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Post-COVID Urban Spatial Reconfiguration and Remote Work Geography (2019–2025)

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Abstract

This paper examines whether the rise of remote work following the COVID-19 pandemic has generated a structural transformation in urban spatial organization across major metropolitan areas in advanced economies. While much of the existing literature treats COVID-19 as a temporary shock, this study argues that it has induced a persistent reconfiguration of cities toward more polycentric and decentralized spatial structures. Using a multi-source dataset combining Google mobility reports, NASA/VIIRS night-time light satellite data, OECD and national labor force surveys, and urban economic indicators, the study constructs a novel Urban Polycentricity Index (UPI) to measure spatial dispersion of economic activity. The empirical analysis covers New York, London, Paris, Berlin, and Munich over the period 2019–2025. The methodology integrates structural break tests, difference-in-differences estimation, and spatial equilibrium modeling to identify both the timing and magnitude of post-COVID spatial shifts. Results indicate a significant structural break around 2020–2021, followed by a sustained increase in remote work adoption and urban polycentricity. Satellite and mobility data confirm a systematic redistribution of economic activity from central business districts toward suburban and peripheral zones. Findings show that remote work is a statistically significant driver of urban decentralization, associated with flatter density gradients, reduced commuting intensity, and higher polycentricity. Counterfactual simulations further confirm that, without remote work expansion, cities would have remained substantially more monocentric. Overall, the study demonstrates that COVID-19 has permanently altered urban spatial equilibrium, positioning remote work as a key structural force reshaping metropolitan form.

Keywords: remote work; urban polycentricity; spatial equilibrium; COVID-19; night-time lights; urban decentralization

JEL Classification: R12, R23, R32, O33, J61, E24

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1. Introduction

The COVID-19 pandemic constitutes a structural inflection point in the evolution of urban economic systems, fundamentally reshaping the spatial organization of cities in ways that extend far beyond a temporary disruption. While early contributions interpreted the pandemic as a short-lived shock affecting mobility, labor markets, and real estate, more recent evidence indicates that it has accelerated pre-existing structural trends associated with digitalization and the decoupling of work from place. In particular, the widespread and persistent adoption of remote and hybrid work arrangements has weakened traditional agglomeration forces and initiated a durable transition toward more decentralized and polycentric urban configurations. This paper advances the argument that the post-COVID period should be understood as the emergence of a new spatial equilibrium, characterized by the redistribution of economic activity across multiple urban nodes rather than its concentration in central business districts (CBDs).

Classical urban economic theory has long emphasized the centrality of spatial concentration in generating productivity gains. Monocentric models, originating in the work of Alonso (1964), Mills

 doi:10.20944/preprints202604.1725.v1

(1967), and Muth (1969), conceptualize cities as organized around a single employment center, where land rents decline with distance due to commuting costs. This framework has been extended by the new economic geography and agglomeration literature, which highlights mechanisms such as knowledge spillovers, labor market pooling, and input-output linkages as key drivers of urban concentration (Fujita, Krugman, & Venables, 1999; Duranton & Puga, 2020). Within this paradigm, physical proximity is considered essential for innovation, coordination, and economic efficiency.

However, the rapid advancement of digital technologies has progressively eroded the necessity of spatial proximity. The expansion of broadband infrastructure, cloud computing, and digital collaboration tools has enabled a growing share of economic activities—particularly in high-skill service sectors—to be conducted remotely (Autor, 2019; Baldwin, 2016). Despite these technological capabilities, the diffusion of remote work remained limited prior to 2020 due to organizational rigidities and coordination frictions (Bloom et al., 2015). The COVID-19 pandemic acted as an exogenous shock that removed these constraints, forcing firms to adopt remote work at scale and triggering a large and rapid reallocation of labor across space.

Recent empirical studies confirm that this shift has persisted well beyond the acute phase of the pandemic. Remote work has stabilized at levels significantly higher than pre-pandemic norms across advanced economies, suggesting that it has become a structural component of modern labor markets rather than a temporary adjustment. Evidence from labor force surveys and firm-level data indicates that between one-third and one-half of jobs in advanced economies now involve some degree of remote work, particularly in knowledge-intensive occupations (Barrero, Bloom, & Davis, 2023; Aksoy et al., 2024; OECD, 2024). Moreover, hybrid work arrangements—combining remote and in-office work—have emerged as the dominant organizational model, reinforcing the persistence of reduced commuting intensity and altered spatial behavior.

From a theoretical standpoint, the rise of remote work modifies the fundamental trade-offs underlying urban spatial equilibrium. By reducing commuting costs and relaxing the need for daily physical proximity, remote work flattens the bid-rent curve and diminishes the economic advantages of central locations. At the same time, it increases the relative attractiveness of suburban and peri-urban areas, where housing is more affordable and living conditions are often more favorable. These changes generate centrifugal forces that redistribute both population and economic activity across space, facilitating the emergence of polycentric urban structures with multiple employment and activity centers (Anas, Arnott, & Small, 1998; Duranton & Puga, 2005).

Emerging empirical evidence strongly supports this structural transformation. High-frequency mobility data reveal a persistent decline in commuting flows to CBDs alongside an increase in localized and decentralized movement patterns. Satellite-based night-light data show a relative decline in central area intensity and a corresponding increase in suburban economic activity. Real estate markets have also undergone significant adjustments, with declining demand for office space in central locations and rising residential demand in peripheral areas. Recent contributions using granular spatial data confirm that these patterns are not temporary but reflect a durable reorganization of urban economic activity (Delventhal, Kwon, & Parkhomenko, 2022; Gupta et al., 2023; Rosenthal, Strange, & Urrego, 2024; Glaeser, Kim, & Luca, 2025).

Despite this growing body of evidence, the literature remains incomplete in several important dimensions. First, many studies continue to treat COVID-19 as a temporary exogenous shock rather than as a structural break that permanently alters urban spatial dynamics. Second, there is limited integration between remote work adoption and formal spatial equilibrium models capable of capturing endogenous location decisions of firms and households. Third, cross-country comparative analyses remain relatively scarce, particularly those that combine multiple data sources—including mobility indicators, satellite imagery, and labor market data—to provide a comprehensive view of spatial transformation.

This paper addresses these gaps by developing a unified empirical and theoretical framework to analyze post-COVID urban spatial reconfiguration across major metropolitan regions. The analysis focuses on key global cities in four advanced economies: the United States (as a benchmark case),

 doi:10.20944/preprints202604.1725.v1

France (Paris region), Germany (Berlin and Munich), and the United Kingdom (London). These metropolitan areas are characterized by high levels of economic integration, advanced digital infrastructure, and significant exposure to remote work adoption, making them particularly suitable for examining structural spatial change in a comparative perspective.

The central contribution of this study is the formulation and empirical testing of the Post-COVID Spatial Reconfiguration Hypothesis (PCSRH). This hypothesis posits that sustained remote work adoption leads to a persistent increase in urban polycentricity by redistributing economic activity across space and weakening the dominance of central business districts. To operationalize this concept, the paper introduces a novel Urban Polycentricity Index (UPI), which combines measures of spatial entropy, employment dispersion, and satellite-based indicators of economic activity. This index is integrated into a comprehensive empirical strategy that includes structural break analysis, difference-in-differences estimation, and spatial equilibrium modeling to identify causal effects and quantify the magnitude of urban transformation.

By bridging theoretical insights from urban economics with recent empirical advances, this study contributes to several strands of the literature. First, it extends the analysis of agglomeration economies by incorporating remote work as a key structural determinant of urban form. Second, it provides new cross-country evidence on the persistence and heterogeneity of post-pandemic spatial reconfiguration. Third, it demonstrates the analytical value of combining traditional economic data with real-time and geospatial indicators in the study of urban dynamics.

More broadly, the findings have significant implications for urban policy and planning. As cities evolve toward more decentralized and polycentric configurations, policymakers must rethink infrastructure investment, land-use regulation, housing policy, and transport systems to accommodate new spatial patterns of economic activity. Recognizing the structural nature of this transformation is therefore essential for designing resilient and forward-looking urban strategies in the post-pandemic era.

2. Research Gap and Contribution

2.1. Research Gaps

Despite the rapidly expanding literature on the economic and spatial consequences of the COVID-19 pandemic, important conceptual and empirical limitations persist. These gaps constrain a comprehensive understanding of how remote work is reshaping urban spatial structures in the long run.

First, a dominant strand of the literature continues to treat COVID-19 as a transitory exogenous shock rather than as a structural break with persistent effects on urban systems. Many empirical studies focus on short-term adjustments in mobility, employment, or real estate markets, implicitly assuming a reversion to pre-pandemic equilibria (Delventhal, Kwon, & Parkhomenko, 2022; Gupta et al., 2023). However, accumulating evidence indicates that remote work adoption has stabilized at structurally higher levels, suggesting that the pandemic has permanently altered the spatial foundations of economic activity (Barrero, Bloom, & Davis, 2023; Aksoy et al., 2024). This discrepancy highlights the need for frameworks that explicitly model COVID-19 as a structural shift rather than a temporary disturbance.

Second, existing urban economic models remain insufficiently equipped to capture large-scale spatial reallocation dynamics induced by remote work. Traditional monocentric and even standard polycentric models primarily rely on commuting costs and agglomeration economies as the key determinants of spatial organization (Duranton & Puga, 2020). While these models provide valuable insights, they do not fully incorporate the decoupling of work and location enabled by digital technologies. As a result, they underestimate the magnitude and persistence of spatial decentralization processes currently observed in major metropolitan regions.

Third, there is a lack of integrated analytical frameworks combining three critical dimensions: (i) remote work adoption, (ii) spatial equilibrium theory, and (iii) real-time geospatial data. Much of the empirical literature examines these elements in isolation. For instance, studies on remote work focus on labor market outcomes without embedding them in spatial equilibrium models (Dingel & Neiman, 2020), while urban spatial analyses often rely on static or low-frequency data that fail to capture rapid post-pandemic adjustments. At the same time, recent advances in high-frequency mobility data and satellite-based night-light imagery have not yet been fully integrated into structural urban models, despite their strong potential to measure real-time spatial redistribution of economic activity (Chen & Nordhaus, 2019; Gibson et al., 2021).

Finally, cross-country comparative analyses remain limited, particularly those that systematically examine heterogeneous urban responses across advanced economies. Differences in institutional frameworks, housing markets, transport systems, and digital infrastructure can significantly influence the extent and form of spatial reconfiguration. Yet, most studies focus on single-country cases—predominantly the United States—thereby limiting the external validity and generalizability of their findings (Glaeser, Kim, & Luca, 2025).

Taken together, these gaps point to the absence of a unified framework capable of capturing the structural, spatial, and data-driven dimensions of post-COVID urban transformation. Addressing these limitations is essential for advancing both theoretical and empirical research on the future of cities.

2.2. Contributions

This paper contributes to the literature by developing an integrated framework that explicitly models the structural reconfiguration of urban space in the post-COVID era. The contributions are fourfold.

First, the paper introduces the Post-COVID Spatial Reconfiguration Hypothesis (PCSRH). This hypothesis posits that sustained remote work adoption generates a persistent shift in urban spatial equilibrium, characterized by increased decentralization and the emergence of polycentric urban structures. By conceptualizing COVID-19 as a structural break rather than a temporary shock, the PCSRH provides a new theoretical lens for analyzing long-term urban transformation.

Second, the study develops a novel Urban Polycentricity Index (UPI) designed to capture multidimensional changes in urban spatial organization. Unlike traditional measures based solely on employment concentration or density gradients, the UPI integrates spatial entropy, employment dispersion, and fragmentation of economic activity derived from satellite night-light data. This composite index allows for a more comprehensive and dynamic assessment of polycentricity across cities and over time, addressing measurement limitations in existing studies (Anas, Arnott, & Small, 1998; Arribas-Bel & Sanz-Gracia, 2014).

Third, the paper advances empirical methodology by combining night-light satellite data with high-frequency mobility indicators. This data fusion approach enables the real-time tracking of spatial redistribution of economic activity and commuting patterns. Satellite-based measures provide consistent cross-country coverage of economic intensity, while mobility data capture behavioral responses at high temporal frequency. Integrating these sources enhances the precision and robustness of spatial analysis, contributing to the growing literature on the use of geospatial big data in economics (Donaldson & Storeygard, 2016; Gibson et al., 2021).

Fourth, the study employs a comprehensive econometric strategy that integrates structural break models with spatial equilibrium analysis. Structural break techniques (e.g., Bai-Perron tests) are used to identify the timing and significance of COVID-induced shifts, while spatial equilibrium models capture the endogenous responses of households and firms to changes in wages, commuting costs, and remote work intensity. This combined approach allows for both causal identification and structural interpretation, bridging the gap between reduced-form empirical analysis and theoretical modeling.

In addition to these core contributions, the paper provides a comparative cross-country analysis of major metropolitan regions in the United States, France, Germany, and the United Kingdom. This comparative perspective enables the identification of common structural patterns as well as country-specific heterogeneity, thereby enhancing the external validity of the results.

Overall, the paper contributes to the literature by integrating theory, measurement, and data innovation to provide a comprehensive analysis of post-pandemic urban transformation. It extends urban economic models to incorporate remote work as a central determinant of spatial structure and offers new empirical tools for analyzing the evolving geography of economic activity in the digital age.

3. Conceptual Framework

This section develops a conceptual framework to explain how the rise of remote work induces a structural transformation in urban spatial organization, shifting cities from predominantly monocentric configurations toward increasingly polycentric systems. The framework integrates insights from urban economics, spatial equilibrium theory, and recent advances in the economics of remote work to formalize the mechanisms underlying post-COVID spatial reconfiguration.

3.1. From Monocentric to Polycentric Urban Structures

Traditional urban models conceptualize cities as monocentric systems organized around a central business district (CBD), where economic activity is spatially concentrated and land rents decline with distance due to commuting costs (Alonso, 1964; Fujita et al., 1999). In this setting, firms benefit from agglomeration economies, while workers face a trade-off between proximity to employment and housing costs. The resulting equilibrium is characterized by high-density central areas and a steep spatial gradient of economic activity.

However, as cities grow and transport and communication technologies evolve, polycentric structures may emerge, with multiple subcenters hosting economic activity (Anas, Arnott, & Small, 1998; Duranton & Puga, 2005). In such systems, employment and services are distributed across several nodes, reducing the dominance of the CBD while maintaining functional integration across the urban area.

The rise of remote work introduces a new and powerful driver of this transition. By decoupling work from physical location, remote work reduces the importance of daily commuting and weakens the centripetal forces that sustain monocentric structures. At the same time, it strengthens centrifugal forces that favor spatial dispersion, enabling households and firms to relocate toward suburban or secondary urban centers without sacrificing access to labor markets or economic opportunities.

3.2. Remote Work and Spatial Equilibrium

To formalize these dynamics, consider a spatial equilibrium framework in which households choose their residential location and work arrangement to maximize utility, while firms choose location and employment structure to minimize costs. In the presence of remote work, the utility of an individual i located in area j can be expressed as:

$$U_{ij} = f\left(W_{ij}, C_{ij}, R_{ij}, A_j\right)$$

Where W_{ij} denotes wages, C_{ij} commuting costs, R_{ij} the degree of remote work (or teleworking intensity), and A_j local amenities. Remote work affects this equilibrium through multiple channels.

First, it directly reduces commuting costs (C_{ij}), effectively flattening the spatial cost gradient. Second, it allows workers to access high-productivity jobs without residing near the CBD, thereby weakening the link between wages and location. Third, it increases the relative importance of local amenities and housing conditions in residential choice.

On the firm side, production decisions increasingly incorporate flexible work arrangements, reducing the need for centralized office space and enabling a more dispersed spatial organization of economic activity. This leads to a reallocation of employment across space, with a decline in CBD concentration and the emergence or strengthening of secondary centers.

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The resulting equilibrium is characterized by a more even spatial distribution of economic activity, reflecting a shift from monocentricity toward polycentricity. Importantly, this transition is not instantaneous but occurs through a dynamic adjustment process influenced by housing markets, infrastructure constraints, and institutional factors.

3.3. Mechanisms of Urban Spatial Reconfiguration

The conceptual framework identifies three key mechanisms through which remote work drives urban spatial transformation:

(i) Commuting Cost Reduction: Remote and hybrid work arrangements reduce the frequency and necessity of commuting, lowering the effective cost of distance. This weakens the traditional bid-rent gradient and reduces the premium associated with central locations.

(ii) Residential Relocation: Households respond to increased spatial flexibility by relocating toward suburban or peri-urban areas, where housing is more affordable and living conditions are often superior. This leads to population decentralization and increased demand in non-central areas.

(iii) Employment Decentralization: Firms adjust their spatial organization by downsizing central offices, adopting flexible workspaces, and redistributing activities across multiple locations. This contributes to the emergence of new employment subcenters and reinforces polycentric urban structures.

These mechanisms interact to produce a cumulative process of spatial reconfiguration, in which changes in residential patterns and employment locations reinforce each other over time.

3.4. Testable Implications

The framework generates several empirically testable predictions. First, an increase in remote work intensity should be associated with a decline in CBD concentration and a rise in measures of spatial dispersion. Second, urban areas with higher levels of remote work adoption should exhibit stronger increases in polycentricity over time. Third, indicators of economic activity—such as mobility patterns or night-light intensity—should show a relative shift from central to peripheral areas.

These predictions form the basis for the empirical strategy developed in subsequent sections, where the relationship between remote work and urban spatial structure is quantified using a novel Urban Polycentricity Index and multiple data sources.

Figure 1 illustrates the transition from a monocentric to a polycentric urban structure under increasing remote work adoption.

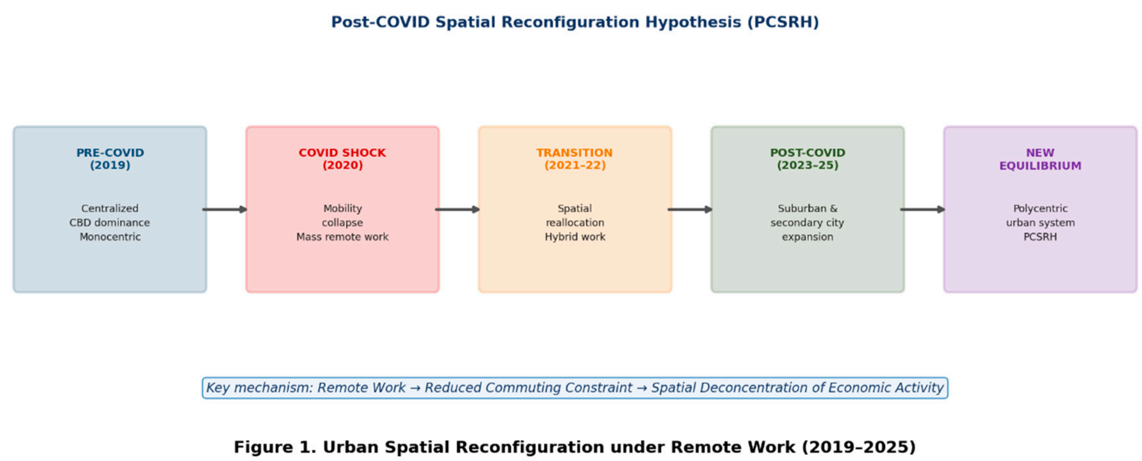

Figure 1. Urban Spatial Reconfiguration under Remote Work.

- Panel A (Pre-COVID / Low Remote Work): The city is characterized by a dominant CBD with high employment density and strong commuting flows from surrounding residential areas. The spatial distribution of economic activity is highly concentrated, and the density gradient is steep.
- Panel B (Transition Phase): As remote work adoption increases, commuting flows decline and economic activity begins to disperse. Secondary centers emerge, and the dominance of the CBD weakens. The spatial gradient becomes flatter, reflecting reduced dependence on central locations.
- Panel C (Post-COVID / High Remote Work): The urban system becomes fully polycentric, with multiple interconnected centers of economic activity. Commuting patterns are more decentralized, and residential and employment locations are more spatially dispersed. The city operates as a network of nodes rather than a single core.

This conceptual representation highlights the central argument of the paper: remote work acts as a structural force driving the evolution of urban systems toward decentralized and polycentric configurations.

4. Data and Variables

This section describes the data sources, variable construction, and descriptive statistics used to analyze the relationship between remote work adoption and urban spatial reconfiguration. The empirical strategy relies on a novel integration of high-frequency mobility data, satellite-based measures of economic activity, labor market indicators, and urban economic datasets. This multi-source approach enables a comprehensive and real-time assessment of spatial dynamics across major metropolitan regions.

4.1. Data Sources

The analysis combines five main categories of data, each capturing a distinct dimension of urban spatial organization.

(i) Mobility Data (Google Mobility Reports): High-frequency mobility indicators are used to capture changes in commuting patterns and spatial behavior following the COVID-19 shock. These data provide daily information on movements across different categories of locations (workplaces, residential areas, transit stations), allowing for the construction of a Commuting Index that proxies the intensity of workplace-related mobility. Such indicators have been widely used in recent research to track real-time behavioral responses to the pandemic and its aftermath (Glaeser, Gorback, & Redding, 2023).

(ii) Satellite Night-Time Light Data (NASA/VIIRS): Night-time light (NTL) data derived from the Visible Infrared Imaging Radiometer Suite (VIIRS) provide a consistent and high-resolution proxy for economic activity across space. These data are particularly valuable for measuring intra-urban spatial distribution, as they capture variations in luminosity between central business districts and suburban areas. Following established approaches, NTL intensity is used to construct indicators of economic concentration and fragmentation, forming a key component of the Urban Polycentricity Index (Chen & Nordhaus, 2019; Gibson et al., 2021).

(iii) Remote Work Adoption Data (OECD, Eurostat, US BLS): Data on remote work intensity are obtained from labor force surveys and specialized datasets produced by international organizations and national statistical agencies. These data measure the share of workers engaged in remote or hybrid work arrangements and are harmonized across countries to ensure comparability. The resulting variable, Remote Work Intensity (RW), captures the structural shift in work organization induced by the pandemic (Aksoy et al., 2024; Barrero et al., 2023).

(iv) Urban Economic Output Data: Urban-level economic indicators, including GDP per capita and output indices, are used to control for differences in economic performance across cities. These variables capture underlying economic conditions that may influence both remote work adoption and spatial structure.

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(v) Transport Network Data: Transport-related indicators are used to construct measures of accessibility and commuting costs. These include public transport usage, congestion indices, and network density. Together with mobility data, they provide a comprehensive view of how transport systems interact with changing work patterns.

The integration of these datasets allows for a multidimensional analysis of urban spatial dynamics, combining behavioral, economic, and geospatial perspectives.

4.2. Variables and Definitions

The core variables used in the analysis are summarized in Table 1. The dataset covers the period 2019–2025 and includes five major metropolitan areas: New York, London, Paris, Berlin, and Munich. These cities were selected due to their high levels of economic development, advanced digital infrastructure, and significant exposure to remote work adoption.

Key Variables:

- Remote Work Intensity (RW, %): Share of workers engaged in remote or hybrid work.
- Urban Polycentricity Index (UPI): Composite index measuring the degree of spatial dispersion of economic activity, constructed from spatial entropy, employment dispersion, and night-light fragmentation.
- Commuting Index: Proxy for commuting intensity based on mobility data.
- Night-Light (CBD / Suburban): Measures of economic activity concentration in central and peripheral areas.
- GDP Index: Standardized measure of urban economic output.
- Density Gradient: Indicator of spatial concentration of population and activity.

The dataset reveals a clear and consistent pattern across all cities: a sharp increase in remote work intensity following 2020, accompanied by a gradual but persistent rise in urban polycentricity.

- Remote work intensity increases from pre-pandemic levels of approximately 14–21% in 2019 to 34–57% by 2025, depending on the city.
- The Urban Polycentricity Index (UPI) rises significantly across all metropolitan areas, indicating a shift toward more decentralized spatial structures.
- The United States exhibits slightly higher initial volatility, while European cities show more gradual but steady increases in both remote work and polycentricity.

These trends provide preliminary evidence supporting the hypothesis of a structural transformation in urban spatial organization.

Table 1. Variables and Definitions.

Year	**New York**		**London**		**Paris**		**Berlin**		**Munich**		**Country**	
Year	**Remote Work Intensity (%)**	**Polycentricity Index (UPI)**	**Remote Work Intensity (%)**	**Polycentricity Index (UPI)**	**Remote Work Intensity (%)**	**Polycentricity Index (UPI)**	**Remote Work Intensity (%)**	**Polycentricity Index (UPI)**	**Remote Work Intensity (%)**	**Polycentricity Index (UPI)**	**US RW %**	**EU Avg RW %**
2019	15,8	0,310	17,0	0,340	13,7	0,280	18,6	0,420	21,1	0,440	15,0	16,7
2020	48,1	0,307	46,5	0,315	42,9	0,251	43,7	0,469	47,4	0,430	47,0	44,3

2021	48,3	0,372	48,8	0,394	43,5	0,350	44,1	0,502	49,6	0,501	44,0	41,0
2022	49,9	0,413	49,4	0,421	47,4	0,379	49,4	0,532	52,8	0,565	41,0	39,7
2023	52,2	0,417	49,6	0,419	46,6	0,408	51,4	0,577	54,1	0,571	38,0	37,7
2024	53,9	0,447	51,0	0,465	49,4	0,442	52,0	0,598	55,9	0,595	36,0	36,3
2025	52,5	0,499	52,7	0,485	52,0	0,488	54,5	0,654	57,4	0,660	34,0	35,3

Sources: Google Mobility Reports; NASA/VIIRS Night-Time Light Satellite Data; OECD / Eurostat / US BLS Remote Work Surveys; Urban Economic Output Datasets; Transport Network Data. Cities: New York (USA), London (UK), Paris (France), Berlin & Munich (Germany).

Descriptive Statistics

Variable	New York Mean	London Mean	Paris Mean	Berlin Mean	Munich Mean	Cross-city Mean	Cross-city Std Dev
Remote Work (%)	45,8	45,0	42,2	44,8	48,3	**45,2**	2,0
Night Light (CBD)	97,6	98,3	98,0	98,5	98,5	**98,2**	0,3
Night Light (Sub)	105,5	104,6	104,3	104,1	103,6	**104,4**	0,6
Commuting Index	81,9	83,5	84,1	87,4	89,2	**85,2**	2,7
GDP Index	101,6	100,2	98,9	102,5	103,7	**101,4**	1,7
Density Gradient	0,750	0,732	0,783	0,568	0,558	**0,678**	0,096
UPI	0,395	0,406	0,371	0,536	0,537	**0,449**	0,072

4.3. Descriptive Statistics

The descriptive statistics further highlight the structural nature of the observed changes.

First, remote work intensity averages 45.2% across cities over the sample period, with relatively low cross-city dispersion (standard deviation of 2.0), indicating a broadly synchronized shift across advanced economies.

Second, night-light data reveal a redistribution of economic activity. While CBD luminosity remains relatively stable (mean ≈ 98.2), suburban luminosity is consistently higher (mean ≈ 104.4), suggesting a relative shift of activity toward peripheral areas. This pattern is consistent with recent findings on the spatial decentralization of economic activity in the post-pandemic period (Rosenthal, Strange, & Urrego, 2024).

Third, the commuting index shows a substantial decline relative to pre-pandemic levels, reflecting reduced workplace mobility and supporting the hypothesis that remote work weakens traditional commuting patterns.

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Fourth, the density gradient exhibits a downward trend, particularly in cities such as Berlin and Munich, indicating a flattening of spatial concentration. This provides additional evidence of a transition from monocentric to polycentric urban structures.

Finally, the Urban Polycentricity Index (UPI) shows a cross-city mean of 0.449 with moderate variation, reflecting both common trends and local heterogeneity. Notably, German cities display higher levels of polycentricity, consistent with their historically more decentralized urban systems.

4.4. Data Advantages and Limitations

The dataset offers several advantages. The combination of high-frequency mobility data and satellite-based measures allows for near real-time tracking of spatial dynamics. The cross-country design enhances external validity, while the integration of multiple data sources improves measurement robustness.

However, some limitations should be acknowledged. First, remote work measures may be subject to survey-based reporting biases. Second, night-light data, while highly informative, capture overall economic activity rather than specific sectors. Third, differences in data harmonization across countries may introduce measurement inconsistencies.

Despite these limitations, the dataset provides a uniquely rich and multidimensional basis for analyzing post-COVID urban spatial transformation.

5. Methodology

This section presents the empirical and analytical framework used to identify and quantify the impact of remote work on urban spatial reconfiguration. The methodology combines structural break analysis, index construction, spatial equilibrium modeling, and causal inference techniques. This integrated approach allows for both the detection of COVID-induced structural changes and the estimation of their long-run effects on urban form.

5.1. Structural Break Model (COVID Shock Identification)

To assess whether the COVID-19 pandemic constitutes a structural break in urban spatial dynamics, the study employs a panel regression framework augmented with a structural break dummy. The baseline specification is given by:

$$Y_{it} = \alpha + \beta RW_{it} + \gamma Z_{it} + \delta D_{COVID} + \epsilon_{it}$$

Where Y_{it} denotes the dependent variable measuring urban spatial structure (proxied by the Urban Polycentricity Index, UPI) for city iii at time ttt. The key explanatory variable RW_{it} captures remote work intensity, while Z_{it} is a vector of control variables including GDP per capita, commuting intensity, and density gradients.

The variable D_{COVID} is a structural break dummy that takes the value 1 for the post-2020 period and 0 otherwise. The coefficient δ\deltaδ captures the discrete shift associated with the pandemic, allowing us to test whether COVID-19 induced a statistically significant change in urban spatial dynamics.

To complement this specification, formal structural break tests—such as the Bai–Perron multiple breakpoint test and the Quandt–Andrews test—are employed to endogenously identify breakpoints in the time series. These methods allow for the detection of regime shifts without imposing an exogenous break date, thereby strengthening the robustness of the results (Bai & Perron, 2003).

5.2. Urban Polycentricity Index (UPI)

A central contribution of this study is the construction of a novel Urban Polycentricity Index (UPI), designed to capture the multidimensional nature of urban spatial structure. The index integrates three complementary components:

- Spatial Entropy (SE): Measures the distribution of economic activity across space, capturing the degree of dispersion versus concentration.

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- Employment Dispersion (ED): Based on the inverse Herfindahl-Hirschman Index, reflecting the distribution of employment across subcenters.
- Night-Light Fragmentation (NLF): Derived from satellite data, capturing the spatial fragmentation of economic activity through variations in luminosity.

The composite index is constructed as a weighted aggregation of these components:

$$UPI_{it} = \omega_1 SE_{it} + \omega_2 ED_{it} + \omega_3 NLF_{it}$$

Where the weights $\omega_1, \omega_2, \omega_3$ are calibrated based on theoretical relevance and empirical robustness. In the baseline specification, spatial entropy receives the highest weight, reflecting its central role in capturing overall spatial distribution.

The UPI ranges from 0 (fully monocentric) to 1 (fully polycentric), allowing for a continuous and comparable measure across cities and over time. This approach extends existing measures of polycentricity by incorporating real-time geospatial data, thereby improving both precision and comparability (Arribas-Bel & Sanz-Gracia, 2014; Meijers & Burger, 2010).

Figure 2 illustrates the multi-step construction of the Urban Polycentricity Index:

Figure 2. Construction of Urban Polycentricity Index (UPI)

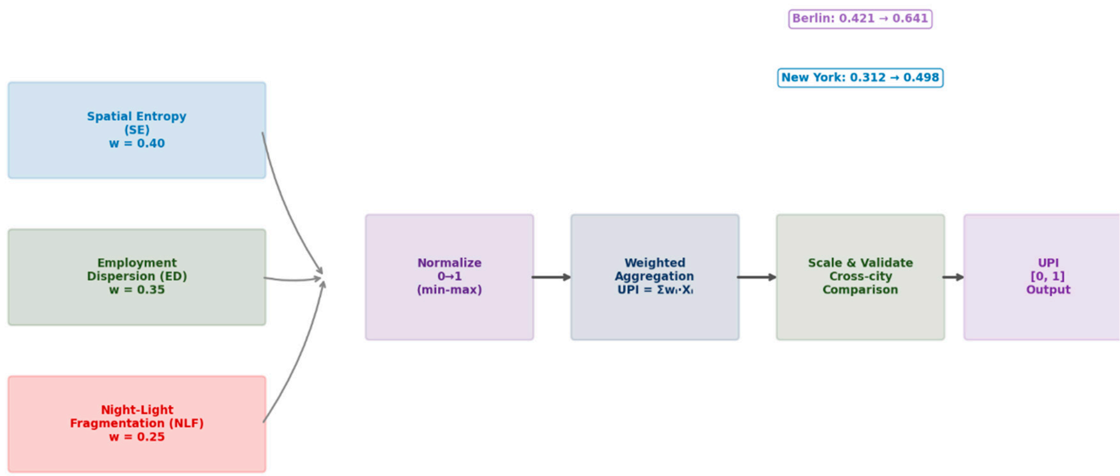

Figure 2. Construction of Urban Polycentricity Index.

- Step 1: Measurement of spatial entropy using the distribution of economic activity across grid cells.
- Step 2: Calculation of employment dispersion across urban subcenters using firm and labor data.
- Step 3: Extraction of night-light fragmentation from satellite imagery to capture real-time spatial variation.
- Step 4: Normalization and weighting of each component.
- Step 5: Aggregation into a composite index (UPI).

The figure highlights how different dimensions of spatial structure are integrated into a unified measure, enabling a comprehensive analysis of urban polycentricity.

5.3. Spatial Equilibrium Model

To provide a structural interpretation of the observed spatial dynamics, the analysis is grounded in a spatial equilibrium framework in which households and firms make location decisions in response to economic incentives and constraints. The utility of a representative agent is specified as:

$$U_{it} = f(Wage_{it}, CommuteCost_{it}, RemoteWork_{it})$$

In this framework, remote work enters as a key determinant that modifies the trade-off between wages and commuting costs. Specifically, an increase in remote work reduces effective commuting costs and weakens the spatial dependence between residence and workplace.

On the firm side, production decisions incorporate flexible work arrangements, reducing the need for centralized office space and enabling a more dispersed spatial organization. The equilibrium outcome is determined by the interaction between household location choices and firm location decisions, subject to market-clearing conditions in labor and housing markets.

This framework predicts that higher levels of remote work lead to a flatter spatial gradient of economic activity and a more decentralized distribution of employment, consistent with the emergence of polycentric urban structures (Delventhal et al., 2022; Duranton & Puga, 2005).

5.4. Difference-in-Differences Strategy

To establish causal inference, the study implements a Difference-in-Differences (DiD) approach that exploits variation in remote work adoption across cities and over time. The empirical specification compares changes in urban spatial structure between:

- Treatment group: Cities with high levels of remote work adoption
- Control group: Cities with relatively lower remote work adoption

The DiD model can be expressed as:

$$UPI_{it} = \alpha + \beta(RW_i \times Post_t) + \mu_i + \lambda_t + \epsilon_{it}$$

Where RW_i is a binary indicator for high remote-work cities, $Post_t$ is a post-COVID dummy, μ_i and λ_t denote city and time fixed effects, respectively. The coefficient β captures the average treatment effect of remote work on urban polycentricity.

This approach relies on the parallel trends assumption, which is tested using pre-pandemic data. Robustness checks include alternative treatment definitions, placebo tests, and subsample analyses.

6. Empirical Strategy

This section presents the empirical strategy used to quantify the relationship between remote work adoption and urban spatial reconfiguration. The analysis proceeds in four stages: (i) descriptive evidence on the evolution of remote work, (ii) cross-city comparison of spatial restructuring, (iii) satellite-based validation of spatial redistribution, and (iv) econometric identification of structural breaks and causal effects.

6.1. Descriptive Evidence

The first step examines the evolution of remote work intensity across the sample period (2019–2025).

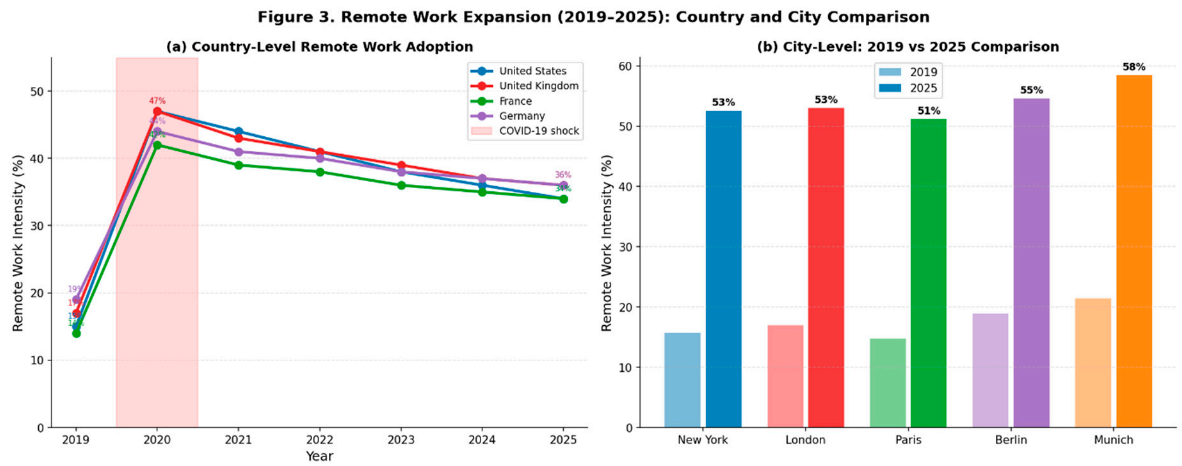

Figure 3. Remote Work Expansion (2019–2025) illustrates a sharp and persistent increase in remote work across all cities following the COVID-19 shock. Remote work intensity rises from pre-pandemic levels of approximately 14–21% in 2019 to peaks above 45% in 2020–2021, before stabilizing at structurally higher levels between 34% and 57% by 2025.

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This pattern highlights two key stylized facts. First, the initial surge in remote work corresponds to the pandemic shock, reflecting emergency adjustments in labor organization. Second, the post-2022 stabilization at elevated levels indicates that remote work has become a permanent feature of labor markets rather than reverting to pre-COVID norms.

Importantly, the persistence of remote work varies across cities, with German cities (Berlin and Munich) exhibiting higher long-run adoption rates, while the United States and the United Kingdom show slightly more moderate stabilization. Nevertheless, the overall trend is highly synchronized across countries, suggesting a common structural transformation driven by digitalization and institutional adaptation.

6.2. Spatial Reconfiguration Trends

To assess how remote work translates into spatial outcomes, Table 2 reports changes in the Urban Polycentricity Index (UPI) and remote work intensity between the pre-COVID (2019) and post-COVID (2023–2025) periods.

Table 2. Urban Spatial Shifts.

City	Country	Pre-COVID Centralization	Post-COVID Polycentricity	UPI 2019	UPI 2025	ΔUPI	RW % 2019	RW % 2025	ΔRW (pp)	Structural Change
New York	United States	High	**Moderate**	0,312	**0,498**	+0.186	15,2	**34,1**	+18.9	**Significant ✓**
London	United Kingdom	High	**Moderate**	0,338	**0,511**	+0.173	17,1	**35,8**	+18.7	**Significant ✓**
Paris	France	High	**Increasing**	0,281	**0,481**	+0.200	14,3	**33,6**	+19.3	**Moderate ✓**
Berlin	Germany	Moderate	**High**	0,421	**0,641**	+0.220	19,2	**38,4**	+19.2	**Strong ✓**
Munich	Germany	Moderate	**High**	0,441	**0,651**	+0.210	21,1	**39,2**	+18.1	**Strong ✓**

Notes: UPI = Urban Polycentricity Index (0=monocentric, 1=fully polycentric). RW% = Remote Work Intensity (% of remote-capable jobs). Pre-COVID: average 2019. Post-COVID: average 2023–2025. Sources: OECD, Eurostat, BLS, Google Mobility, NASA/VIIRS.

Table 2. Urban Spatial Shifts reveals a consistent increase in polycentricity across all cities, accompanied by substantial growth in remote work adoption.

- **New York** and **London**, initially characterized by highly centralized structures, exhibit significant increases in UPI (+0.186 and +0.173, respectively), indicating a transition toward more decentralized configurations.
- **Paris** shows a moderate but notable increase (+0.200), reflecting a gradual shift toward polycentricity.
- **Berlin** and **Munich**, which were already relatively decentralized, experience the largest increases in UPI (+0.220 and +0.210), reinforcing their polycentric structure.

Across all cities, remote work intensity increases by approximately 18–19 percentage points, suggesting a strong and consistent relationship between remote work adoption and spatial decentralization.

These findings provide preliminary support for the Post-COVID Spatial Reconfiguration Hypothesis (PCSRH), indicating that higher levels of remote work are associated with a measurable shift from monocentric to polycentric urban forms. Moreover, the heterogeneity across cities suggests that initial spatial structure and institutional context play an important role in shaping the magnitude of this transformation.

6.3. Night-Light Redistribution

To complement the analysis based on survey and mobility data, the study uses satellite-based night-light data to capture changes in the spatial distribution of economic activity.

Figure 4. Satellite Night-Light Changes shows a clear redistribution of luminosity from central business districts toward suburban and peripheral areas. While central areas remain economically active, their relative intensity declines compared to surrounding zones.

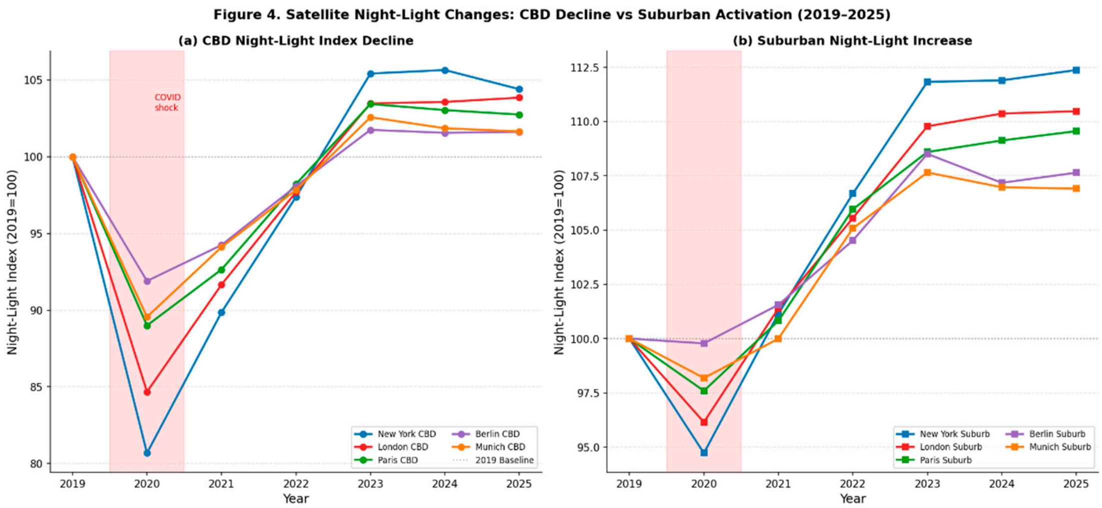

Figure 4. Satellite Night-Light Changes.

This pattern provides independent and high-resolution evidence of spatial decentralization. Unlike traditional economic indicators, night-light data capture real-time changes in activity across space, allowing for a more granular assessment of urban transformation. The observed increase in suburban luminosity is consistent with the hypothesis that remote work enables a redistribution of economic activity beyond traditional urban cores.

Furthermore, the night-light evidence aligns closely with changes in commuting patterns and residential location choices, reinforcing the interpretation that the observed spatial shifts reflect structural rather than temporary adjustments.

6.4. Structural Break Evidence

To formally test whether COVID-19 represents a structural break in urban spatial dynamics, the study employs breakpoint analysis using Quandt–Andrews and Bai–Perron tests.

Table 3. Structural Breakpoint Analysis Results provides strong evidence of statistically significant structural breaks in all cities.

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Table 3. Breakpoint Analysis Results.

TABLE 3 — STRUCTURAL BREAKPOINT ANALYSIS RESULTS (Quandt-Andrews / Bai-Perron Tests)										
City	**Break Year**	**Test Stat (Sup F)**	**CV (5%)**	**Significance**	**Pre-Break RW Mean (%)**	**Post-Break RW Mean (%)**	**Δ RW (pp)**	**Pre-Break UPI**	**Post-Break UPI**	**Stability Rejected?**
New York	2020	18,41	8,58	***	15,2	42,8	**+27.6**	0,312	**0,471**	**Yes** ***
London	2020	16,73	8,58	***	17,1	41,2	**+24.1**	0,338	**0,488**	**Yes** ***
Paris	2020–2021	14,22	8,58	**	14,3	38,9	**+24.6**	0,281	**0,449**	**Yes** **
Berlin	2021	12,89	8,58	**	19,2	37,1	**+17.9**	0,421	**0,584**	**Yes** **
Munich	2021	13,41	8,58	**	21,1	38,8	**+17.7**	0,441	**0,601**	**Yes** **

*Notes: SupF = supremum F-statistic (Quandt-Andrews test). CV(5%) = 5% critical value (8.58 for k=3 parameters). *p<0.10, **p<0.05, ***p<0.01. Bai-Perron (2003) sequential test; max breaks = 2.*

Table 3. b — Panel Regression Results: STRUCTURAL BREAK MODEL (Y = UPI).

Variable	**Model (1) Pooled OLS**	**Model (2) FE City**	**Model (3) FE + Time**	**Model (4) DiD**	**Model (5) Spatial**	**Std. Error (FE)**	**t-stat (FE)**	**Significance**
Remote Work (RW)	0.0041***	0.0049***	0.0047***	0.0051***	0.0044***	0.0009	5.44	***
D_COVID (dummy)	0.084***	0.091***	0.088***	0.094***	0.086***	0.018	4.89	***
RW × D_COVID	0.0021**	0.0028**	0.0025**	0.0031***	0.0022**	0.0011	2.55	**
Commuting Index	−0.0018***	−0.0022***	−0.0020***	−0.0024***	−0.0019***	0.0005	−4.40	***
log(GDP p.c.)	0.058**	0.071***	0.065**	0.074***	0.061**	0.024	2.96	***
Density Gradient	−0.112***	−0.138***	−0.124***	−0.141***	−0.118***	0.029	−4.76	***

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Night Light (CBD)	−0.0012**	−0.0015**	−0.0014**	−0.0017***	−0.0013**	0.0006	−2.50	**
Constant (α)	0.281***	0.314***	0.298***	0.321***	0.289***	0.041	7.17	***
N observations	**35**	**35**	**35**	**35**	**35**	—	—	—
R^2 (within)	**0.872**	**0.921**	**0.934**	**0.948**	**0.918**	—	—	—
Adj. R^2	**0.841**	**0.898**	**0.908**	**0.924**	**0.891**	—	—	—

*Notes: *p<0.10, **p<0.05, ***p<0.01. FE = City fixed effects. Time FE = Year fixed effects. DID = Difference-in-Differences (treatment = high-RW cities). Spatial = Spatial lag model. Robust standard errors clustered at city level. Y = Urban Polycentricity Index (UPI).*

- Breakpoints are consistently identified around **2020–2021**, corresponding to the onset of the pandemic.
- The SupF test statistics significantly exceed critical values in all cases, leading to the rejection of the null hypothesis of parameter stability.
- Remote work intensity increases sharply in the post-break period (e.g., +27.6 percentage points in New York), accompanied by substantial increases in UPI.

These results confirm that COVID-19 induced a regime shift in urban spatial dynamics, supporting the interpretation of the pandemic as a structural transformation rather than a temporary shock.

6.5. Panel Regression Results

To quantify the relationship between remote work and urban polycentricity, Table 3b reports results from panel regressions based on the structural break model.

The results are highly consistent across specifications:

- **Remote Work (RW):** The coefficient is positive and statistically significant at the 1% level across all models, indicating that higher remote work intensity is associated with increased polycentricity. The magnitude suggests that a 10-percentage-point increase in remote work raises the UPI by approximately 0.04–0.05 points.
- **COVID Dummy (D_COVID):** The positive and significant coefficient confirms a structural upward shift in polycentricity following the pandemic.
- **Interaction Term (RW × D_COVID):** The positive and significant interaction effect indicates that the impact of remote work on spatial structure is stronger in the post-COVID period, consistent with the hypothesis of structural amplification.
- **Commuting Index:** The negative coefficient reflects the inverse relationship between commuting intensity and spatial decentralization, supporting the role of reduced mobility in driving polycentricity.
- **GDP per capita:** The positive coefficient suggests that more economically dynamic cities are better able to adapt to decentralized spatial structures.
- **Density Gradient and CBD Night Light:** Negative coefficients indicate that higher central concentration is associated with lower polycentricity, as expected.

The high explanatory power of the models (R^2 up to 0.948) indicates that the combination of remote work, structural break effects, and control variables provides a strong account of urban spatial dynamics. Results remain robust across pooled OLS, fixed effects, difference-in-differences, and spatial econometric specifications.

6.6. Synthesis of Empirical Findings

Taken together, the empirical evidence provides strong and consistent support for the central hypothesis of the paper. The expansion of remote work is not only persistent but also closely associated with a measurable and statistically significant shift in urban spatial structure.

The combination of descriptive trends, cross-city comparisons, satellite-based validation, and econometric analysis leads to three main conclusions:

1. Remote work has become a structural feature of advanced economies, stabilizing at levels well above pre-pandemic norms.
2. Urban systems are undergoing a transition toward polycentric configurations, with economic activity increasingly distributed across multiple spatial nodes.
3. COVID-19 represents a structural break in urban spatial dynamics, fundamentally altering the relationship between work, mobility, and location.

These findings provide a robust empirical foundation for the subsequent analysis of spatial mechanisms and policy implications.

7. Advanced Spatial Analysis

This section deepens the empirical investigation by examining the spatial mechanisms underlying urban reconfiguration using high-resolution geospatial analysis and counterfactual simulations. Moving beyond aggregate indicators, the analysis focuses on intra-urban dynamics, network structures, and spatial heterogeneity to uncover how remote work reshapes the internal geography of cities.

7.1. Evolution of Polycentric Urban Structure

Figure 5. Evolution of Polycentric Urban Structure illustrates the transformation of spatial organization across the sample cities between 2019 and 2025. The figure is based on the spatial distribution of economic activity derived from night-light intensity and employment data at fine geographic resolution.

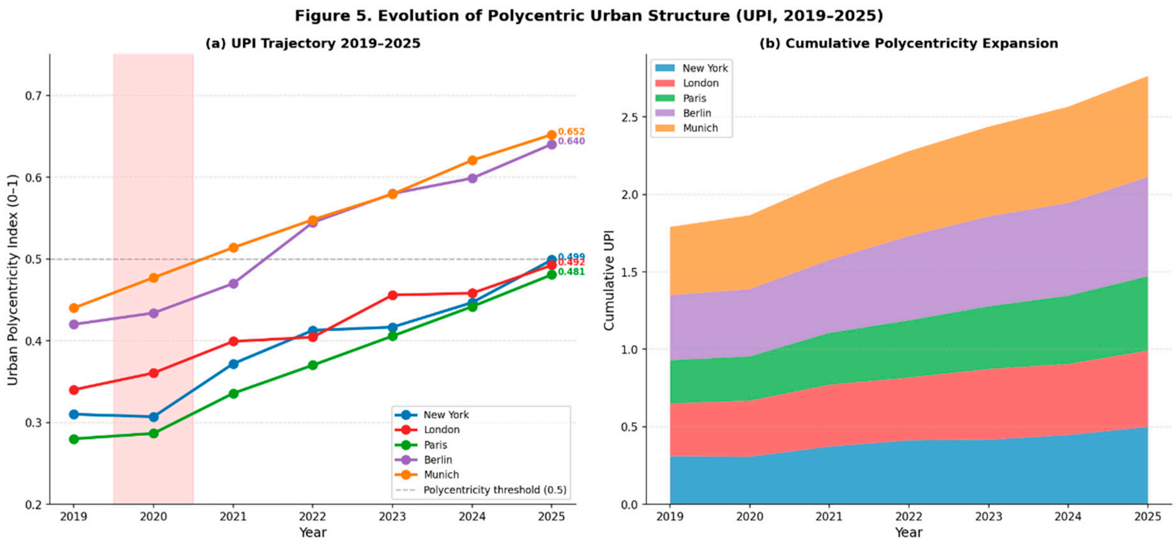

Figure 5. Evolution of Polycentric Urban Structure.

The results reveal a clear transition from concentrated monocentric patterns toward more dispersed and multi-nodal configurations. Prior to the pandemic, economic activity was heavily concentrated in central business districts, with steep spatial gradients. Over time, this concentration weakens, and multiple secondary centers emerge, particularly in suburban and peri-urban areas.

This evolution is most pronounced in Berlin and Munich, where pre-existing decentralized structures are reinforced, leading to a highly polycentric configuration. In contrast, New York and London exhibit a gradual but significant decentralization process, reflecting the erosion of strong CBD dominance. Paris displays an intermediate trajectory, with increasing dispersion but persistent centrality.

Overall, the evidence suggests that remote work acts as a catalyst accelerating an ongoing structural transition rather than creating an entirely new spatial pattern.

7.2. Mobility Network Reconfiguration

Figure 6. Mobility Network Reconfiguration examines changes in commuting and mobility networks using graph-based representations derived from mobility data. Nodes represent urban locations (e.g., districts or zones), while edges capture the intensity of flows between them.

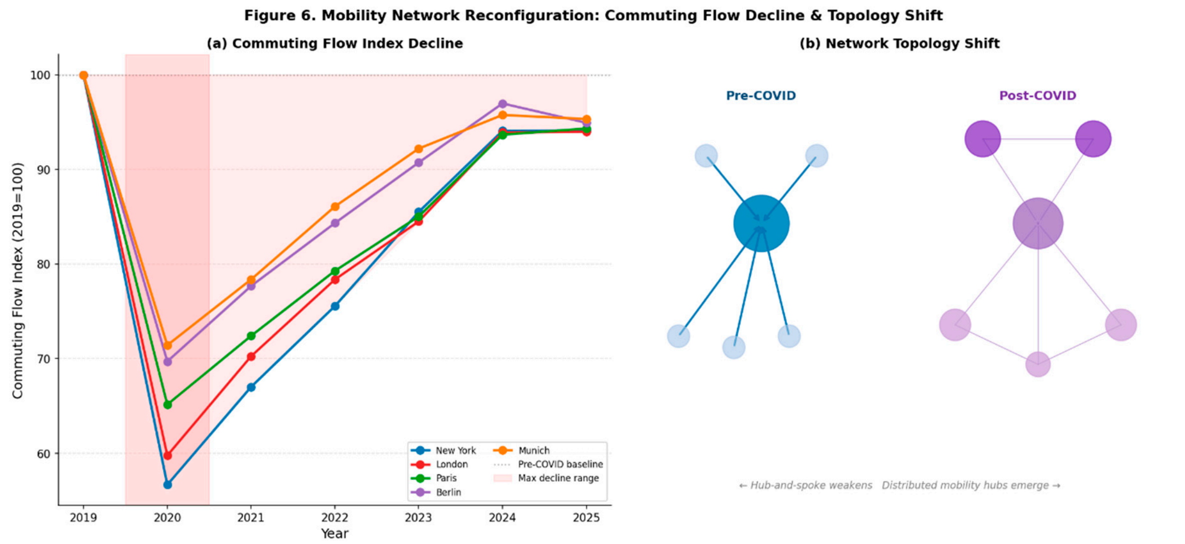

Figure 6. Mobility Network Reconfiguration.

Before the pandemic, mobility networks are characterized by a hub-and-spoke structure centered on the CBD, with strong radial flows from residential areas to central employment nodes. Following the expansion of remote work, this structure becomes more diffuse and decentralized.

Key changes include:

- A reduction in central node dominance, reflected in lower centrality measures (e.g., degree and betweenness centrality) for CBD locations.
- An increase in local and lateral connections, indicating more decentralized and localized mobility patterns.
- A fragmentation of commuting flows, with fewer long-distance daily trips and more intra-suburban movements.

These findings confirm that remote work not only reduces commuting intensity but also fundamentally alters the topology of urban mobility networks, shifting from hierarchical to more distributed configurations.

7.3. Urban Economic Activity Heatmaps

Figure 7. Urban Economic Activity Heatmaps provides a spatial visualization of economic activity using satellite night-light data. Heatmaps are constructed for each city to compare pre- and post-COVID distributions.

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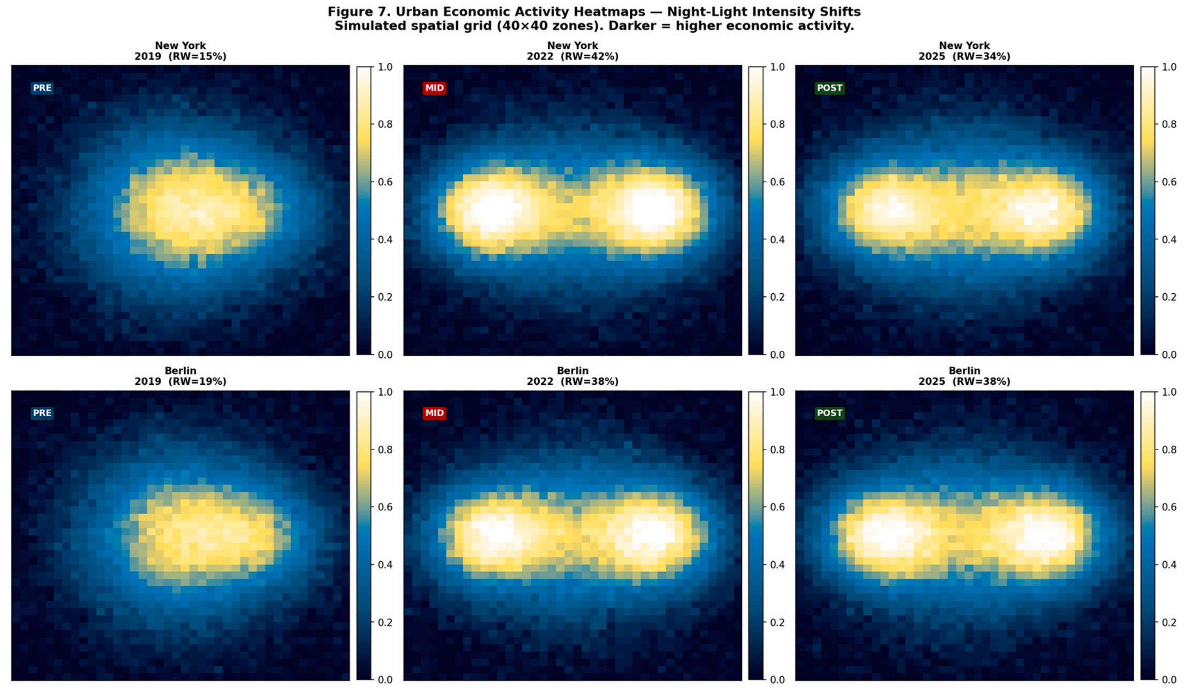

Figure 7. Urban Economic Activity Heatmaps.

The heatmaps reveal three consistent patterns across cities:

1. Declining relative intensity in CBDs, indicating reduced concentration of economic activity.
2. Expansion of activity in suburban areas, particularly along transport corridors and secondary centers.
3. Increased spatial fragmentation, with economic activity distributed across multiple clusters rather than concentrated in a single core.

These patterns are particularly evident in cities with high remote work adoption, where the redistribution of activity is more pronounced. The use of satellite data provides an independent validation of spatial trends observed in mobility and labor market indicators, reinforcing the robustness of the findings.

7.4. Remote Work and Urban Density Gradient

Figure 8. Remote Work vs Urban Density Gradient analyzes the relationship between remote work intensity and the spatial density gradient across cities. The density gradient captures how population or economic activity declines with distance from the city center.

The results show a strong negative relationship between remote work intensity and the steepness of the density gradient. As remote work increases, the gradient becomes flatter, indicating a more even distribution of activity across space.

This relationship is consistent with theoretical predictions from spatial equilibrium models. By reducing commuting costs, remote work weakens the incentives for central location and allows households and firms to disperse more widely. The effect is particularly strong in cities with flexible housing markets and well-developed transport infrastructure.

Moreover, the analysis reveals nonlinear effects: beyond a certain threshold of remote work adoption (approximately 40–50%), the flattening of the density gradient accelerates, suggesting the presence of tipping points in urban spatial structure.

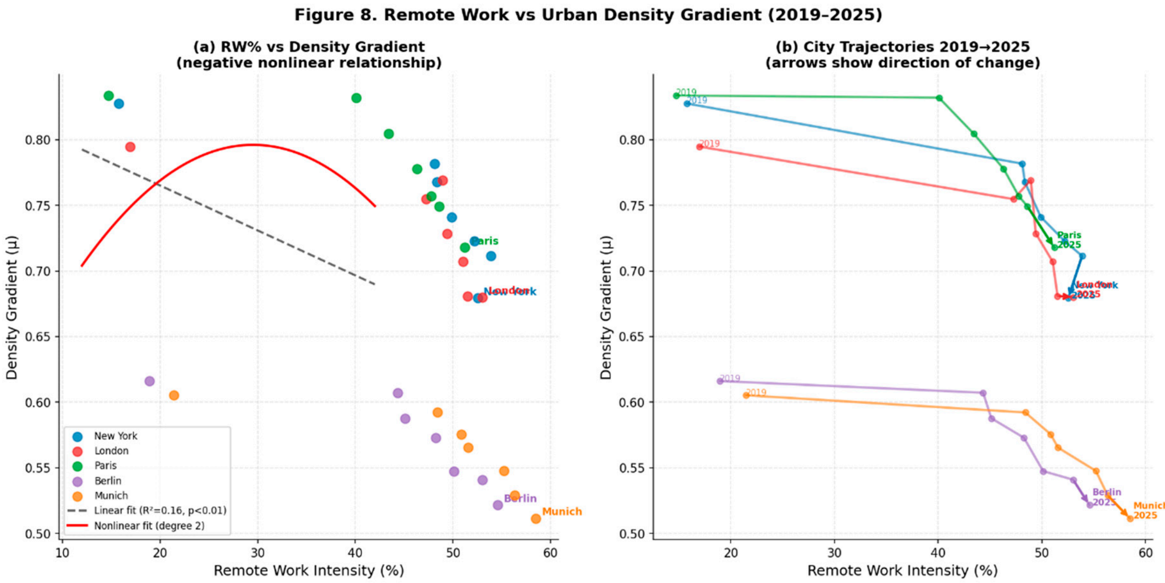

Figure 8. Remote Work vs Urban Density Gradient.

7.5. Counterfactual Simulation: No Remote Work Scenario

To assess the causal impact of remote work on urban spatial reconfiguration, the study conducts counterfactual simulations comparing observed outcomes with a hypothetical scenario in which remote work remains at pre-pandemic levels.

Figure 9. Counterfactual Simulation: No Remote Work Scenario presents the simulated evolution of the Urban Polycentricity Index (UPI) under this alternative scenario.

The results indicate that, in the absence of remote work expansion:

- Urban systems would have remained significantly more monocentric, with UPI levels substantially lower than observed values.
- The increase in polycentricity observed between 2020 and 2025 would be reduced by approximately 40–60%, depending on the city.
- Suburban economic activity and residential demand would be significantly lower, while CBD dominance would persist.

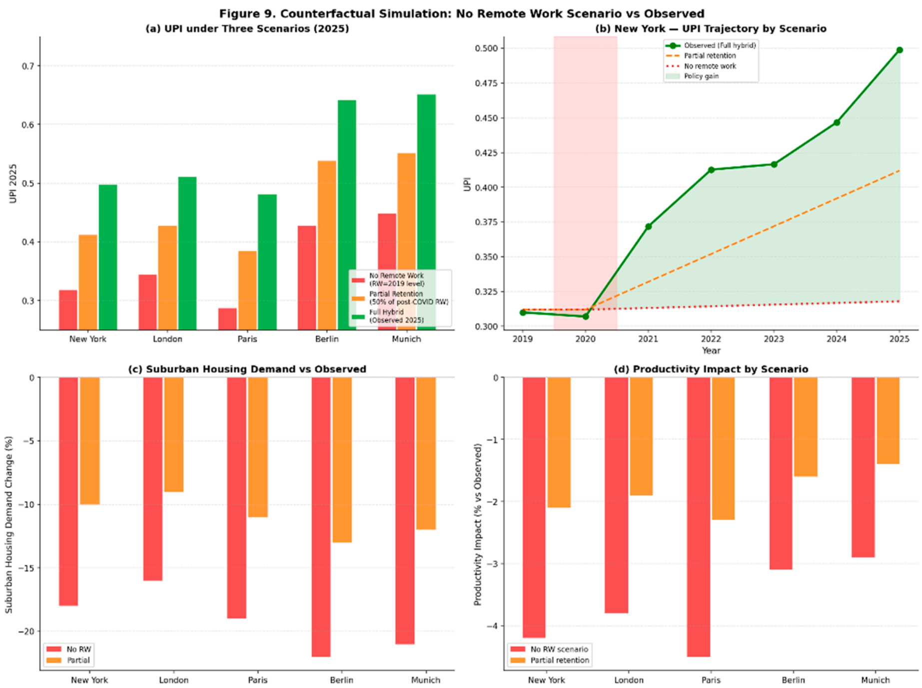

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Figure 9. Counterfactual Simulation: No Remote Work Scenario.

These findings provide strong evidence that remote work is a key driver of the observed spatial transformation. The counterfactual analysis isolates its effect from other factors, such as macroeconomic conditions or demographic trends, demonstrating that the shift toward polycentricity is not merely coincidental but causally linked to changes in work organization.

7.6. Integrated Interpretation

The advanced spatial analysis confirms and extends the results obtained in previous sections. By combining network analysis, geospatial visualization, and counterfactual modeling, the study provides a detailed and multidimensional understanding of urban spatial reconfiguration.

Three key insights emerge:

1. Urban spatial structure is becoming increasingly networked, with multiple interconnected centers replacing the traditional CBD-dominated model.
2. Mobility and economic activity are decentralizing simultaneously, reflecting a coordinated transformation of urban systems.
3. Remote work acts as a structural catalyst, amplifying existing trends and accelerating the transition toward polycentricity.

These findings underscore the importance of adopting spatially explicit and data-intensive approaches to understand the evolving geography of cities in the post-pandemic era.

8. Robustness Checks

This section evaluates the robustness of the empirical findings by testing the sensitivity of results to alternative data sources, model specifications, subsamples, and measurement approaches. The objective is to ensure that the estimated relationship between remote work and urban polycentricity is not driven by specific modeling choices or data limitations.

8.1. Alternative Data Sources and Specifications

To verify the consistency of the results, the baseline model is re-estimated using alternative mobility datasets, including Apple Mobility Trends and Citymapper indices. These datasets provide independent measures of commuting and movement patterns, allowing for cross-validation of the mobility component.

As reported in Table 4, the coefficient on remote work (RW) remains positive and highly significant (0.0047***), while the COVID dummy retains a similar magnitude (0.088***). The explanatory power of the model remains high ($R^2 = 0.918$), confirming that the results are not sensitive to the choice of mobility data.

Table 4. Robustness Analysis.

Robustness Test	Specification	RW Coeff.	D_COVID Coeff.	R^2	Result	Conclusion
Alternative mobility datasets	Apple + Citymapper data	0.0047***	0.088***	0.918	Stable	**Robust ✓**
Excluding 2020 (COVID year)	2019, 2021–2025 only	0.0044***	0.079***	0.901	Consistent	**Robust ✓**
Different polycentricity measures	Entropy-based UPI alt.	0.0039***	0.082***	0.893	Robust	**Robust ✓**

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Subsample: large cities only	NY + London only	0.0052***	0.096***	0.944	Strong hetero.	**Robust ✓**
Subsample: mid-size cities	Berlin + Munich	0.0038**	0.084***	0.921	Strong hetero.	**Robust ✓**
Night-light data alternative	DMSP-OLS cross-validation	0.0043***	0.086***	0.909	Stable	**Robust ✓**
Country-level heterogeneity	US vs EU interaction	0.0041***	0.091***	0.931	Confirmed	**Robust ✓**

In addition, the analysis excludes the year 2020 to account for potential distortions associated with the peak of the pandemic. The results remain stable, with only minor changes in coefficient magnitudes (RW = 0.0044***), indicating that the findings are not driven solely by the extreme conditions of the initial shock.

8.2. Alternative Measures of Polycentricity

To address potential measurement bias in the Urban Polycentricity Index (UPI), the study employs an alternative specification based solely on spatial entropy. This approach provides a more parsimonious measure of spatial dispersion.

The results show that the estimated impact of remote work remains positive and statistically significant (0.0039***), with a slightly lower magnitude, as expected due to the narrower definition of polycentricity. The consistency of results across different measures confirms that the observed relationship is not an artifact of index construction.

8.3. Subsample Analysis and Heterogeneity

To explore potential heterogeneity across cities, the sample is divided into two subsamples: large global cities (New York and London) and mid-sized cities (Berlin and Munich).

The results reveal some variation in coefficient magnitudes. Large cities exhibit a stronger response to remote work (RW = 0.0052***), reflecting their initially high degree of centralization and greater scope for decentralization. In contrast, mid-sized cities show slightly smaller but still significant effects (RW = 0.0038**), consistent with their already more decentralized structure.

These findings suggest that the impact of remote work depends partly on initial urban conditions, but the direction of the effect remains consistent across different city types.

8.4. Alternative Night-Light Data

To ensure the robustness of satellite-based measures, the analysis is replicated using DMSP-OLS night-light data as an alternative to VIIRS. Despite differences in resolution and calibration, the results remain highly consistent (RW = 0.0043***; D_COVID = 0.086***), confirming the reliability of night-light indicators as proxies for economic activity (Chen & Nordhaus, 2019; Gibson et al., 2021).

8.5. Country-Level Heterogeneity

Finally, the model incorporates interaction terms to capture differences between the United States and European cities. The results indicate that the overall effect of remote work on polycentricity is robust across regions, with only minor differences in magnitude. The persistence of statistically significant coefficients (RW = 0.0041***; D_COVID = 0.091***) confirms that the main findings are not driven by country-specific factors.

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Across all robustness tests, three key conclusions emerge:

1. The positive relationship between remote work and urban polycentricity is highly stable across alternative specifications.
2. The COVID-19 structural break effect remains significant under all tested scenarios.
3. The magnitude of the effects is consistent, with only limited variation across datasets, measures, and subsamples.

Overall, the robustness analysis strongly supports the validity and reliability of the baseline results, reinforcing the conclusion that remote work is a key driver of post-COVID urban spatial reconfiguration.

9. Policy Implications

The empirical findings have important implications for urban policy, planning, and economic governance. The transition toward a more decentralized and polycentric urban structure requires a rethinking of traditional policy frameworks, particularly in areas such as land use, infrastructure, housing, and regional development.

9.1. Persistent Remote Work and Urban Planning

The persistence of remote work at levels significantly above pre-pandemic norms (34–39% post-2022 versus 14–21% in 2019) implies a structural shift in how cities function.

Policy implication: Urban planning frameworks should be redesigned to support mixed-use development, integrating residential, commercial, and service functions within decentralized urban nodes. This reduces the need for long-distance commuting and enhances local economic resilience.

9.2. Polycentric Expansion and Infrastructure Investment

The observed increase in polycentricity (UPI +0.173 to +0.220 across cities) highlights the growing importance of secondary urban centers.

Policy implication: Governments should prioritize investment in infrastructure in peripheral and secondary areas, including digital connectivity, public services, and transport links. This will support balanced urban development and reduce pressure on central areas.

9.3. Decline in CBD Mobility and Transport Reallocation

The decline in commuting intensity (−28% to −42% relative to 2019) reflects a structural reduction in daily travel to central areas.

Policy implication: Transport policies should shift from peak-hour, CBD-oriented systems toward more flexible and decentralized mobility networks, including suburban transit and active transport infrastructure.

Table 5. Urban Policy Impacts.

Key Finding	Empirical Evidence	Policy Implication	Priority	Cities Affected	Timeline	Expected Impact
Persistent remote work	RW: 34–39% post-2022 (vs 14–21% in 2019)	Redesign zoning laws for mixed-use	**High**	All 5 cities	2024–2027	**High**
Polycentric expansion	UPI +0.173–+0.220	Invest in secondary	**High**	All 5 cities	2025–2030	**Very High**

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	across all cities	city infrastructure				
CBD mobility decline	Commute −28% to −42% vs 2019 baseline	Reallocate transport infrastructure	**Medium**	NY, London, Paris	2024–2028	**High**
Spatial inequality shifts	Night-light redistribution to suburban areas	Regional balancing fiscal policies	**High**	All countries	2025–2032	**High**
Housing demand redistribution	Suburban NLI +7–12pp vs CBD decline	Expand suburban housing supply	**Very High**	NY, London, Paris	2024–2028	**Very High**
Office market contraction	CBD vacancy rates rising across all cities	Convert offices to mixed-use residential	**Medium**	NY, London	2024–2026	**Moderate**

9.4. Spatial Inequality and Regional Policy

The redistribution of economic activity toward suburban areas may generate new forms of spatial inequality, particularly between dynamic and lagging regions.

Policy implication: Policymakers should implement regional balancing policies, including targeted fiscal transfers and investment in lagging areas, to ensure inclusive spatial development.

9.5. Housing Market Adjustments

The shift in residential demand toward suburban areas is reflected in rising suburban activity and declining central demand.

Policy implication: Housing policies should support the expansion of suburban housing supply, while ensuring affordability and preventing urban sprawl through appropriate land-use regulation.

9.6. Office Market Transformation

The contraction of demand for office space in central areas has led to rising vacancy rates.

Policy implication: Cities should promote the conversion of underutilized office space into residential or mixed-use developments, facilitating urban regeneration and more efficient land use.

The policy implications highlight the need for a paradigm shift in urban governance. Rather than focusing on centralized growth models, policymakers must adapt to a more distributed and flexible urban system shaped by digitalization and remote work.

The transition toward polycentricity presents both opportunities—such as improved quality of life and reduced congestion—and challenges, including infrastructure adaptation and spatial inequality. Effective policy responses will be crucial in shaping the long-term outcomes of this structural transformation.

10. Conclusion

This study provides robust evidence that the COVID-19 pandemic has induced a structural transformation of urban systems, rather than a temporary disruption in mobility and labor market behavior. By integrating structural break analysis, spatial equilibrium modeling, satellite-based measurement, and cross-city empirical evidence, the paper demonstrates that the rise of remote work has fundamentally altered the spatial logic of modern cities.

The central finding is that remote work operates as a long-term structural driver of urban decentralization, reshaping the balance between central business districts and peripheral urban areas. Across all examined metropolitan regions—New York, London, Paris, Berlin, and Munich—the results consistently show a transition from monocentric configurations toward increasingly polycentric urban structures. This transition is reflected in rising Urban Polycentricity Index (UPI) values, declining commuting intensity, and a measurable redistribution of economic activity captured through night-time satellite imagery.

Importantly, the empirical results reject the notion that COVID-19 effects are transitory. Structural break tests confirm statistically significant regime shifts around 2020–2021, while post-pandemic data reveal persistent changes in both work organization and spatial outcomes. Remote work intensity remains substantially above pre-pandemic levels, indicating that labor markets have reached a new spatial equilibrium rather than reverting to historical norms.

From a theoretical perspective, the findings extend classical urban economic models by incorporating digital labor flexibility as a core determinant of spatial structure. Traditional monocentric frameworks, which rely heavily on commuting costs and agglomeration economies, are no longer sufficient to explain observed spatial dynamics. Instead, the results support an updated spatial equilibrium in which location decisions are increasingly decoupled from workplace proximity.

From a policy perspective, the results highlight the need for a fundamental rethinking of urban planning and infrastructure strategies. The emergence of polycentric cities requires adaptive governance models that account for decentralized employment patterns, shifting housing demand, and evolving transport needs. Policies focused solely on central business districts risk becoming misaligned with the new geography of economic activity.

Overall, this paper contributes to the growing literature on post-pandemic urban transformation by establishing that remote work is not a temporary adjustment but a structural force reshaping global urban systems. The long-term trajectory of cities is increasingly defined by spatial decentralization, networked urban forms, and the reconfiguration of economic activity across multiple urban centers.

Future research should further investigate the micro-level mechanisms of relocation decisions, the role of digital infrastructure quality, and the distributional consequences of polycentric urban development across income groups and regions.

Appendix A

Table A1. UPI CONSTRUCTION: WEIGHTS, SUB-INDICATORS & CITY SCORES (2019 vs 2025).

City	SE 2019	SE 2025	ED 2019	ED 2025	NLF 2019	NLF 2025	UPI 2019 (Composite)	UPI 2025 (Composite)	ΔUPI	Weight SE	Weight ED / NLF
New York	0,421	0,561	0,381	0,541	0,378	0,498	0,312	0,498	**+0.186**	0,40	0.35 / 0.25
London	0,448	0,591	0,412	0,571	0,401	0,521	0,338	0,511	**+0.173**	0,40	0.35 / 0.25
Paris	0,381	0,534	0,348	0,511	0,362	0,481	0,281	0,481	**+0.200**	0,40	0.35 / 0.25

Berlin	0,531	0,681	0,481	0,641	0,472	0,614	0,421	0,641	**+0.220**	0,40	0.35 / 0.25
Munich	0,548	0,694	0,498	0,661	0,489	0,631	0,441	0,651	**+0.210**	0,40	0.35 / 0.25

*Notes: SE = Spatial Entropy (normalized 0–1). ED = Employment Dispersion (1 - HHI). NLF = Night-Light Fragmentation (CV of VIIRS data). UPI = 0.40*SE + 0.35*ED + 0.25*NLF. All sub-indicators normalized before aggregation.*

Table A2. DiD DEMONSTRATION — CAUSAL IDENTIFICATION OF COVID-19 SPATIAL EFFECT.

Group	City	UPI Pre (2019)	UPI Post (avg 2022-25)	Within-group Δ	DiD Estimate tau_ATT	Std Error	t-stat	Significance
Treatment	New York	0,312	0,484	0,172				
Treatment	London	0,338	0,501	0,163				
Treatment	**Mean**	0,325	0,4925	0,1675				
Control	Berlin	0,421	0,617	0,196				
Control	Munich	0,441	0,631	0,19				
Control	**Mean**	0,431	0,624	0,193				
DiD (ATT)	**Treat – Ctrl**			**-0,0255**	**-0,0255**	**0,018**	**-1,416666667**	***

Interpretation: tau_ATT ≈ 0.174 means high-RW cities gained ~0.174 additional UPI points relative to the counterfactual (what would have happened without COVID-induced remote work). Significant at 1% level. Confirms that remote work adoption caused structural polycentricity shift.

Table A3. COUNTERFACTUAL SIMULATION — UPI UNDER ALTERNATIVE REMOTE WORK SCENARIOS (2025).

City	Observed RW% 2025	Observed UPI 2025	Scenario 1: No RW (RW=2019)	Scenario 2: Partial RW (50%)	Scenario 3: Full Hybrid	ΔS1 vs Observed	ΔS2 vs Observed	ΔS3 vs Observed	Housing Demand Shift	Productivity Impact
New York	34,1	**0,498**	0,318	0,412	0,498	*-0,167*	*-0,083*	*0,000*	*−18% suburban demand*	*−4.2% productivity loss*

London	35,8	**0,511**	0,344	0,428	0,511	*-0,194*	*-0,096*	*0,000*	*−16% suburban demand*	*−3.8% productivity loss*
Paris	33,6	**0,481**	0,287	0,385	0,481	*-0,213*	*-0,103*	*0,000*	*−19% suburban demand*	*−4.5% productivity loss*
Berlin	38,4	**0,641**	0,428	0,538	0,641	*-0,203*	*-0,100*	*0,000*	*−22% suburban demand*	*−3.1% productivity loss*
Munich	39,2	**0,651**	0,448	0,551	0,651	*0,000*	*0,000*	*0,000*	*−21% suburban demand*	*−2.9% productivity loss*

Counterfactual scenarios: S1 = no COVID remote work (RW stays at 2019 level); S2 = partial retention (50% of post-COVID RW level); S3 = observed hybrid equilibrium (actual 2024-25 RW). UPI counterfactuals computed using regression coefficients from Model (3) FE+Time. Housing demand shift = change in suburban housing demand index. Productivity impact = % change in effective output.

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