Metropolitan Futures Initiative (MFI) Quarterly Report:

Understanding Business Churning Dynamics and their Spatial Variation

Presented by the Metropolitan Futures Initiative (MFI)
School of Social Ecology
University of California, Irvine

UCI School of Social Ecology

Understanding Business Churning Dynamics and their Spatial Variation

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About the Metropolitan Futures Initiative (MFI)

The Metropolitan Futures Initiative (MFI) in the School of Social Ecology at the University of California, Irvine aims to develop an improved understanding of communities and their potential for integrative and collaborative planning and action to ensure a bright future for the region. It approaches these goals by bringing together an interdisciplinary research team along with the insights and techniques of "big data" research.

By combining various large longitudinal and spatial data sources, and then employing cutting edge statistical analyses, the goal is to come to a better understanding of how the various dimensions of the social ecology of a region move together to produce the outcomes observed within our neighborhoods.

With initial focus on Orange County and its location within the larger Southern California area, The Metropolitan Futures Initiative is a commitment to build communities that are economically vibrant, environmentally sustainable, and socially just by partnering the School of Social Ecology's world class, boundary-crossing scholarship with expertise throughout Southern California.

The *MFI Quarterly Report* series presents cutting edge research focusing on different dimensions of the Southern California region, and the consequences for neighborhoods in the region. Reports released each quarter focus on issues of interest to the public as well as policymakers in the region. In addition, the MFI webpage (mfi.soceco.uci.edu) provides interactive mapping applications that allow policymakers and the public to explore more deeply the data from each Quarterly Report.

The MFI gratefully acknowledges the Heritage Fields El Toro, LLC for their funding support.

The MFI Research Team:

John R. Hipp is the Director of the Metropolitan Futures Initiative (MFI). He is a professor in the Department of Criminology, Law and Society, the Department of Policy, Planning, and Design, and the Department of Sociology, at the University of California Irvine. He is also co-director of the Irvine Lab for the Study of Space and Crime (ILSSC). His research interests focus on how neighborhoods change over time, how that change both affects and is affected by neighborhood crime, and the role networks and institutions play in that change. He approaches these questions using quantitative methods as well as social network analysis.

Jae Hong Kim is a member of the MFI Executive Committee and a faculty member in the Department of Planning, Policy, and Design at the University of California, Irvine. His research focuses on urban economic development, land use change, and the nexus between these two critical processes. His academic interests also lie in institutional environments — how institutional environments shape urban development processes — and urban system modeling. His scholarship attempts to advance our knowledge about the complex mechanisms of contemporary urban development and to develop innovative urban planning strategies/tools for both academics and practitioners.

Kevin Kane is a postdoctoral research fellow in the Department of Planning, Policy and Design at the University of California, Irvine. He is an economic geographer interested in the quantitative spatial analysis of urban land-use change and urban development patterns, municipal governance, institutions, and economic development. His research uses land change as an outcome measure – in the form of changes to the built environment, shifting patterns of employment, or the socioeconomic composition of places – and links these to drivers of change including policy, structural economic shifts, or preferences for how we use and travel across urban space.

Young-An Kim is a Ph.D. student in the department of Criminology, Law and Society, at the University of California, Irvine. His research interests focus on crime patterns at micro places, effects of structural characteristics of street segments on crime, and immigration and crime. Besides criminology, he is interested in sociology of health, urban sociology, and quantitative research methods.

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Results in Brief

- In general, total figures for employment growth and decline in any region mask substantial changes to the economic landscape that take place at finer spatial scales: what we term as **business churning**.
- We find that business churning varies substantially across locations within the Southern California metropolitan area, given spatial variation in industrial composition, business climate, and other socio-economic factors.
- In this Report, inter-sectoral churning – the degree of job reallocation across industrial sectors – is higher in suburban counties (e.g., Imperial and Riverside), but establishment churning – the rate of births and deaths of business establishments overall – does not show such a clear difference between core and periphery parts of the region.
- Business churning at the neighborhood level appears to be related to neighborhood residential stability and some other attributes, but in a complex fashion.
- When census tracts are systematically classified by their business establishment and socio-demographic characteristics, two distinctly different low-churn typologies emerge which cover about 60% of Southern California:
    - » Tracts with lower resident incomes, a low percentage of White population, high levels of retail and accommodation and food services, and fewer establishments overall.
    - » Tracts with higher incomes, a high percentage of White population, a small proportion of manufacturing activities, and a larger number of establishments per tract.
- Higher-churning tracts, which cover approximately 25% of the region, also fall into two distinct categories:
    - » Tracts with higher incomes, a high percentage of White population, more knowledge intensive service sectors, and high educational attainment.
    - » Tracts with lower incomes, a high proportion of retail, and low residential stability.
- Overall, business churning is weakly associated with growth in employment, median home values, and median household income. **However**,
    - » A more spatially-explicit investigation (using geographically-weighted regression techniques) finds notable exceptions to this trend across Southern California.
    - » Areas on the region's far fringes have a positive relationship between churn and job growth, while in the heavily populated coastal portion of Los Angeles county, churn is associated with employment decline.
    - » Churn near the large employment centers of Irvine and West Los Angeles tends to have a positive impact on home values, though churn has a negative effect on home value growth in South Central and East L.A.

Understanding Business Churning Dynamics and their Spatial Variation

The economic dynamism of any region relies in large part on the presence of jobs, and the generation of new jobs. For this reason, some analyses focus on net changes in the aggregate number of jobs or establishments in a region. Although such information is important, it does not enable us to fully understand the complexity of underlying economic dynamics. Real transformation of our economy takes place at a much more dramatic rate than perceived. For instance, in the United States in 2013, approximately 600,000 business establishments ceased their operations, while 678,000 new ones emerged.[1] Furthermore, frequent job turnovers often occur in the existing businesses.

Understanding this dynamic process – often called **churning** – is crucial, as it is likely to be associated with our economic well-being and societal changes. Does churning indicate "creative destruction" needed for productivity growth and a process toward a more efficient allocation of labor in our economy, as suggested by some economists?[2] Or, alternatively, does it lead to unexpected, negative consequences? In short, how does churning take place within our metropolitan region?

In this Report, we look into business churning by analyzing both births and deaths of establishments and jobs as opposed to simple net changes in order to reveal the full dynamics of the contemporary economic landscape. A business establishment is an individual location where business takes place.

The Report takes the following form. First, we describe the macro patterns of business churning across the entire Southern California region. Then, we visually show how this establishment churning plays out at the neighborhood-level across the region. Next we spatially explore the extent to which churning in neighborhoods is similar to the churning occurring in nearby neighborhoods and present maps showing this pattern across the region. We then use a novel, model-based clustering technique which allows us to characterize the types of establishment churning observed across the southern California region into six broad categories. The final part of this report uses spatial statistical analyses to describe the ways churning is related to three measures of neighborhood economic vibrancy: job growth, income growth, and home value growth. Our analysis shows how business churning has different implications for neighborhoods across different parts of the region.

Churning in the Seven-County Southern California Region

Churning can be measured in various ways and a metric which has often been used in the literature is job turnover rates – i.e., what percentage of the total jobs in an economy is separated from an existing worker or given to a new person. The US Census Bureau provides such a job turnover information for the nation, states, and counties, via its Longitudinal Employer-Household Dynamics (LEHD) program. More specifically, the turnover rates for each quarter are "calculated by summing the number of stable hires in the reference quarter and stable separations in the next quarter, and dividing by the average full-quarter employment." (See Technical Appendix 1.A for details.)

Figure 1 demonstrates the trend of yearly turnover rates (i.e., the average of the rates for four quarters in each year calculated based on the census' quarterly rates) for seven Southern California counties and the State of California. Overall, economic churning in this sense has been dampened during the first decade of the twenty-first century. However, a substantial degree of inter-county variation exists; suburban (or smaller) counties have exhibited a relatively higher rate of job turnover than Los Angeles. It also needs to be noted that the turnover rates tend to be higher in the first quarter than other time periods, although not demonstrated in Figure 1. A higher degree of seasonal fluctuation is detected in Imperial County.

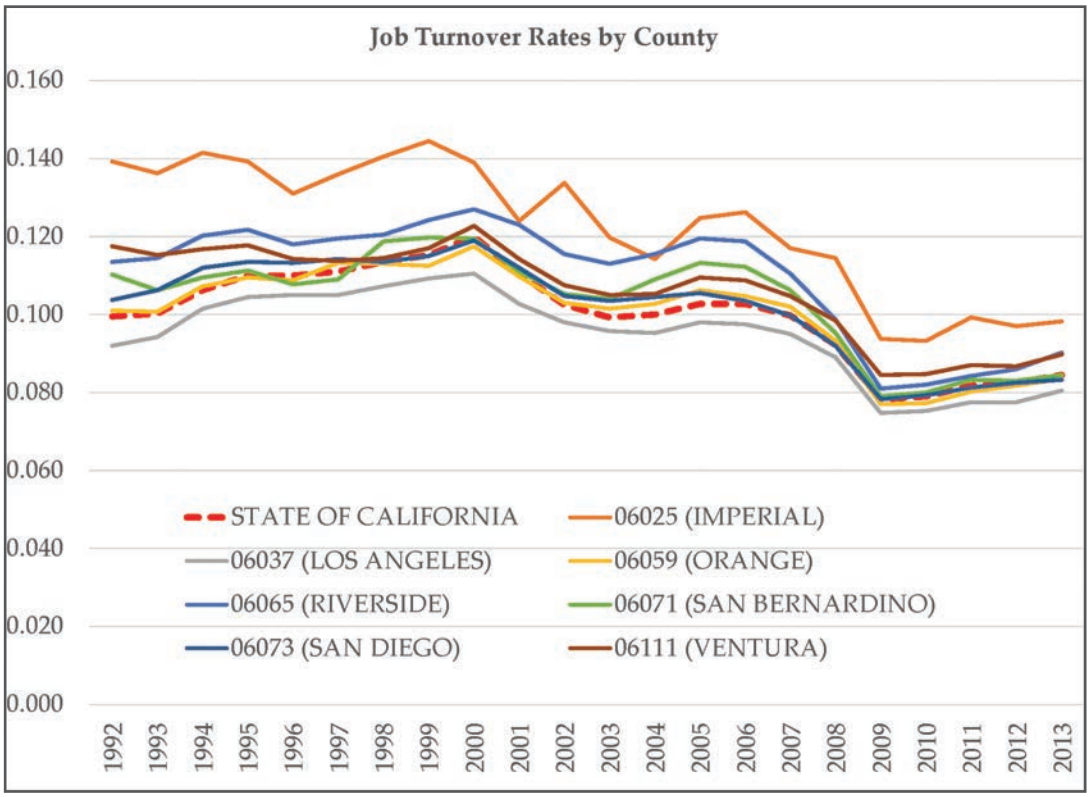


Figure 1: Job Turnover Rates by County

Recent studies1 have also measured "industry churning" by quantifying the degree of job reallocation across industrial sectors, as opposed to simple job turnover rates. In this report, using the data from the US Bureau of Economic Analysis (BEA), we calculate such an industrial churning index for seven counties and present the results in Figure 2 and Table 1. First we divide the economy into 20 sectors representing 2-digit codes from the North American Industry Classification System (NAICS). We then calculate the index which aggregates the amount of year-over-year employment changes across these economic sectors (see Technical Appendix 1.B). For example, a county with an increase in retail jobs but a decrease in manufacturing jobs would have a positive value for churning – even if its total employment number remained the same. When this new metric is used, churning (2001-2013) is lowest in San Diego County and highest in Imperial County, similarly showing the highest level of churning in terms of job turnover rates.

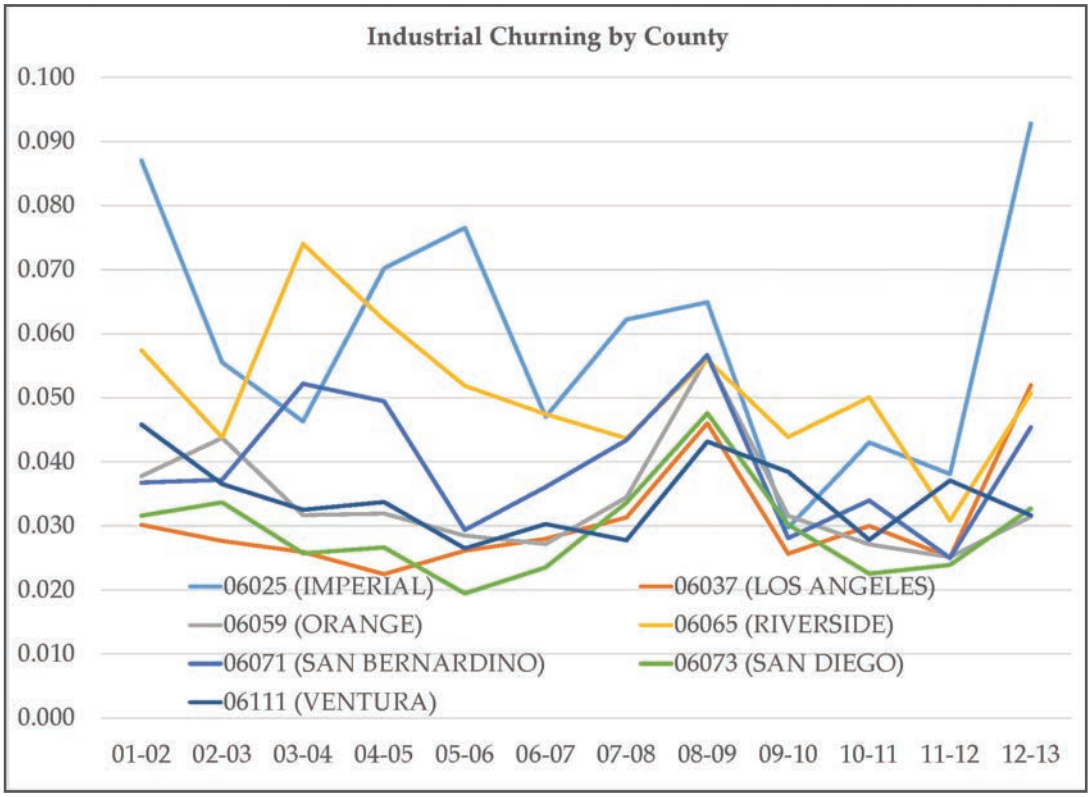


Figure 2: Industrial Churning by County

County	Mean (Ind. Churn.01-13)	Variance (Ind. Churn.01-13)	Total Emp. Growth Rates, 2001-2013
Imperial	0.059	0.00039	30.20%
Los Angeles	0.031	0.00008	9.20%
Orange	0.034	0.00008	9.40%
Riverside	0.051	0.00012	33.10%
San Bernardino	0.039	0.0001	22.40%
San Diego	0.029	0.00006	12.30%
Ventura	0.034	0.00004	9.70%

Table 1: Industrial Churning by County

Using the Reference USA point-based establishment data[4], we analyze how individual business establishments open and close at the county level. Here, business churning is calculated by adding the number of new establishments that opened in a year to the number that closed during that year and dividing by the total number of businesses (see Technical Appendix 1.C). While Imperial County showed a high degree of industrial churning, its business dynamics at the establishment level turned out to be relatively stable. Overall, county-level churn by business establishment is not as clear as job turnover and industrial sector-based churning (Table 2 and Figure 3).

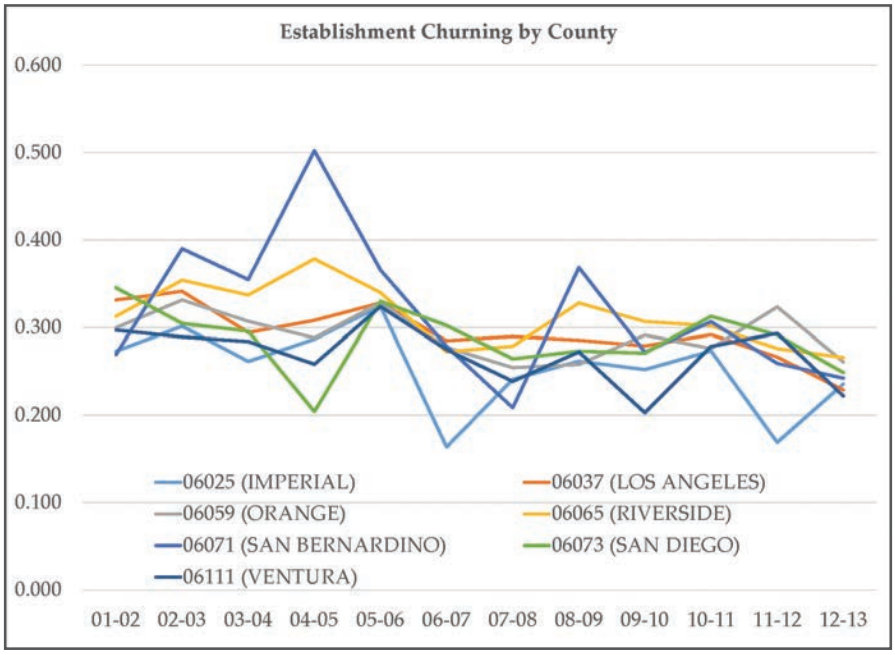
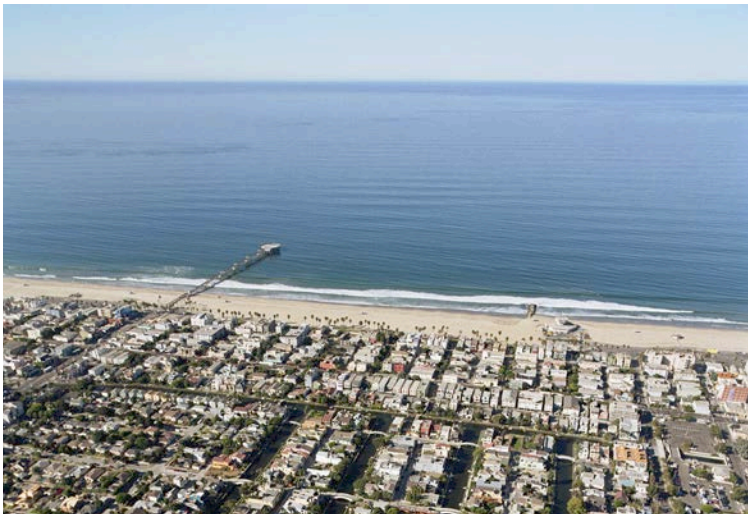


Figure 3: Establishment Churning by County

County	Mean (Ind. Churn.01-13)	Variance (Ind. Churn.01-13)	Total Emp. Growth Rates, 2001-2013
Imperial	0.254	0.133	0.12
Los Angeles	0.294	0.155	0.139
Orange	0.291	0.158	0.134
Riverside	0.313	0.174	0.138
San Bernardino	0.318	0.174	0.144
San Diego	0.287	0.155	0.132
Ventura	0.27	0.147	0.122

Table 2: Industrial Churning by County

Business Churning by Census Tract



In order to analyze the more-detailed spatial distribution of churning, we again use Reference USA data from 1997-2014. A similar churning index is calculated for establishment-level churning, but at the census tract level instead of the county level. Census tracts were created by the U.S. Census Bureau, have an average population of about 4,000 persons, and are meant to serve as a proxy for "neighborhoods". Since many tracts do not have a high amount of business activity, we exclude census tracts with fewer than 100 establishments in 1997 and therefore focus on a total of 2,004 tracts in Southern California. The mean value for establishment churning by census tract is 0.352, with a standard deviation of 0.05015. A spatial depiction of churning levels can be seen in Figure 4.

In addition, we explore the extent to which tracts with similar values of churning cluster spatially using a technique known as LISA clustering[1] in Figure 5. Using LISA (Local Indicators of Spatial Autocorrelation), contiguous tracts are put into five groupings based on a test of statistical significance:

1. High-High: high churning tracts surrounded by other high churning tracts
2. Low-Low: low churning tracts surrounded by other low churning tracts
3. Low-High: low churning tracts surrounded by high churning tracts
4. High-Low: high churning tracts surrounded by low churning tracts
5. Tracts with no significant clustering

The results show that major areas with a geographical concentration of high churning tracts include a section of tracts stretching from LAX airport through Beverly Hills to downtown Los Angeles, Irvine, and Pomona/Montclair. These mirror some of the larger employment subcenters found in another Metropolitan Futures Initiative (MFI) Quarterly Report titled "Detecting Job Density Over Time." Notable clusters of low job churning include Ventura, the San Gabriel Valley, and the Palos Verdes peninsula.

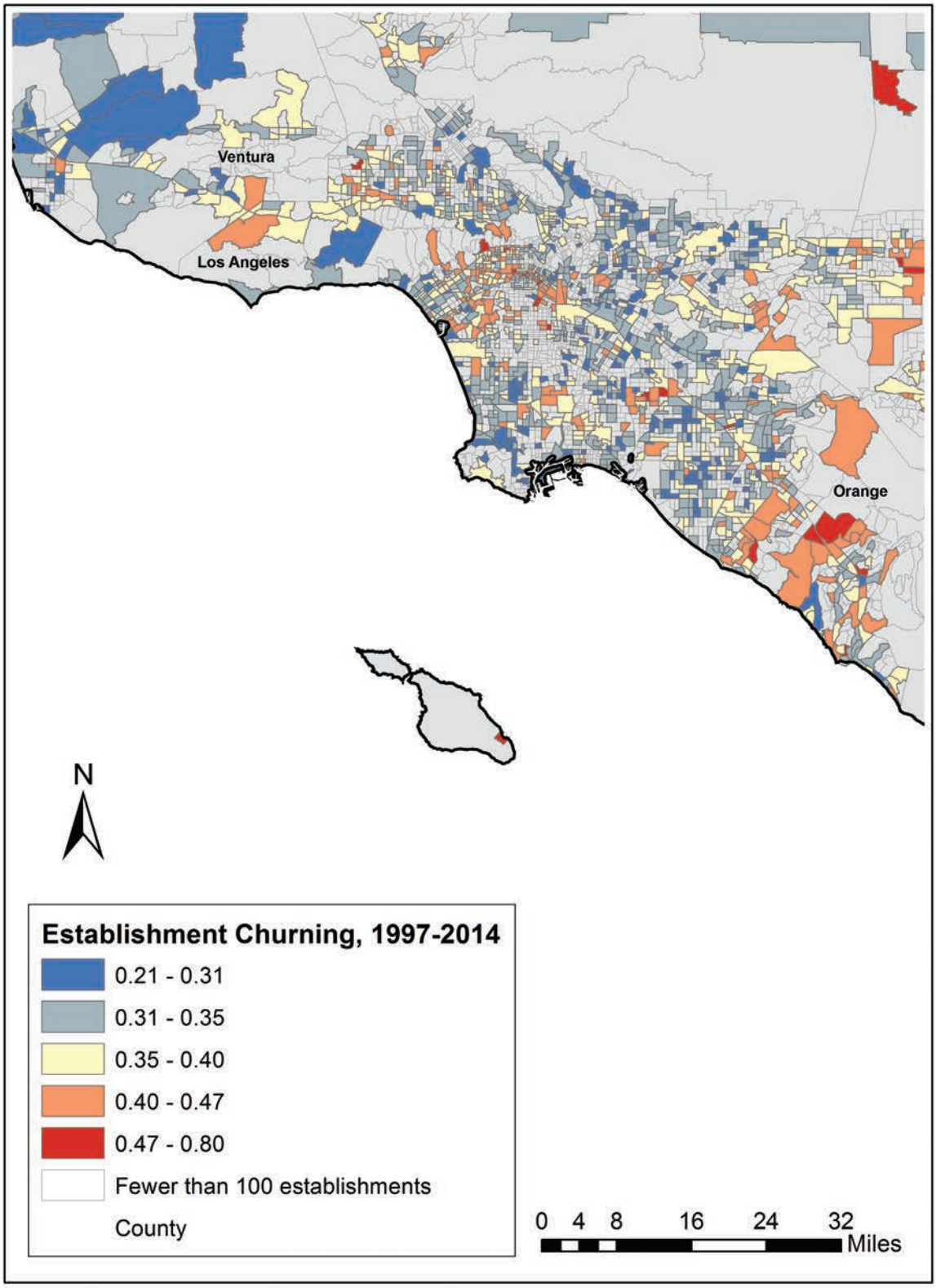


Figure 4: Business Establishment Churning by Census Tract, 1997-2014

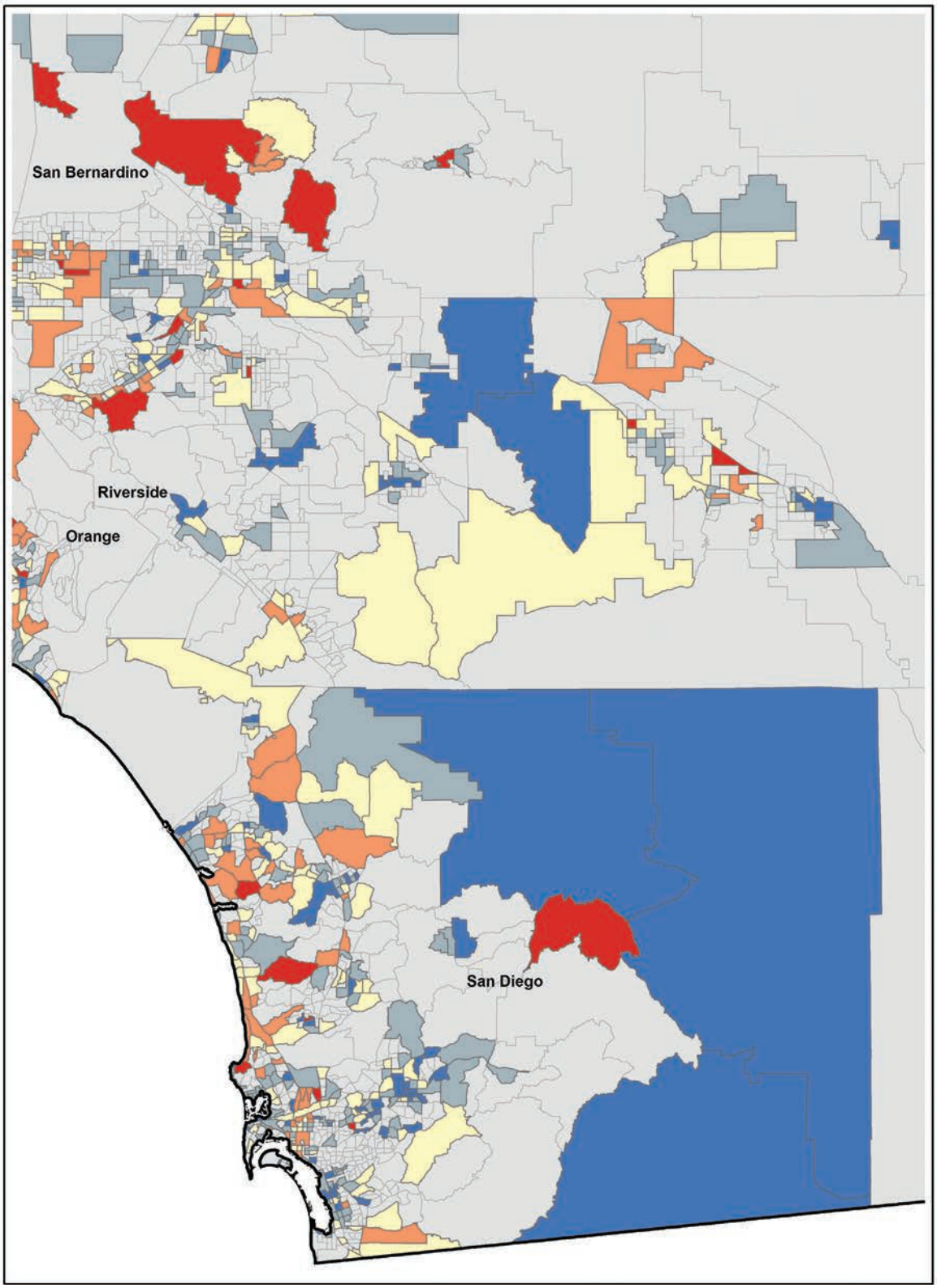


Figure 4: Business Establishment Churning by Census Tract, 1997-2014, Continued

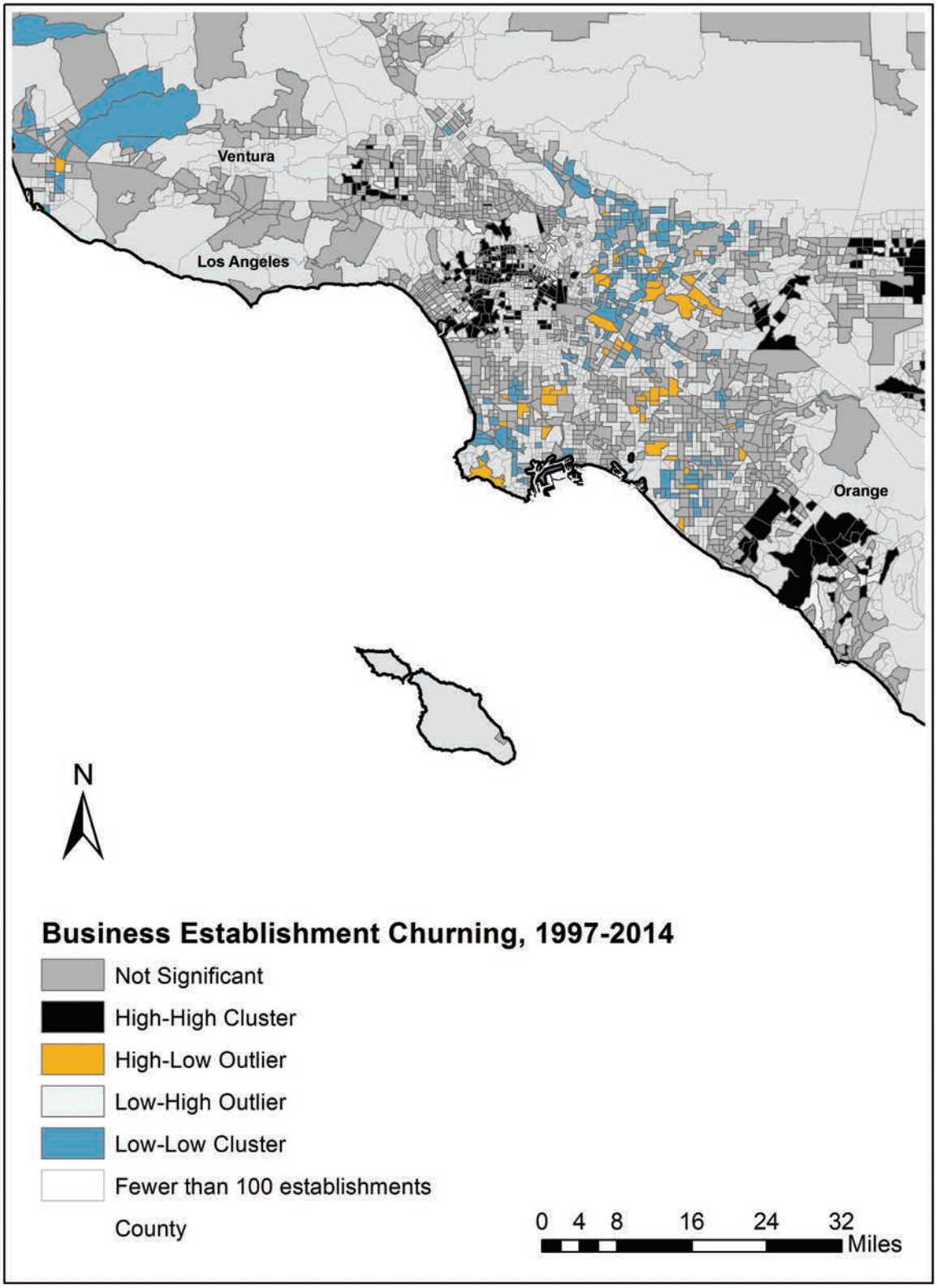


Figure 5: LISA (Spatial) Clustering of Churning Values

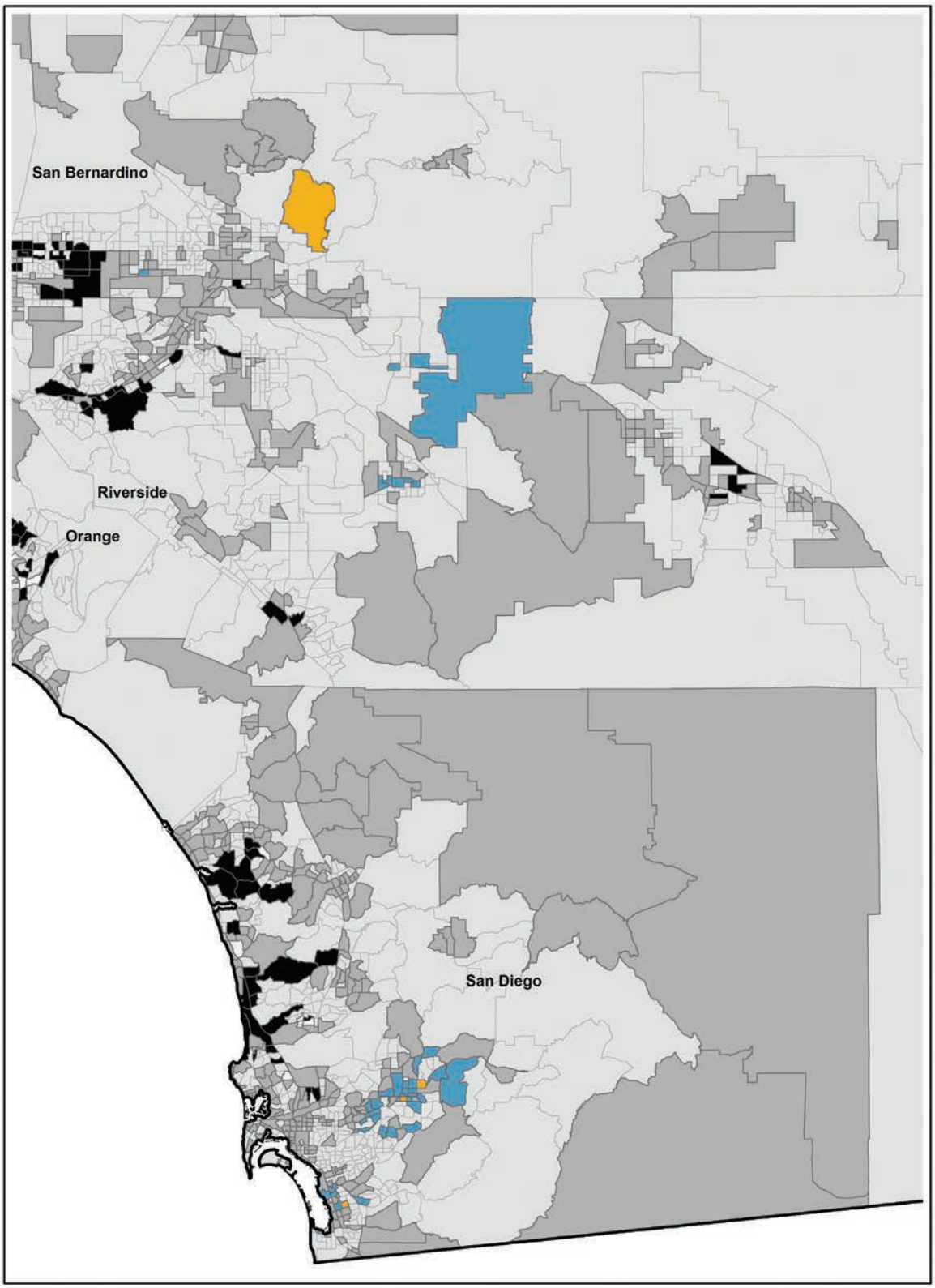
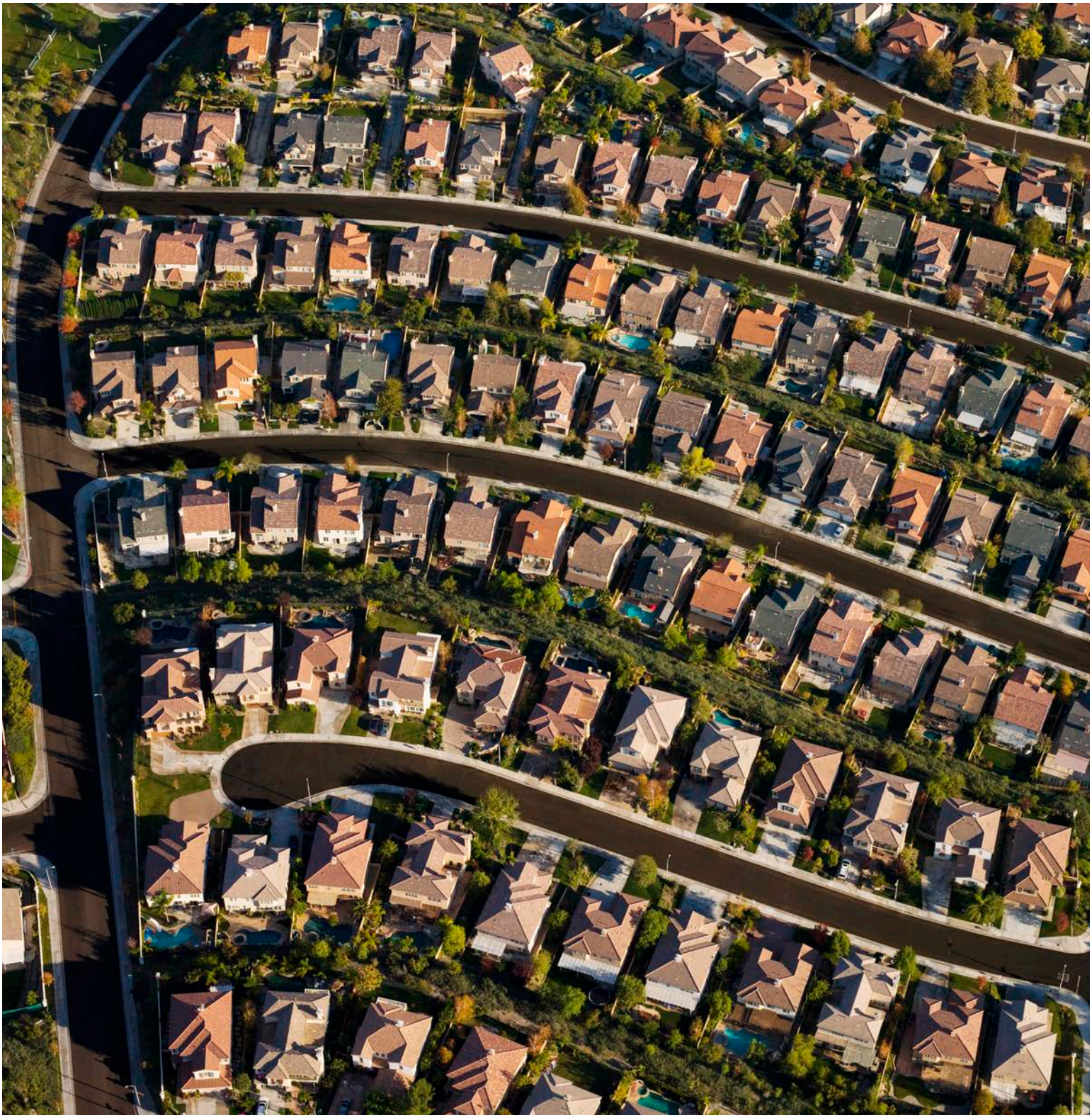


Figure 5: LISA (Spatial) Clustering of Churning Values, Continued



Neighborhoods Classified by Churning Patterns

In this section, we explore the extent to which we can categorize the patterns of establishment churning in various neighborhoods into a small number of categories. To do this, we used a number of key variables capturing establishment churning in neighborhoods and subjected them to a non-spatial statistical clustering procedure to determine which neighborhoods exhibited patterns that were similar to one another (See Technical Appendix 2 for a more detailed description). Neighborhood similarity was based on: 1) average annual establishment birth rates across the years of the study; 2) average annual establishment death rates across the years of the study; 3) average establishment growth rate in each year; 4) the variance in establishment growth rate across the years (that is, higher values will capture neighborhoods that experience large establishment number growth in some years, but no growth or net losses in other years; on the other hand, low values indicate neighborhoods in which the level of churning is relatively constant from year to year); 5) average number of establishments in the tract across the years; 6) percentage of establishments in knowledge intensive industries; 7) percentage of establishments in high technology industries; 8) percentage of establishments in creative economy industries; 9) percent of establishments in retail industries; 10) percentage of establishments in manufacturing industries; 11) percentage of establishments in accommodations and food industries. Therefore, the clustering routine groups neighborhoods that are most similar based on these 11 variables.

After performing the clustering analysis, we detected six distinct groups of neighborhoods, as explained below. Table 3 presents the summary statistics for these groups of neighborhoods, or what we refer to as "classes." The top part of the table shows the average value of these neighborhoods based on the 11 measures used in the clustering routine (Input Variables). The bottom part of the table (Other Variables) then displays some average values of demographic characteristics of the neighborhoods contained in each of these classes.

Again, we exclude census tracts with fewer than 100 establishments in the initial year, 1997, from this analysis. The data used for this section come from the Reference USA historical business dataset[6], the US Census Decennial Censuses and American Community Surveys, and parcel-level land use data files from the Southern California Association of Governments (SCAG)[7].

Descriptions continued on page 19

	Class 1	Class 2	Class 3	Class 4	Class 5	Class 6
Number of tracts	22 1.10%	629 31.39%	596 29.74%	288 14.37%	154 7.68%	315 15.72%
Input Variables						
Avg. Estab. Births	0.224	0.170	0.168	0.193	0.193	0.185
Avg. Estab. Deaths	0.207	0.159	0.158	0.177	0.172	0.172
Average Growth Rate	1.074	1.017	1.016	1.029	1.042	1.020
Variance - Growth Rate	0.210	0.005	0.007	0.017	0.033	0.007
Average # of Businesses	130.4	311.1	163	276.1	304.4	720.6
% Knowledge-based	15.9	21.4	14.5	25.5	14.9	19.7
% High Tech	0.9	0.8	0.8	1.3	0.6	1.7
% Creative Industry	3.1	1.3	1.4	2.2	1.3	1.1
% Retail	18.1	14.8	18.9	12	22.1	14.2
% Manufacturing	3.1	2.1	5.1	2.4	3.6	11.3
% Food/Lodging	13.7	6.6	7.9	6.1	6.5	3.8
Other Variables						
Jobs - Growth Rate	1.03	1.01	1.01	1.02	1.02	1.01
Residential Stability	-0.14	-0.09	-0.09	-0.20	-0.27	-0.11
% White	41.5	44.1	27.6	47.8	30.2	30.4
% Asian	11.0	14.7	12.1	13.2	15.0	13.6
% Black	1.7	4.5	7.1	5.4	6.1	5.1
% Latino	39.1	33.8	50.9	30.4	45.9	48.2
Racial/Ethnic Variation	41.51	50.89	47.18	52.04	50.50	49.32
% with Bachelor's	24.0	35.3	23.4	39.9	25.8	26.5
% with H.S. Diploma	74.4	83.6	73.2	86.1	75.3	75.2
Median Income (HH)	59,168	65,250	55,143	69,744	56,607	60,890
Poverty Rate	20.8	14.7	19.4	14.5	18.2	17.4
Unemployment Rate	10.7	10.7	12.7	10.7	11.9	11.4
Population Density	6,586	9,092	10,802	9,989	11,300	5,758
% of Homes Occupied	77.3	92.5	93.2	90.7	91.5	93.4
% Owner-occupied	51.6	48.4	47.1	47.5	43.7	48.5
% Industrial Land	4.0	2.6	8.3	3.6	7.5	26.2
% Office Land	1.7	5.0	3.4	7.2	5.2	7.6
% Retail Land	11.9	10.7	10.5	8.4	14.9	10.3
% Vacant Land	29.5	6.3	7.0	10.4	9.5	5.5
Establishment Churning	**Highest**	**Low**	**Low**	**Relatively High**	**Relatively High**	**Middle**

Table 3: Neighborhood Classifications

Neighborhoods Classified by Churning Patterns Continued

Class #1: This class of neighborhoods is characterized as a small number of high growth (and high churning) tracts with a high housing vacancy and poverty, while the unemployment rates are generally low. In terms of industrial composition, they have high percentages of creative industries and accommodation & food services. It needs to be stressed that this class exhibits a relatively short average length of residence, despite the high home owner percentage. This is the smallest class, describing only 22 neighborhoods. Many of these neighborhoods are located near universities (e.g., USC, UCI, UCSD) or tourist destinations (e.g., Disneyland).

Class #2: This low-churn class of neighborhoods is characterized by a large number of stable tracts (629 tracts, accounting for approximately 30% of all tracts analyzed) with a low poverty rate, high housing occupancy, and a relatively longer length of residence. Compared with other tracts, these neighborhoods have a lower percentage of manufacturing. Location-wise, they are quite dispersed rather than being concentrated in a specific county.

Class #3: This low-churn class of neighborhoods is characterized as another group of stable (and slowly growing) tracts, but having the lowest income level and a higher unemployment rate. A large percentage of the residents are Hispanic, and the share of retail and accommodation & food services tends to be large in these areas., Similar to Classes #2 and #6, this group shows a widespread pattern, although a considerable number of these neighborhoods are found in the central Southern part of Los Angeles County (e.g., Gardena, Walnut Park, South Gate, Bell) and inland San Diego.

Class #4: This high churning class of neighborhoods is characterized as tracts showing a modest growth rate. These tracts have the highest median household income, educational attainment, percentage of knowledge intensive service sectors, racial/ethnic heterogeneity, and percentage of White. This group's poverty rate is lower than that of any other classes. Small clusters of the census tracts are found around Hollywood, Redlands, and in northern San Diego County.

Class #5: This high churning class of neighborhoods is characterized as census tracts showing a modest growth rate with a high percentage of retail businesses and low residential stability. These neighborhoods also have high population density, a somewhat higher percent Asian, and a high percentage of renters, which may be associated with the relatively short length of residence in these areas. Neighborhoods in Artesia and Cerritos fall in this category.

Class #6: This medium-churn class of neighborhoods is characterized as census tracts with a high percentage of manufacturing (and industrial land and office buildings), and growing slowly. These neighborhoods have a much larger number of establishments compared to other neighborhoods, and a high percentage of high technology establishments. Although they have high housing occupancy rate, they have low population density. The class shows a widespread pattern of locational distribution, involving tracts in and around Commerce, Torrance, Vernon, Irvine (the northwestern part of the city and the Great Park area), San Marcos, and many other municipalities.

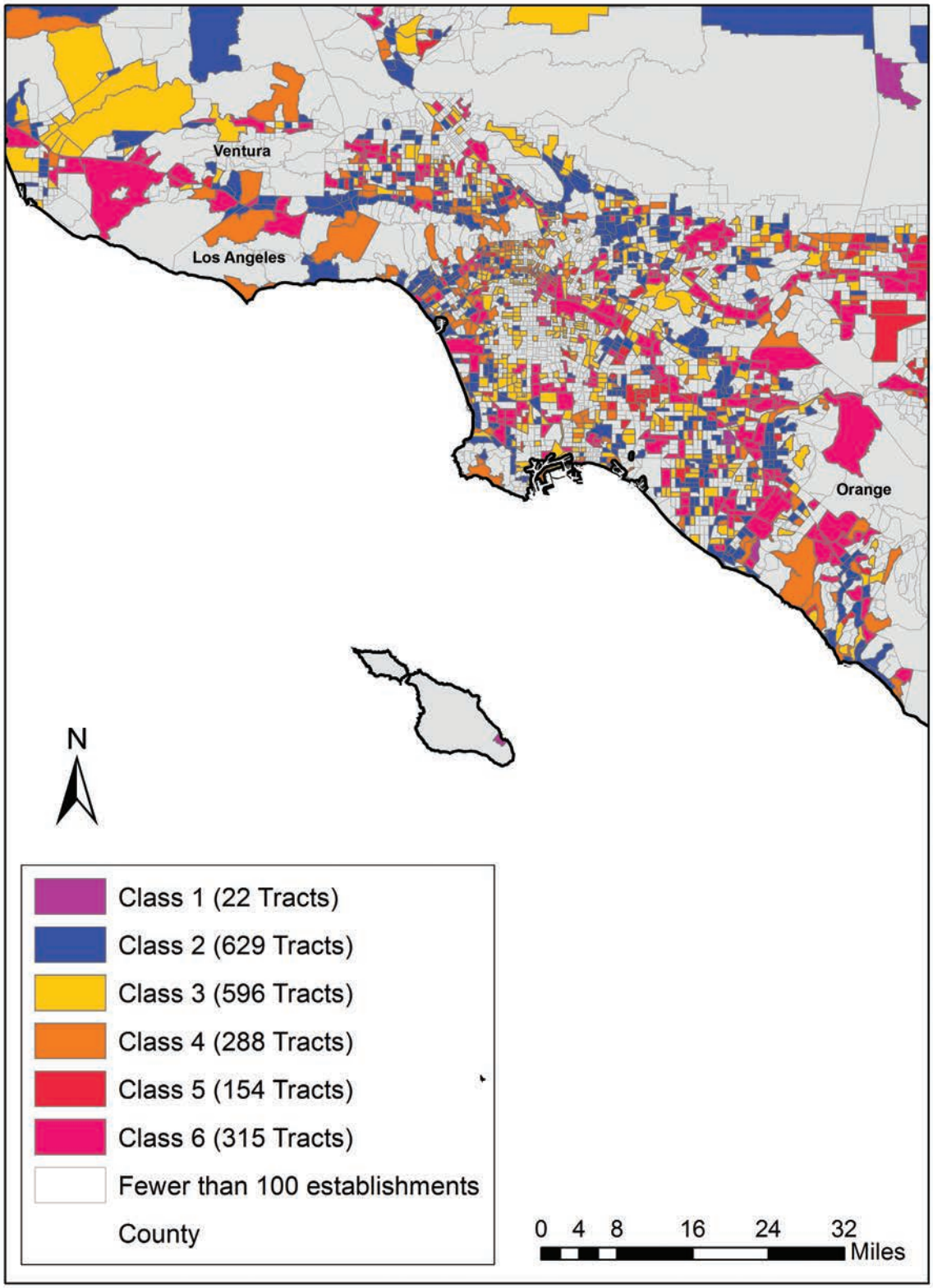


Figure 6: Tracts classified by churning patterns

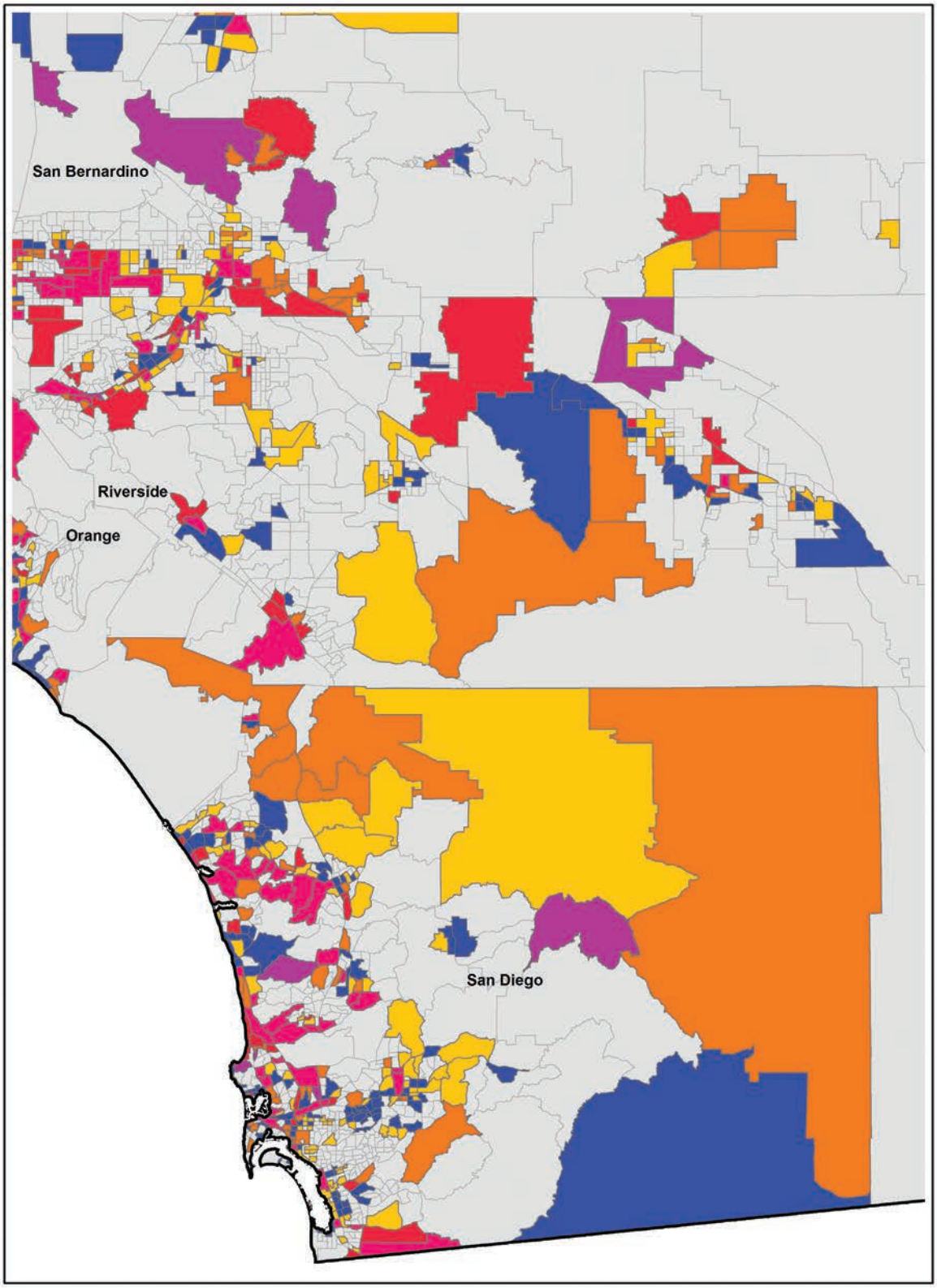


Figure 6: Tracts classified by churning patterns, continued

Thus, we see that the amount of establishment churning differs across the neighborhoods of the southern California region in systematic ways. Two distinctly different low churn typologies emerge which cover about 60% of the region: one characterized by generally lower incomes (Class #3) and one characterized by stability and low poverty (Class #2). Similarly, two distinctly different high churn typologies emerge which cover about 25% of the region: one characterized by high incomes and knowledge-intensive sectors (Class #4) and one characterized by retail and low residential stability (Class #5). These classes do not indicate that churning is altogether associated with positive or negative neighborhood characteristics; rather, high or low churning can be associated with either. Establishment churning may have positive impacts in some circumstances and negative impacts in others. The following section builds on this finding and analyzes the outcomes of churning more explicitly.

Spatial Analysis: Establishment Churn's Impact on Socioeconomic Indicators

Whereas the previous section of the Report explored the level of business churning across the neighborhoods of the region, in this section we compare business establishment churning from 2000-2012 to changes in socio-economic measures of neighborhood well-being over the same time period. We look at three measures of neighborhood well-being and how they changed over this period: 1) employment growth; 2) home value growth; 3) average income growth. These three measures capture dimensions of the economic environment that are of importance to residents in neighborhoods.

We perform two sets of analyses. In the first set of analyses, we explore the relationship between establishment churning and these three measures with the assumption that this relationship is the same across all neighborhoods in the region. For example, we find that business establishment churn in a tract has a reasonable positive relationship with that tract's employment growth rate over the same period ($r = 0.206$). However, we find much more modest relationships between establishment churning and same-neighborhood home value growth ($r = 0.043$) and its level of household income growth ($r = 0.086$).

The fairly weak relationship between job churn and the three socio-economic outcome measures may be due to the fact that the churn process does not impact these phenomena at the tract level specifically – the impact of churning in a neighborhood may be seen at a larger spatial scale. Therefore, our second set of analyses adopt an explicitly spatial statistical approach to take into account broader spatial trends: this approach is Geographically Weighted Regression (GWR). The details of these analyses are provided in Technical Appendix 3.

The Spatial Pattern of Churning and Job Growth

GWR uses an algorithm to optimally select the number of nearby tracts over which to observe an outcome. In our first model, we test the relationship between establishment churning in a tract and employment growth using the nearest 85 neighboring tracts. Directly adjacent tracts are weighted heavily, tracts farther away are weighted less, and tracts beyond the 85th-closest are not included in weighting at all.

This approach has a much better statistical fit and explains much more of the variance in the data, as our variance explained improves from 4.9% in the initial analyses to 38.4% in the GWR model. The map in Figure 7 demonstrates how dramatically the relationship varies across space1. While a one percent increase in churning will increase job growth by 3.7% percent on average, the impact of a one percent increase in churning varies from -13.4% to 31.7% percent across the region. Thus, in some neighborhoods higher levels of churning will result in less job growth (the negative coefficients), but in other neighborhoods higher levels of churning will result in more job growth (the positive coefficients). Thus, the importance of churning is very dependent on where it occurs.

Outlying portions of San Bernardino and Riverside Counties, south Orange County, and northern San Diego County have the strongest positive relationship between churning and employment growth. However, job churning is associated with employment decline in most of coastal Los Angeles County stretching from Malibu to the Palos Verdes Peninsula, as well as in the San Gabriel Valley and central Orange County (Irvine and Newport Beach). In these places, business establishment stability (as opposed to churn) is associated with job growth. Inland San Diego County, areas near Palm Springs, and other small pockets in Orange and Los Angeles Counties demonstrate a weakly positive relationship between churning and job growth – just a bit higher than the average relationship region-wide. Job growth in Anaheim, Burbank, Beverley Hills, and much of Ventura County has a weakly negative relationship with churning, while job growth in Ontario, Chula Vista, and Long Beach has a weakly positive relationship with churning, mirroring the average trend region-wide.

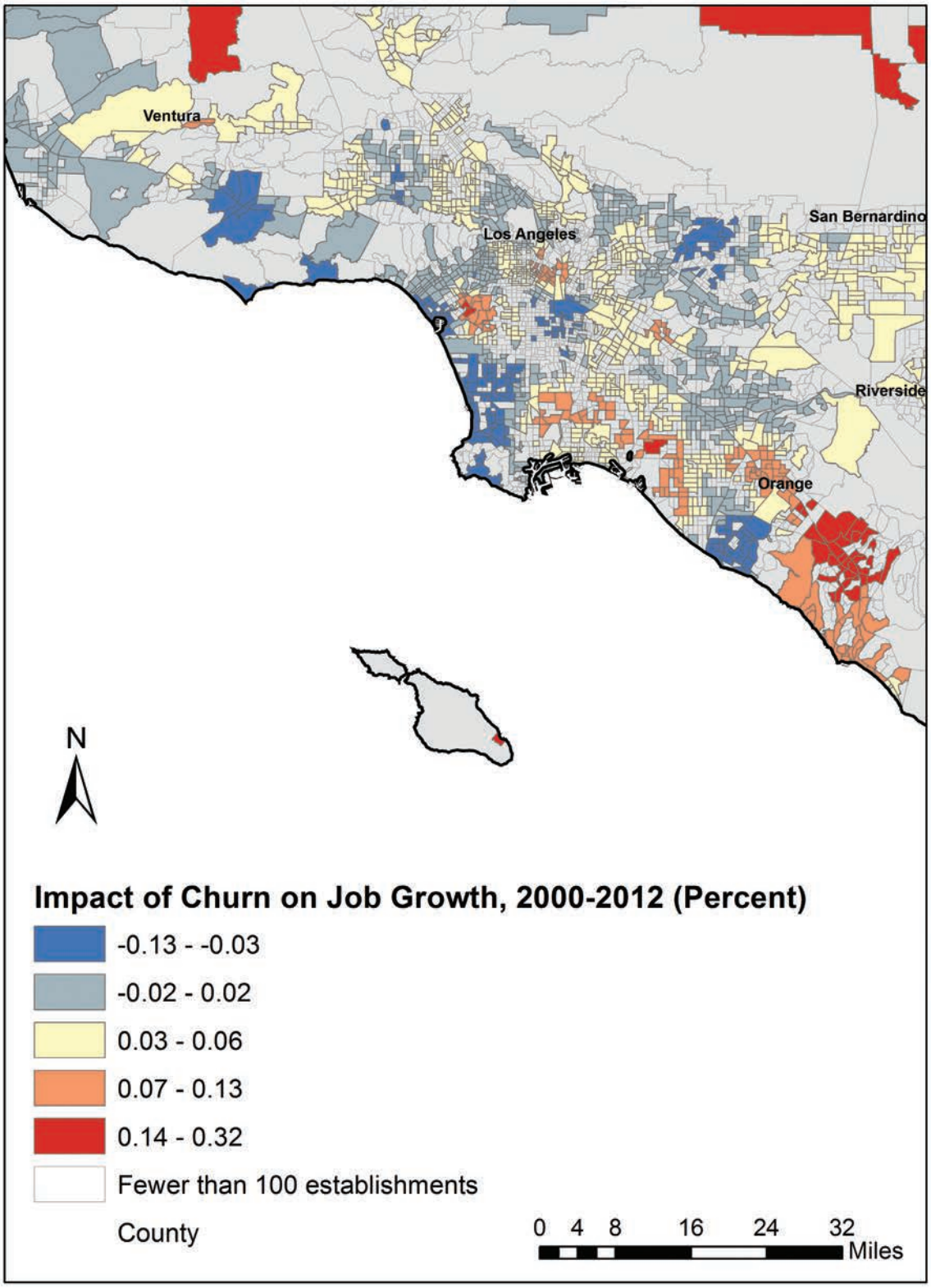


Figure 7: Geographically Weighted Regression Results (Job Growth)

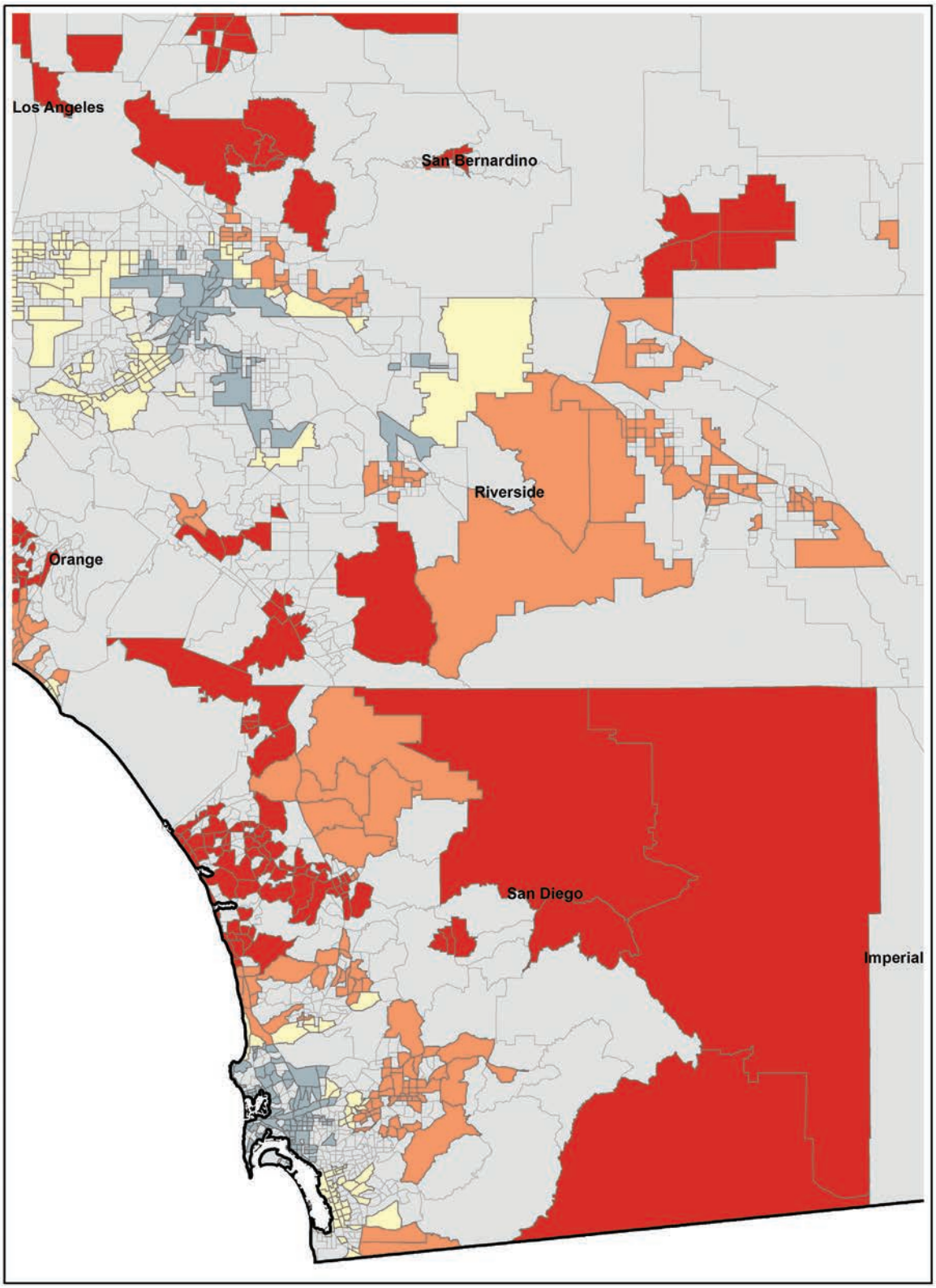


Figure 7: Geographically Weighted Regression Results (Job Growth)

The Spatial Pattern of Churning and Home Value Appreciation

Figure 8 examines the relationship between churning and median home value growth in a tract. On average, in a non-spatial analysis a one percent increase in churning will result in a 0.76 percent increase in home values (logged relationship). Our spatial analysis does a much better job explaining this relationship, as the variance explained increases from just 0.2% in the non-spatial analysis to 29.2% in the GWR analysis that takes into account an optimal 125 neighboring tracts. While on average a one percent increase in churn will increase home values by 0.76%, its impact in the GWR analysis varies from -21.8% to 25.7% percent over the region.

Palm Springs, Ontario, Buena Park, and the South Bay/Palos Verdes Peninsula are areas where job churn has the strongest positive relationship with neighborhood-level home value appreciation. Central Orange County (i.e. Irvine and Newport Beach), Beverley Hills, Long Beach, and the communities inland and to the north of San Diego (e.g. Carlsbad, El Cajon) also show a fairly strong positive relationship between job churning and home value growth. Contrastingly, South Orange County, Anaheim, the communities surrounding LAX Airport, the northern portion of San Diego City, and most of Ventura County show a strong negative relationship between churn and home value growth, i.e. job stability is associated with increases in home values. The average effect region-wide is a slightly positive relationship between job churn and home value growth. This average effect is exemplified by places like north Orange County, Lancaster, and the San Gabriel Valley.

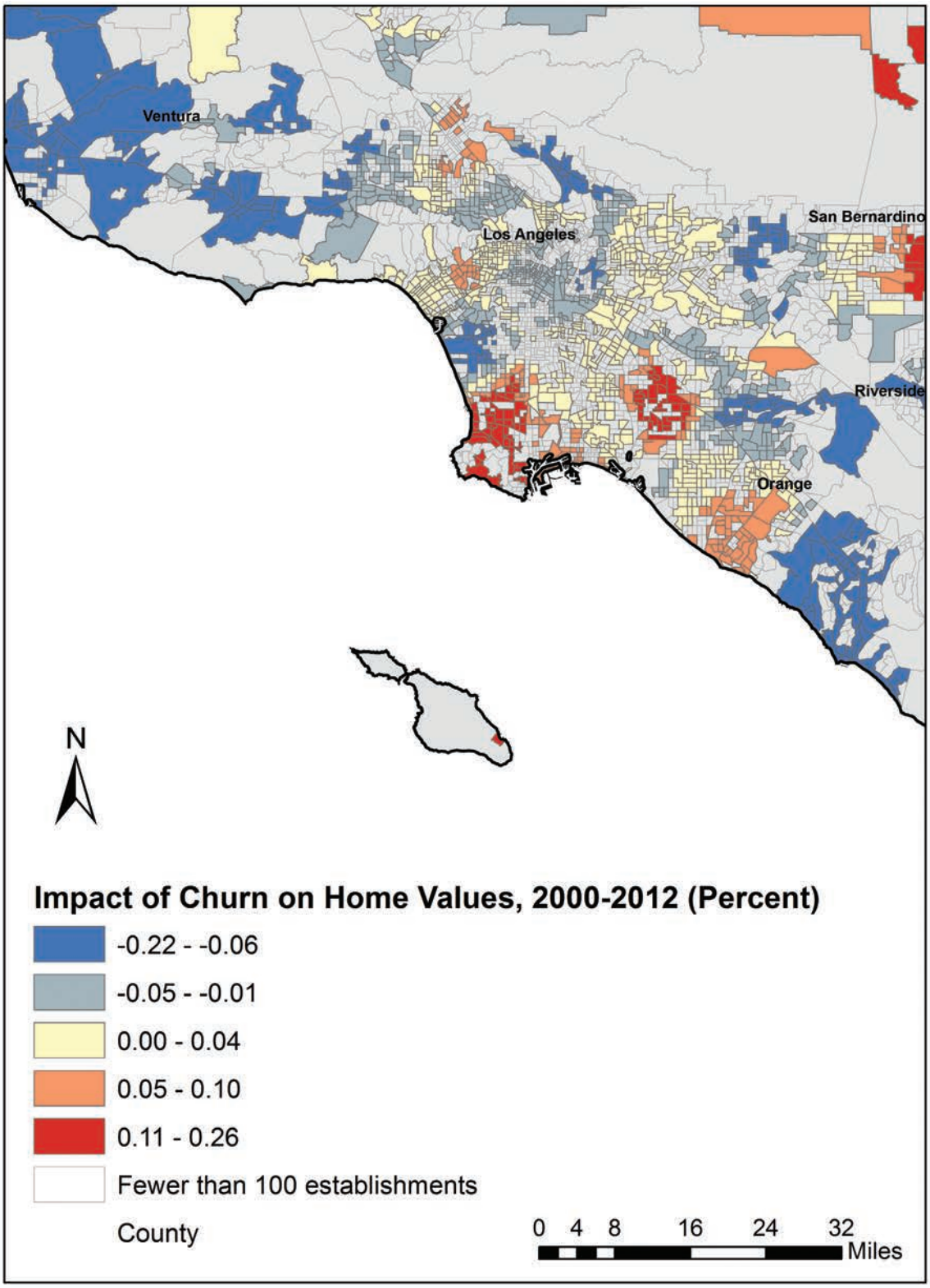


Figure 8: Geographically Weighted Regression Results (Home Values)

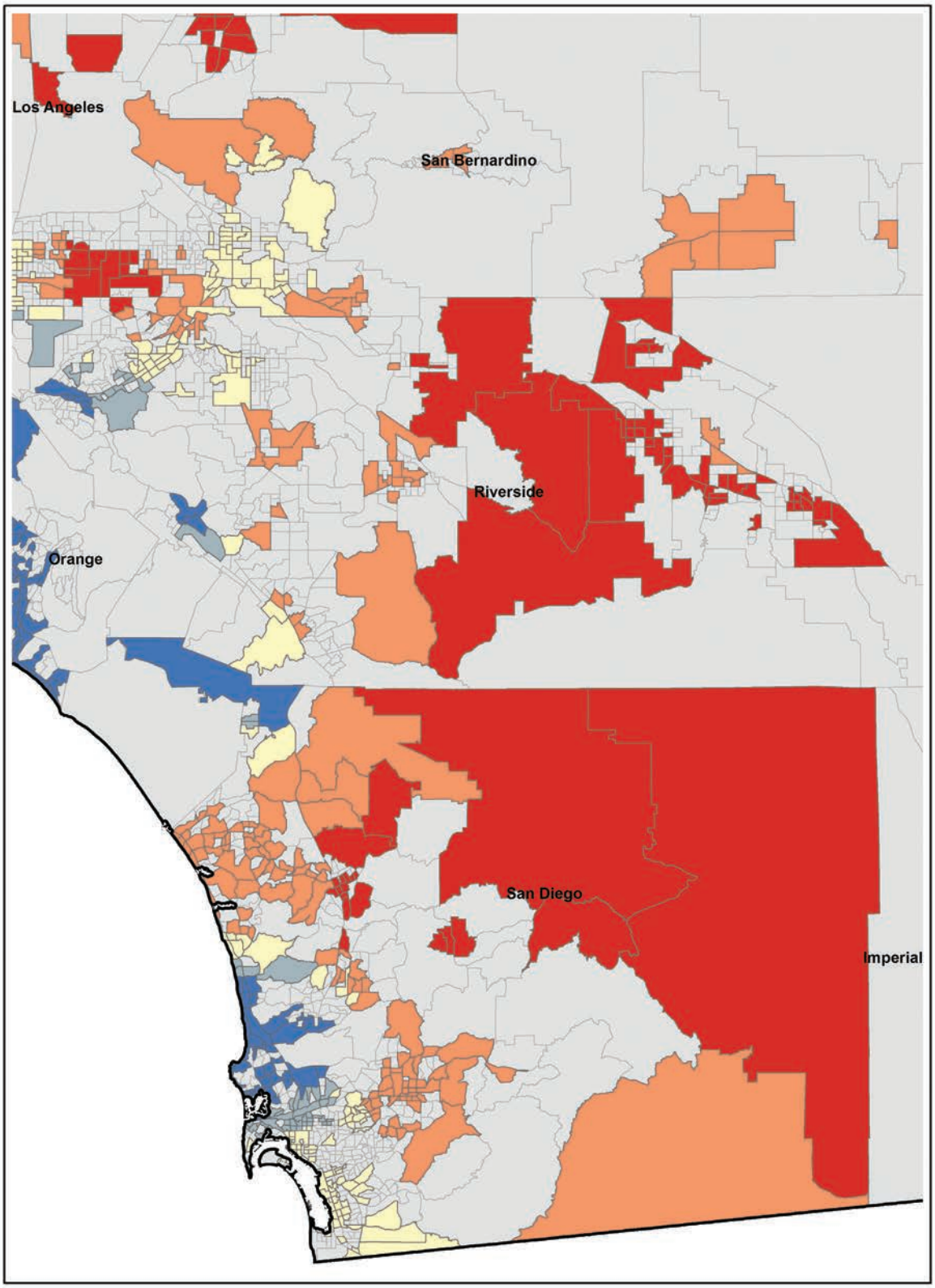


Figure 8: Geographically Weighted Regression Results (Home Values)

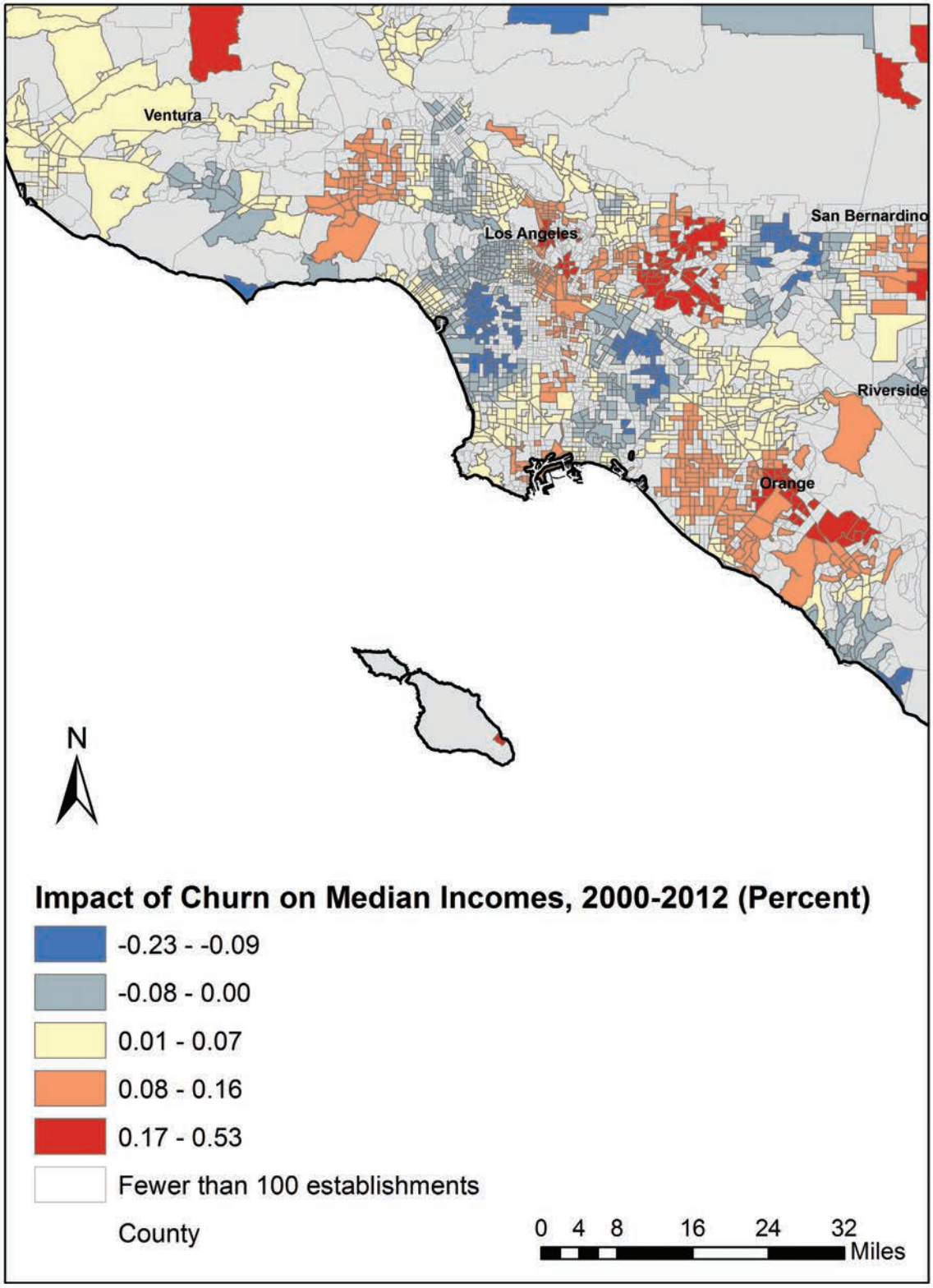


Figure 9: Geographically Weighted Regression Results (Income Growth)

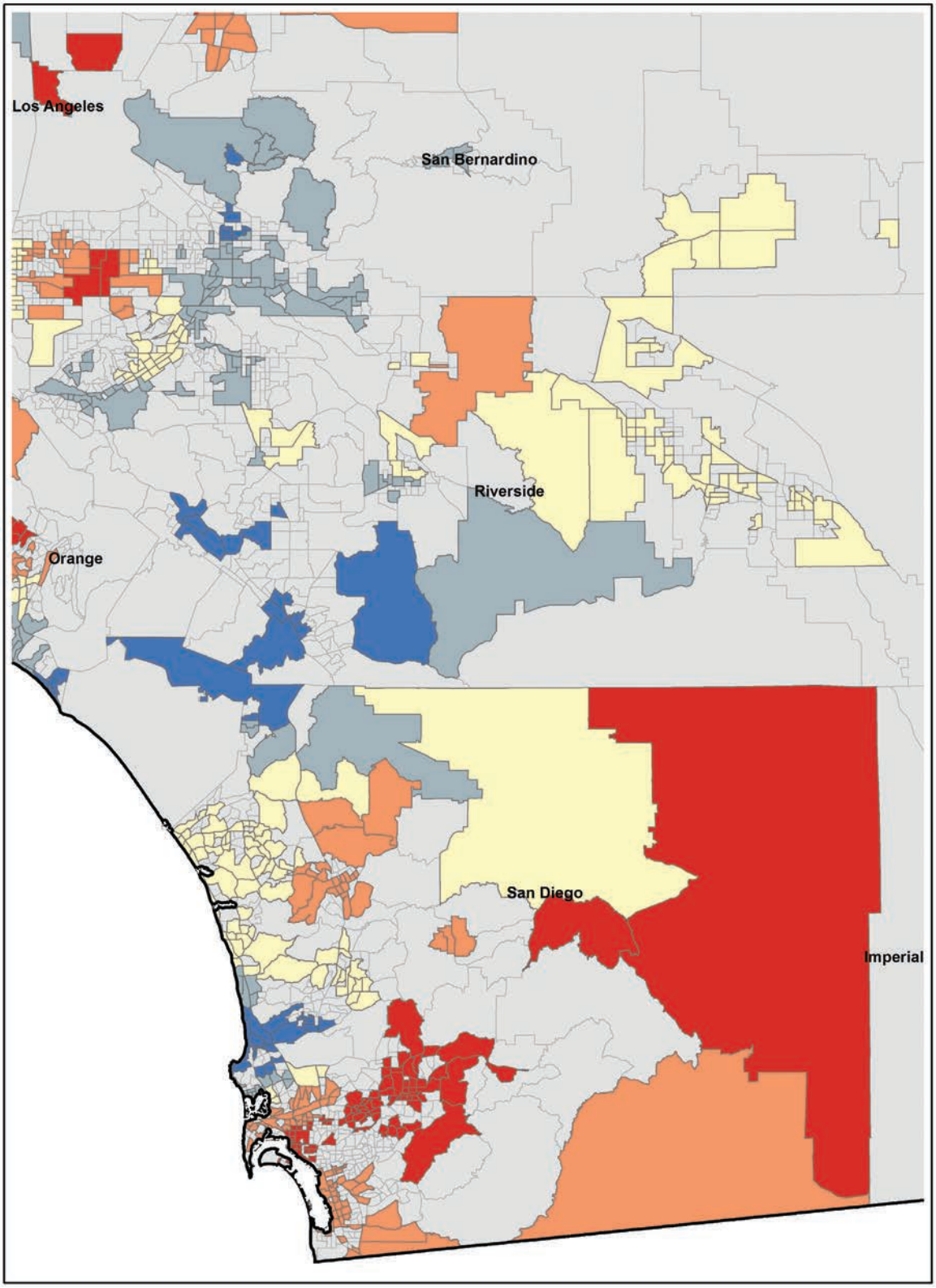


Figure 9: Geographically Weighted Regression Results (Income Growth)

The Spatial Pattern of Churning and Household Income Growth

Figure 9 examines the relationship between churning and growth in median household incomes, and how it varies spatially. On average, a one percent increase in churning will result in a 4.02% percent increase in household incomes. Our spatial model considerably improves the fit of the model, as the non-spatial model explains 1.6% of the variance in the relationship between establishment churning and average household income change, whereas the GWR explains fully 31% of the variance. The model detects that the impact of a one percent increase in churning on household income change varies from -22.5% to 53.5% percent over the region.

Areas where business establishment churning has the strongest positive impact on median household income growth include downtown San Diego and its inland suburbs and the San Gabriel Valley. Downtown Los Angeles, Orange County (north of Laguna Beach), Chula Vista, and the western portion of the San Fernando Valley all exhibit a fairly strong relationship between job churning and median household income growth. In contrast, the north side of the city of San Diego, San Dimas, and a stretch of tracts running from Culver City to Hawthorne show a strongly negative relationship; i.e. job stability is associated with median income growth. This is also the case – albeit not as strongly – for the heavily populated areas in Central and West Los Angeles and the South Bay beach communities. The weakly positive average relationship between job churning and household income growth is exhibited in places like Santa Monica, Anaheim, and most of Ventura County.

Conclusion

While the "creative destruction" behind churning is generally seen as a component of regional economic growth, its implications are rarely analyzed at the neighborhood level. In particular, the outcome of a churning process may mean job gains for some communities and job losses in others. Taking churning and other socioeconomic characteristics into account, it is clear that certain "classes" of tracts emerge. While relationships between churning and neighborhood well-being (measured by job growth, home value growth, and median income growth) appear weakly positive overall, there are dramatic differences across the region, including areas where churning has negative impacts.

Low churning areas fall into two major categories: those characterized by low resident incomes, or those which have stable, low-poverty residents. High churning areas come in a higher-income, knowledge-intensive employment variety as well as a lower-income class characterized by retail employment. High-churning areas characterized by high incomes and knowledge-intensive employment somewhat mirrors some of the region's large employment centers (see the July, 2016 Metropolitan Futures Initiative (MFI) Quarterly Report "Detecting Job Density Over Time"). A section of high-churn tracts stretching from LAX airport through Beverly Hills to downtown Los Angeles, Irvine, and Pomona – are particularly vibrant employment centers. However some areas like Irvine and coastal L.A. County actually demonstrate a negative relationship between churning and job growth.

Policymakers should be aware of this intra-regional variation. While this study does not imply causation (e.g. churning causes household incomes to grow or vice versa), the statistical analyses we perform are evocative of some patterns. Most importantly, local economic development plans should strive to be keenly aware not only of region-wide trends in job churning, but also how it might impact well-being in particular neighborhoods.

Notes

1. US Census Business Dynamics Statistics, http://www.census.gov/ces/dataproducts/bds/

2. See, e.g., Davis, Steven J., John Haltiwanger, and Ron Jarmin. "Young Businesses, Economic Churning, and Productivity Gains." *Kaufman Foundation Research Series: Turmoil and Growth. Kansas City, MO: Ewing Marion Kauffman Foundation* (2008). and Lazear, Edward P., and James R. Spletzer. *The United States labor market: Status quo or a new normal?*. No. w18386. National Bureau of Economic Research, (2012).

3. See e.g., Findeisen, S., & Suedekum, J. (2008). Industry churning and the evolution of cities: Evidence for Germany. Journal of Urban Economics, 64(2), 326-339.

4. Infogroup. (2015) Reference USA Historical Business Dataset. Papillon, NE.

5. Anselin, Luc. (1995). "Local indicators of spatial association—LISA." *Geographical Analysis* 27.2. 93-115.

6. Ibid. 4

7. SCAG. (2012). Existing Land Use. Retrieved from: http://gisdata.scag.ca.gov/

8. Note: a tract's (logged) total number of establishments is controlled for in these regressions

Technical Appendix 1: Churning Indicators

A. Job turnover rates

The US Census LEHD Quarterly Workforce Indicators (QWI) provides an indicator of job turnover for each quarter, as follows.

$$Quarterly\ job\ turover\ rate = \frac{Hires\ (Stable)\ + Seperations\ (Stable)}{2 \times Full\ Quarter\ Employment\ (Stable)}$$

Based on the quarterly statistics, we derived yearly turnover rates by calculating the average of the rates for four quarters in each year.

B. Industrial churning

As done in Findeisen and Suedekum (2008) and other studies, we measured industrial churning for each year increment, as follows.

$$Industrial\ Churning\ (t{\sim}t+1) = \sum_i \frac{|Employment\ (i,t+1) - Employment\ (i,t)|}{Total\ Employment\ (t)}$$

where t and i denote year (time) and industrial sector, respectively.

C. Establishment churning

Our establishment churning indicator is calculated for each county or census tract, as follows. The indicator is derived for each year increment (t~t+1) by counting establishment births and deaths during the year based on the Reference USA historical business dataset.

$$Establishment\ Churning\ (t{\sim}t+1) = \frac{|Est.Births\ (t{\sim}t+1)| + |Est.Deaths\ (t{\sim}t+1)|}{Total\ Number\ of\ Business\ Establishments\ (t)}$$

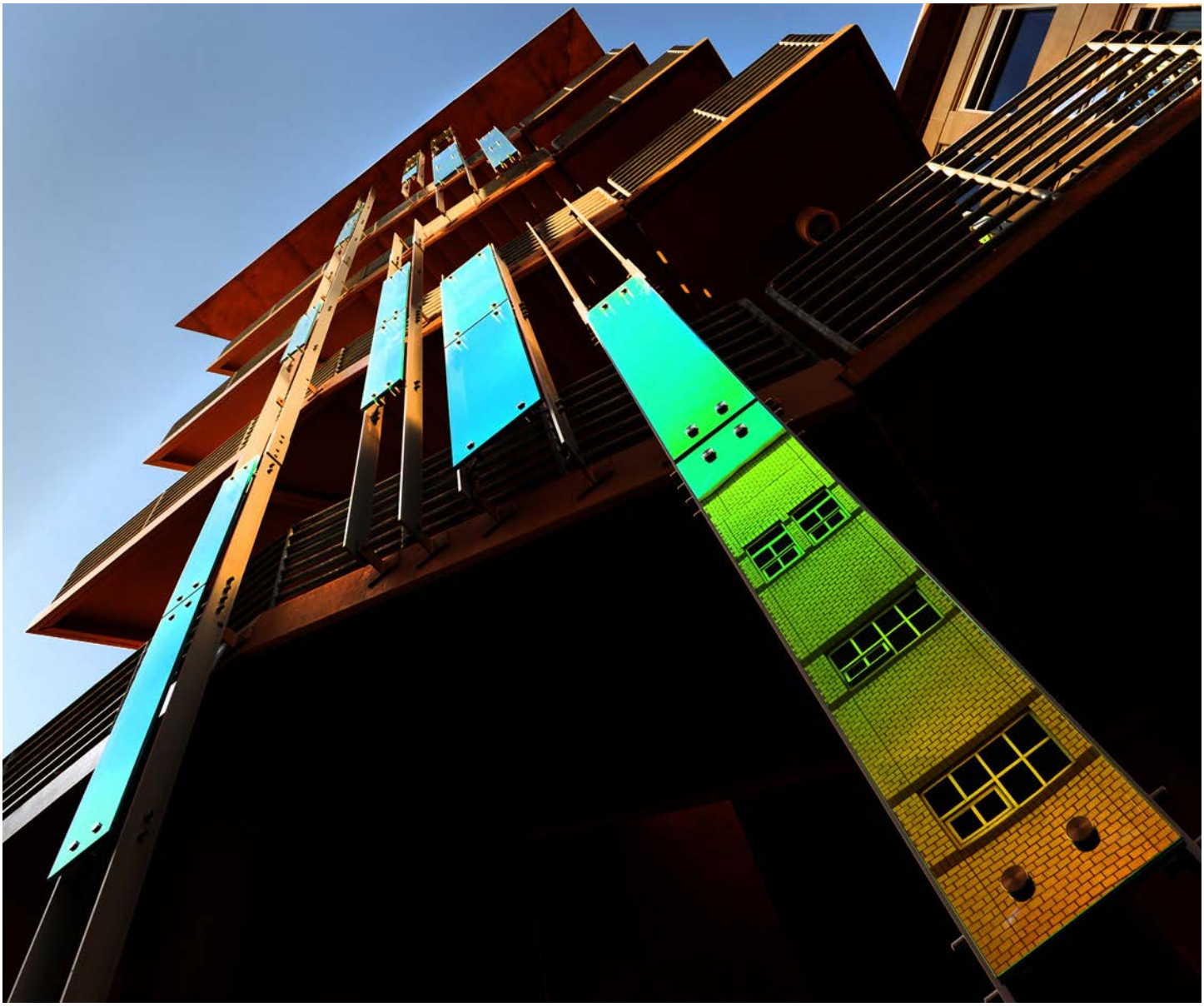
Technical Appendix 2: Cluster Analysis

Although there are various cluster analysis techniques available to researchers, we employed a model-based clustering approach, available in the R package *mclust*. This approach utilizes both "parameterized Gaussian hierarchical clustering algorithms and the EM [Expectation-Maximization] algorithm for parameterized Gaussian mixture models" (refer to Fraley, C., & Raftery, A. E. (1999). MCLUST: Software for model-based cluster analysis. *Journal of Classification*, 16(2), 297-306.). The optimal number of latent classes (six groups of census tracts, in our case) was endogenously determined based on the data patterns. Our results show such a data-oriented way to classify neighborhoods, which exhibits a higher BIC (Bayesian Information Criterion) than any other categorizations.

Technical Appendix 3: Geographically Weighted Regression

Geographically Weighted Regression (GWR) is a principally exploratory statistical technique used to enhance the understanding of the spatially-varying component of traditional regression analysis. While global relationships between covariates and an outcome measure may be robust, there may be underlying non-stationarity in regression results (for a more complete treatment, see Fotheringham, Stewart A., Brundson, Chris, & Charlton, Martin. (2002). *Geographically weighted regression: The analysis of spatially varying relationships:* John Wiley & Sons).

While a number of packages are available for running GWR including an open source GUI-based software of the same name (see https://geodacenter.asu.edu/software) and the R package of the same name, this analysis uses ESRI's ArcGIS software Spatial Statistics toolbox for its convenient ability to visualize GWR results. The regressions run used logged measures of employment growth, home value growth, and household income growth over 2000-2012 as outcome measures, controlling for their values in the base year. A fixed kernel bandwidth is used, selected by AICc optimization. Results showed no perceptible spatial patterning of residuals.



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