}}{\pi_j P_{ji}}. \quad (15)$$

The ratio compares the centrality-weighted flow from i to j with the reciprocal centrality-weighted flow from j to i . For observed off-diagonal flows, values of $R_{ij} < 1$ are classified as reverse commuting relative to the endogenous commuting hierarchy.

The lazy transition matrix does not alter this classification for off-diagonal tract pairs because, for $i \neq j$, both P_{ij}^L and P_{ji}^L are multiplied by the same factor $(1 - \lambda)$ relative to the original transition matrix. Thus, the lazy modification ensures aperiodic convergence without changing the off-diagonal directional comparisons used to classify reverse commuting. If an observed flow from i to j has no reciprocal flow from j to i , then $P_{ji} = 0$ and the corresponding ratio is interpreted as infinite; such flows are not classified as reverse.

B. Regression data description

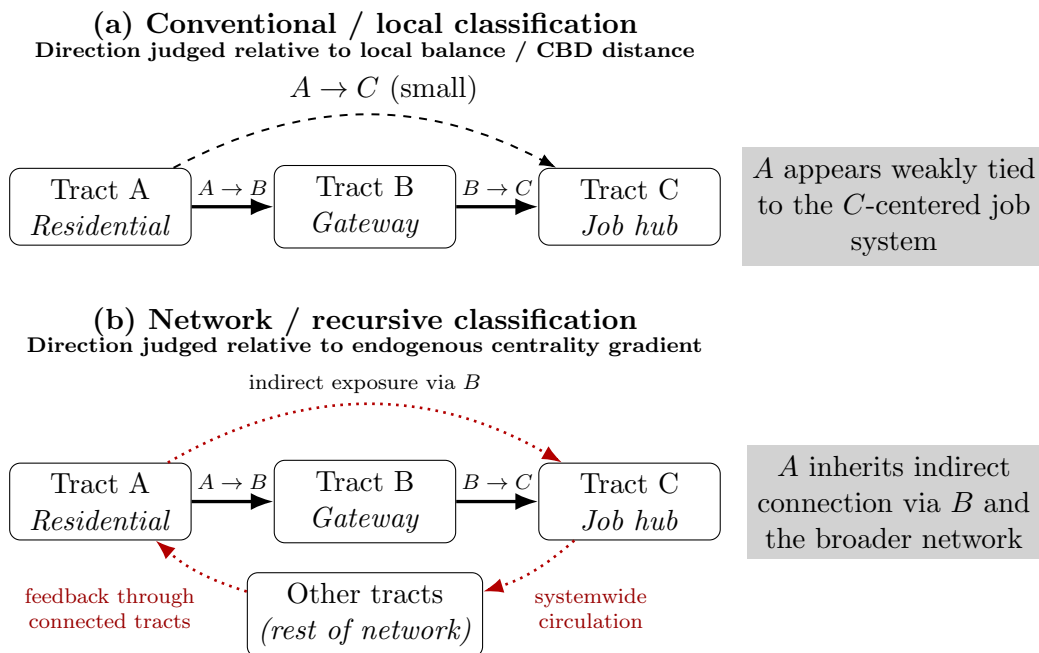
Table B1: Construction of metropolitan covariates used in descriptive regressions

Variable	Regression measure	Agency	Source	Construction / preparation
Network share	reverse weighted reverse-commuter share	Census Bureau	LODES Origin-Destination Employment Statistics (LODES)	Computed from tract-to-tract commuting flows using the network benchmark described in Section 3. Commute links are classified according to the relative directional likelihood implied by the metropolitan commuting network and aggregated using commuter counts as weights.
In/Out bias	Difference between network and in/out benchmark shares	Census Bureau	LODES	Constructed as $\hat{R}_{mt}^{Network} - \hat{R}_{mt}^{In/Out}$, where benchmark reverse-commuting shares are commuter-weighted.
Distance bias	Difference between network and distance benchmark shares	Census Bureau	LODES	Constructed as $\hat{R}_{mt}^{Network} - \hat{R}_{mt}^{Distance}$, where benchmark reverse-commuting shares are commuter-weighted.
Employment entropy	en-normalized employment dispersion index	Census Bureau	LODES	Workplace activity is aggregated to the tract level using destination totals from commuting matrices. Let s_{im} denote tract i 's workplace share within metropolitan area m . Entropy is calculated as $H_m = -\frac{\sum_i s_{im} \ln(s_{im})}{\ln(N_m)},$ where N_m denotes the number of workplace tracts. Larger values indicate more spatially dispersed employment activity.
Log population	Natural log of metropolitan population	Census Bureau	American Community Survey (ACS), Table B01003	Population estimates obtained directly from ACS and transformed using the natural logarithm.
Log median wages	Natural log of average annual wages	Bureau of Labor Statistics	Quarterly Census of Employment and Wages (QCEW)	Average annual wages are constructed as total annual wages divided by annual employment and transformed using the natural logarithm. County-level values are aggregated to metropolitan areas using county-CBSA crosswalks.
Unemployment rate	Annual metropolitan unemployment rate	Bureau of Labor Statistics	Local Area Unemployment Statistics (LAUS)	Annual metropolitan unemployment estimates obtained directly from BLS.
Average commute time	Average commuting duration	Census Bureau	ACS Tables B08013 and B08303	Constructed as aggregate commuting minutes divided by commuting workers.
Vehicle access	Share of households with access to at least one vehicle	Census Bureau	ACS Table B25044	Calculated as one minus the share of owner- and renter-occupied households reporting no available vehicle.
Bachelor's+ share	Share of adults age 25+ with at least a bachelor's degree	Census Bureau	ACS Table B15002	Constructed as the proportion of adults aged 25 years and older with bachelor's, master's, professional, or doctoral degrees.
Housing price index change	Annual metropolitan house price growth	Federal Housing Finance Agency	FHFA House Price Index	Annual percentage change in metropolitan all-transactions house price indexes.
New construction permits per 100	Residential permits per 100 residents	Census Bureau	Building Permit Survey (BPS)	Annual housing permits authorized within metropolitan areas normalized by population.
Amenity establishments per 100	Amenity establishments per 100 residents	Bureau of Labor Statistics	QCEW (NAICS 71, 72)	Establishments in arts, entertainment, recreation (NAICS 71) and accommodation and food services (NAICS 72) aggregated to metropolitan areas and normalized by population.
Amenity employment share	Share of employment in amenity sectors	Bureau of Labor Statistics	QCEW (NAICS 71, 72)	Employment in arts, entertainment, recreation and accommodation/food service industries divided by total private employment (NAICS 10).
Professional services share	Share of employment in professional services	Bureau of Labor Statistics	QCEW (NAICS 54)	Employment in professional, scientific, and technical services divided by total private employment (NAICS 10).

C. Supplementary time-series evidence

This appendix reports the time-series comparison referenced in Section 4. The figure is not used as the primary empirical evidence in the main text, but it provides additional descriptive context on how network-based reverse-commuting shares and benchmark gaps evolve within metropolitan areas over time. The patterns should be interpreted as descriptive rather than causal.

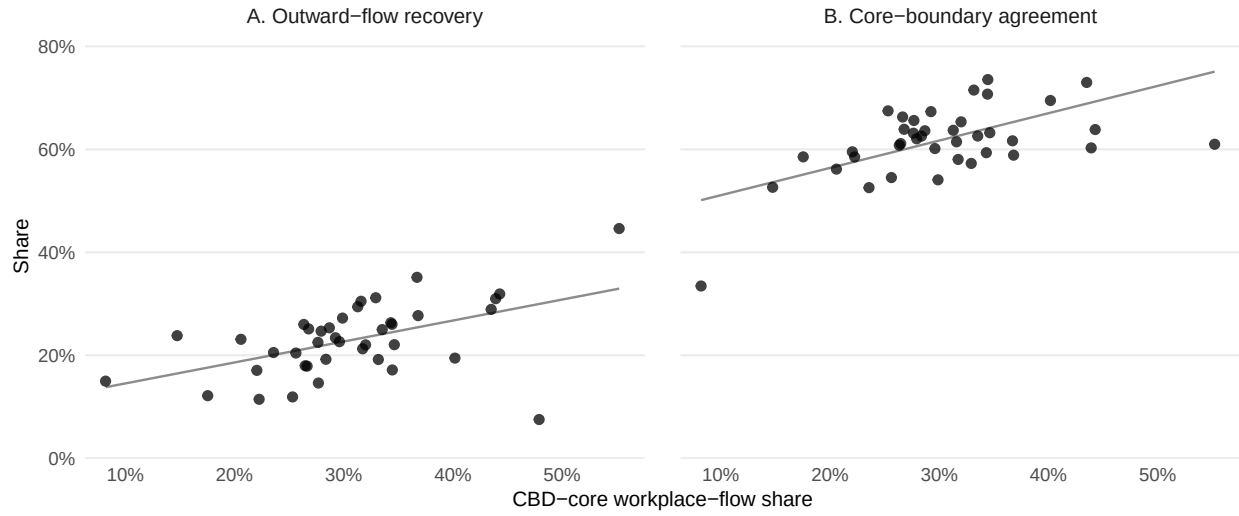
Figure 1: Difference of network-based definition of reverse commuting from local classifications.



Panel (a) illustrates a conventional local classification. Tract A sends many workers to intermediary Tract B , and B sends many workers to major employment hub C , but direct $A \rightarrow C$ flows are small. Measures based on direct bilateral flows or distance to an exogenously chosen center therefore treat A as only weakly connected to the employment system centered on C .

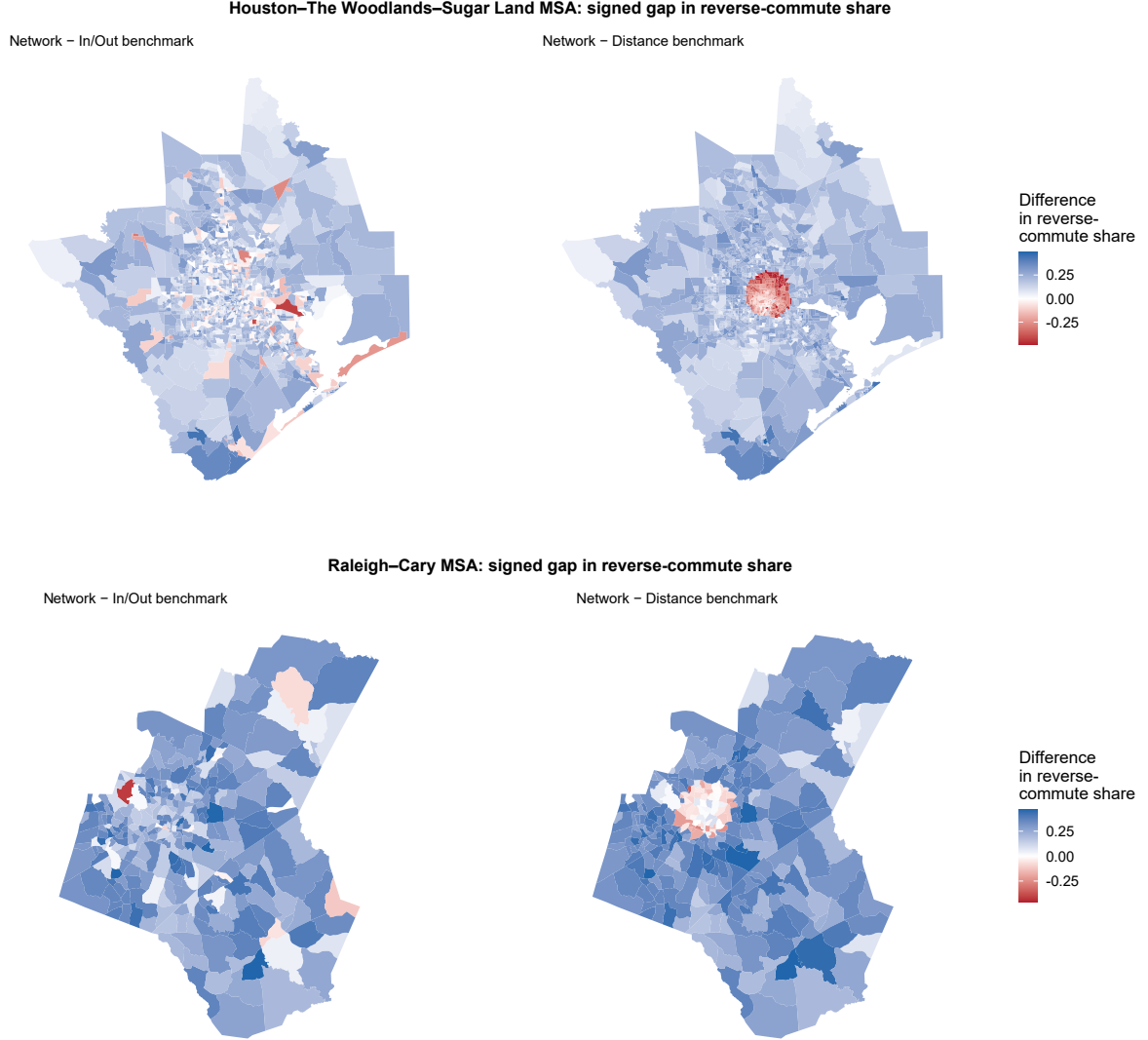
Panel (b) illustrates the network-based view. Even when direct $A \rightarrow C$ commuting is limited, A may remain strongly integrated into the metropolitan labor market because it is connected to C through gateway tract B and through circulation involving the rest of the commuting network. In this sense, employment activity at C indirectly supports activity in B , which in turn supports residential viability and labor-market access in A . Dotted arrows represent indirect network support and recursive propagation of centrality rather than observed tract-to-tract commuter flows. The figure therefore motivates defining commute direction relative to endogenous centrality gradients in the full commuting network, rather than only direct local ties or exogenous spatial anchors.

Figure 2: Construct validity across metropolitan forms



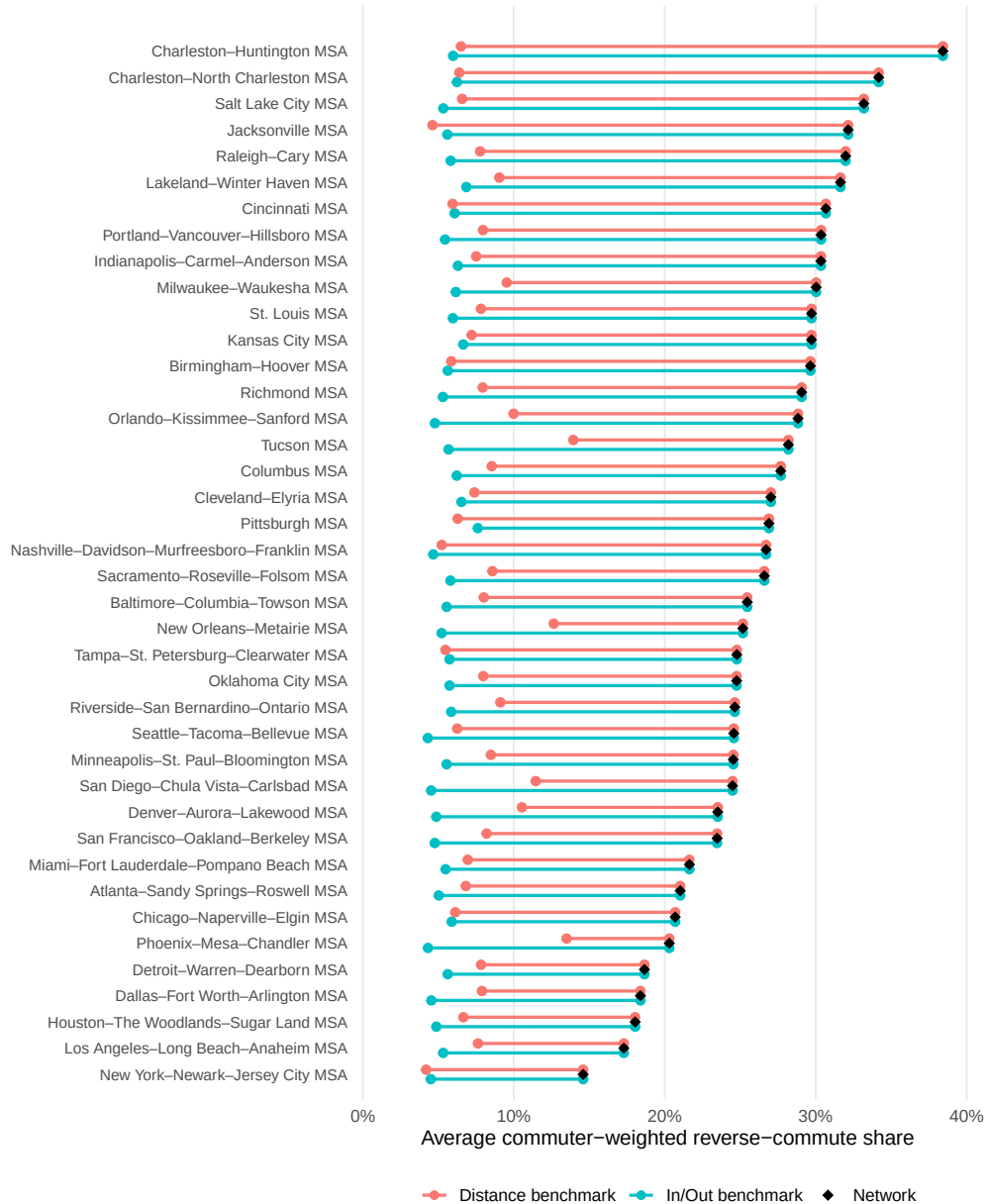
Each point represents one metropolitan statistical area, constructed by pooling commuter flows over 2002–2021. The horizontal axis reports the share of observed intertract commuting flows terminating in the closest-to-CBD quintile of tracts. Panel A reports the commuter-weighted share of conventionally defined core-to-periphery trips that are also classified as reverse by the network measure. Panel B reports agreement between the network and distance-based classifications among all flows crossing the CBD-core boundary. Lines show unweighted ordinary least squares fits across the 40 metropolitan areas.

Figure 3: Tract-level disagreement between reverse-commuting measures in selected metropolitan areas.



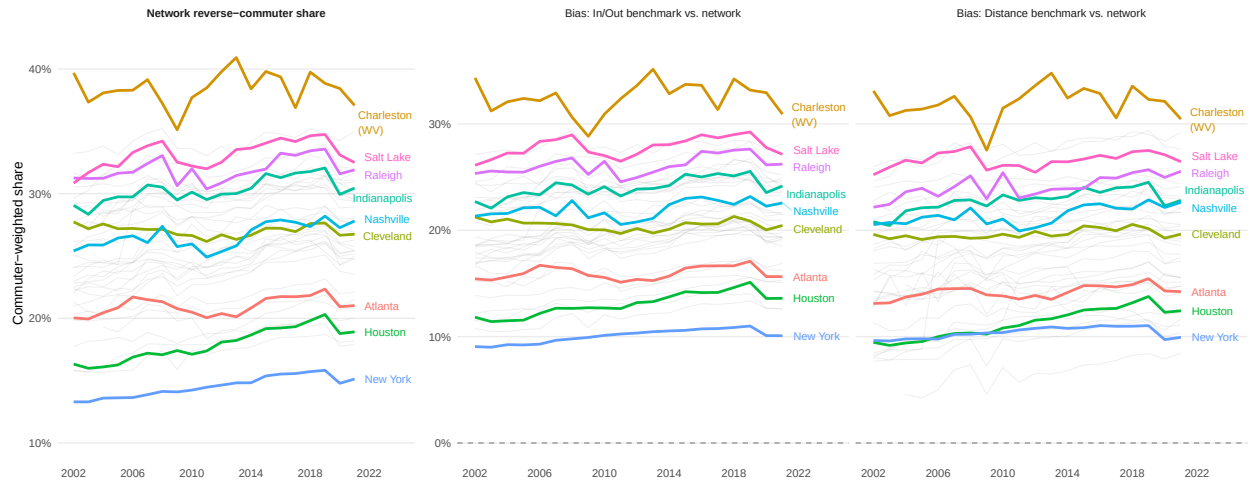
Each panel maps the signed tract-level difference in estimated reverse-commute share between the network measure and two alternative measures: an in/out centrality benchmark (left column) and a distance-to-CBD benchmark (right column). For tract i , the plotted quantity is $\Delta_i = \hat{s}_i^{\text{Network}} - \hat{s}_i^m$, where $m \in \{\text{In/Out, Distance}\}$ and $\hat{s}_i$ denotes the share of commuters residing in tract i whose workplace tract is classified as reverse under a given method. Positive values indicate tracts where the alternative measure classifies a smaller share of commuters as reverse than the network measure, while negative values indicate tracts where it classifies a larger share. The upper panels report results for Houston and the lower panels report results for Raleigh.

Figure 4: Reverse-commuting shares across metropolitan areas under alternative classification methods.



The figure compares metropolitan-level average commuter-weighted reverse-commuting shares generated by the network-based framework to those obtained using distance-to-CBD and in/out centrality benchmarks across 40 U.S. metropolitan statistical areas (MSAs). For each MSA-year, the reverse-commuting share is computed as the share of commuters traveling on tract-to-tract OD pairs classified as reverse under each method; plotted values are averaged over the full 2002–2021 panel for each metropolitan area. Black diamonds denote the average reverse-commuting share implied by the network measure, while colored endpoints indicate the corresponding average shares generated by the alternative classification methods. Horizontal segments connect each benchmark measure to the network estimate within the same metropolitan area, with longer segments indicating larger disagreement between conventional and network-based classifications. Metropolitan areas are ordered according to the network-based average reverse-commuting share. Systematic gaps between the network and conventional measures indicate that local and distance-based rules frequently classify fewer commutes as reverse than does the recursively structured directional rule implied by the metropolitan commuting network.

Figure C1: Evolution of disagreement between network-based and conventional reverse-commuting measures.



The figure illustrates the evolution of commuter-weighted reverse-commuting shares and benchmark disagreement across 40 metropolitan areas from 2002–2021. The left panel plots reverse-commuting shares implied by the network framework. The middle panel plots the difference between the network-based reverse-commuting share and the share implied by tract-level in/out measures, while the right panel compares the network framework to distance-to-CBD classifications. Positive values indicate that the alternative benchmark classifies a smaller share of commuters as reverse than the network framework. Colored trajectories highlight selected metropolitan areas for visual clarity, while remaining metropolitan trends are shown in grey. The figure shows substantial heterogeneity across metropolitan systems and provides supplementary descriptive evidence on within-metropolitan changes over time.