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**An Empirical Exploration of Southeast Asian American Residential Patterns in the
San Francisco Bay Area (2000–2019)**

Minh Q. Nguyen
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Abstract

This paper explores three methods of reporting residential patterns: (1) *concentration profiles*, (2) *density maps*, and (3) *proximity profiles*. I analyze U.S. Census data to map and evaluate the residential patterns for Southeast Asian Americans in the nine-county San Francisco Bay Area. Drawing from the field of urban planning, I report two measures of segregation and concentration: (a) dissimilarity indices and (b) spatial proximity indices, and I discuss their limitations. Since mapping and spatial statistics are essential to understanding the histories, development, and advancement of Southeast Asian American communities, it is important to promote their broad usage. The paper's findings lend evidence to three arguments: (1) pioneering moments (the establishment of new immigrant communities) can in fact start path-dependent community growth, (2) clustering and dispersion to some extent can be predicted by classic theories of spatial assimilation, but new dynamics are playing out in today's communities from Asian and Latino origins, including Southeast Asian American communities, and (3) residential clustering cases are circumstantial, dependent on unique local circumstances.

Keywords: concentration profiles, density maps, proximity profiles, regional context, residential patterns, spatial and demographic analysis

Introduction

Scholars have long documented the spatial ordering of incoming Southeast Asian refugees via a federal dispersion policy (Desbarats, 1985; Kogan & Vencill, 1984); the challenges and hopes of secondary migration, chain migration, and family reunification (Detzner, 2004; Smith, 1984); and the rise, fall, and evolution of ethnic communities and spaces of resilience



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and survival (Aguilar-San Juan, 2009; Ong, 2003; Tang, 2015; Zhou & Bankston, 1999). Many of these studies provide in-depth analysis of day-to-day life (through interviews, surveys, and ethnographies) and policy impacts on educational and socioeconomic outcomes (through policy analysis, economic analysis, and historical studies). There is broad consensus that in-depth, regional context (through mapping and demographic analysis) provides empirical information that is pertinent to studying localized placemaking. Recent works apply spatial data to studies of communities, and spatial analysis has been employed in research on immigrant socioeconomic outcomes, intergenerational migration, and integration within the broader society (Bankston & Zhou 2020; Tran, 2020).

I explore methods that provide descriptive measures of spatial segregation and concentration, and I discuss why concentration profiles, proximity profiles, and density mapping are preferred. The methods rely on U.S. Census data to map and evaluate the residential patterns for Southeast Asian Americans in the San Francisco Bay Area. These analyses provide statistics about the local and regional demographics of Southeast Asian American communities. The paper is divided into four parts. First, I discuss general descriptive statistics about Southeast Asian American communities. Second, I discuss (a) *dissimilarity indices* and (b) *spatial proximity indices*, two measures of segregation. I provide calculations of these two indices for Southeast Asian American communities in the Bay Area and discuss their theoretical and practical limitations. Third, I provide three other spatial methods: (1) *concentration profiles*, (2) *density maps*, and (3) *proximity profiles*, and I explain why they are preferred methods. Last, I discuss the implications of my descriptive work on spatial concentration.

Regional Context

By regional context, I refer to quantitative data analyzed at the regional scale; this data informs further community documentation at more localized scales, such as neighborhoods and buildings. Regional demographics help make sense of localized placemaking. Regarding the data, I start with summary statistics, using United States Census data on Cambodian, Hmong, Laotian, and Vietnamese ethnic groups—which I summarize under a Southeast Asian American (SEAA) category. Then, I report spatial statistics regarding the residential patterns of the communities, while discussing the strengths and limitations of each metric. For each of the three points in time—2000, 2010, and 2019—I provide maps of residential density, concentration indices, and proximity indices. Calculations are for the Bay Area region, which uses the standard nine-county geography.¹ I explain what these data reveal and how they can be incorporated into broader community studies.

Data have shown an increase in the national SEAA population in the past few decades, as well as an increased concentration of Southeast Asian American residents in states such as California. In Table 1 below, demographic numbers show a continued increase of the Southeast Asian American population in the United States and a high concentration of growth in California. By 2019, California accounted for over a third of the United States' Southeast Asian residents, and the Bay Area itself was home to about 10% of SEAA nationwide—continuing the diversifying trends of previous decades.

This table reveals how the SEAA population has grown immensely from 2000 to 2019, with an over 40% increase in California and an over 35% increase in the Bay Area alone. Table 1 data reflect the United States' changing demographics, a diversifying trend we will see in the coming decades (Portes & Rumbaut, 2001; 2014).² These data also raise many

questions about the growing population. Where exactly in the Bay Area do SEAA communities reside? How do community residential patterns relate to other communities? Why do some communities persist over time, while others fade? And what does this tell researchers and advocates about the social and economic realities faced by Southeast Asian Americans? To begin addressing these questions, I turn to measures of residential patterns to demonstrate both the insights and challenges in empirical data. I will then present empirical context for my larger body of research to demonstrate its usefulness in community documentation. Implications are examined in the discussion section.

Table 1
Population of Southeast Asian Americans (Thousands)

	United States			California			Bay Area		
	2000	2010	2019	2000	2010	2019	2000	2010	2019
Population	281,422	308,746	324,698	33,872	37,254	39,283	6,784	7,151	7,190
Asian ^a	10,019	14,314	17,924	3,611	4,726	5,692	1,263	1,620	2,030
SEAA	1,633	2,219	2,562	638	814	901	169	212	233
Cambodian	172	232	258	70	86	89	10	13	11
Hmong	170	248	293	65	87	96	1	1	2
Laotian	169	191	202	55	58	62	12	12	13
Vietnamese	1,123	1,548	1,809	447	582	654	146	186	206

^a Total Asian with One Asian Category

Sources: Data collected through the U.S. Census Bureau—via <https://api.census.gov/data/> and using R Studio software. The datasets were: Census 2000 and 2010, and ACS 2019 (5-Year Estimates); Social Explorer used for data exploration (<https://www.socialexplorer.com/a52f33ef12/view>). Citation for Social Explorer data is as follows: Social Explorer Dataset (SE), Census 2000 on 2010 Geographies, Social Explorer; U.S. Census Bureau; Social Explorer Tables (SE), Census 2010, Census Bureau; Social Explorer; Social Explorer Tables: ACS 2019 (5-Year Estimates) (SE), ACS 2019 (5-Year Estimates), Social Explorer; U.S. Census Bureau. From the Census 2000, Census 2010, and ACS 2019, data from “Asian by Specific Origin (Asian with One Asian Category for Selected Groups)” is used, with totals from the categories for Cambodian, Hmong, Laotian, and Vietnamese; this data is found under the category of “Asian and Hispanic Groups.” The census tract is the smallest scale available for this data, and totals are summarized for larger geographies of the 9-county region (Bay Area), state, and nation. ACS estimates are not as accurate as Census data, and the margins of error will be used in subsequent quantitative analysis.

Measures of Residential Patterns

There is a robust literature on the various metrics of residential patterns and the geographies of different communities; these metrics capture the degree of segregation between groups, the concentration of different populations, and residential patterns of clustering. Calculated from Census and American Community Survey data, these metrics can also tell us about SEAA residential trends over the past few decades. The units of analysis are the census tracts; for each tract, data on race and ethnicity are used to calculate the following indices. I start by critiquing two less-preferred methods, (a) dissimilarity indices and (b) spatial proximity indices. Then, I present and apply three preferred methods: (1) concentration profiles, (2) density maps, and (3) proximity profiles.

Dissimilarity Indices

A widely used index for measuring group segregation is the dissimilarity index. Research featuring the dissimilarity index includes policy-oriented reports (Menendian & Gambhir, 2019), historical documentation (Freeman, 2019), and sociology studies (Xiong, 2015). Ranging from 0 to 1, the dissimilarity index measures the relative segregation of two groups, with 0 indicating a completely interspersed group and 1 indicating two completely segregated groups. More precisely, a dissimilarity index of 0 indicates that 0% of a group must move in order to achieve full integration, while an index of 1 indicates that 100% of a group must move in order to achieve full integration. The unit of analysis for the indices below is the census tract, and data for three cross-sections are provided. The comparison group is SEAA—hence the group’s exclusion from Table 2.

Table 2

Dissimilarity Indices for Bay Area Southeast Asian Residents

Bay Area Dissimilarity Indices for Southeast Asian and Select Ethnicity and Race Categories			
	2000	2010	2019
Asian (non-SEAA)	0.46	0.45	0.48
White (non-Hispanic)	0.64	0.61	0.62
Black (non-Hispanic)	0.64	0.62	0.64
Latino	0.51	0.51	0.52

The category “Asian” includes all groups except Cambodian, Hmong, Laotian, and Vietnamese, and indicates only records of “Asian with One Asian Category.” The category “Latino” indicates records of “Hispanic or Latino” of any origin or race. Data is from the Census and American Community Survey. 2019 data does not account for margins of error in 5-Year Estimates.

The indices above indicate that the Southeast Asian American communities of the Bay Area are moderately segregated from Asian (non-SEAA), White (non-Hispanic), Black (non-Hispanic), and Latino racial and ethnic groups. Dissimilarity index values in the middle range (between 0.4 and 0.6) across the board indicate that compared with each group, SEAs are neither completely interspersed nor completely segregated. Asian/SEAA dissimilarity indices appear lowest, followed by Latino/SEAA indices, and then both White (non-Hispanic)/SEAA and Black (non-Hispanic)/SEAA indices. Looking closely at data for 2010, the dissimilarity index for Asian (non-SEAA) and SEAA is 0.45—indicating some segregation of SEAA from other Asian ethnic groups. The dissimilarity index for Latino ethnic groups and SEAA is 0.51—also indicating some segregation, but not complete segregation. For the dissimilarity indices for White (non-Hispanic)/SEAA and Black (non-Hispanic)/SEAA, a value of approximately 0.6 indicates that SEAA populations are more isolated from White and Black neighbors—compared to SEAA isolation from Asian (non-SEAA) and Latino neighbors. The indices alone suggest that SEAA populations are more spatially similar to other Asian groups, followed by Latino populations. Based on three points in time, the dissimilarity indices appear to be relatively stable over the past two decades.

Many authors discuss the limitations of the dissimilarity index as a measure of segregation. Menendian and Gambhir (2019) discuss the abstractness of the dissimilarity index. They expose the metric’s limitations when applied at a regional scale; the dissimilarity

index does not speak to whether a group is proportionally represented across differing geographic units of analysis. In other words, the dissimilarity index only uses one geographic unit in its analysis; in the example above, only the geographic unit of the Bay Area (nine-county region) is used. A more informative metric would consider tract, city, or county data in conjunction with regional data.³ In fact, the index does not account for place at all and considers only theoretical space.⁴ Hong et al. (2014) similarly comment on the aspatial and two-group limitations of the measure. Most relevant to my own research, the dissimilarity index does not account for patterns of clustering and incomplete integration that are context-specific, and it does not allow researchers to see change—particularly since movement and residential pattern changes may not be captured in dissimilarity indices. Researchers are also keenly aware that such change is historically specific and cannot be predicted empirically; geopolitical, social, and economic factors certainly play key roles in clustering and segregation. Despite these limitations, the statistic allows us to compare the residential integration of SEAA to other groups in the Bay Area.

Spatial Proximity Indices

The spatial proximity index gives a single statistical value that summarizes group segregation at an even higher summary level. According to Hong et al. (2014), the spatial proximity index “returns a single numeric value indicating the degree of segregation: a value of one means absence of segregation, and values greater than one indicate clustering” (Hong et al., 2014, pp. 5–6). The spatial proximity index values for SEAs in census datasets for all years are approximately equal to 1—suggesting no segregation and no clustering. This result contradicts other evidence and highlights a major limitation of the spatial proximity index: “It tends to neglect geographic patterns of small minorities by definition” (Hong et al., 2014, p. 6). Indeed, the statistic is skewed by the fact that the SEAA community is relatively small and that SEAA clusters are scattered across the region. To understand the concentration and segregation of Bay Area SEAA communities, other metrics are more useful. In the next section, I employ analyses that tell us more about SEAA community clusters and how they relate to the larger, regional picture.

Concentration Profiles

Concentration profiles, as defined by Hong and Sadahiro (2014), provide more accurate and useful information on residential patterns. Hong and Sadahiro (2014) argue that as a “useful tool to inspect the evenness aspect of segregation” (Hong & Sadahiro, 2014, p. 216), concentration profiles are a meaningful measure of segregation. The measure focuses particularly on clustering and density. Akin to the Lorenz curve, the concentration profile graphs the population proportion at different threshold levels. Building on Poulsen et al.’s (2002) work on measuring ethnic enclaves, Hong and Sadahiro (2014) formally define the concentration profile as “a graphical expression showing the proportions of an individual ethnic group’s population at some predefined threshold levels” (Hong & Sadahiro, 2014, p. 216). The threshold levels reflect the percentage of the population at a regional level. Additionally, a value of R provides a succinct statistic that “ranges between 0 and 1 and can be interpreted in a similar manner to the index of dissimilarity: a small value indicates that the [given] group comprises similar proportion of the population in all census tracts, and a large value implies a high degree of residential concentration” (Hong & Sadahiro, 2014, p. 217). In short, the *concentration profile* compares the local (tract-level) to the regional (nine-

county total) concentration of the Southeast Asian American community; likewise, the *R statistic* is one number summary of this observable concentration.

Following Hong and Sadahiro's (2014) analysis of the Māori population in Auckland, I have used the R package "seg" (Hong et al., 2014) to analyze Southeast Asian American populations in the Bay Area, along with other racial and ethnic categories. For the thresholds of each race or ethnicity category, I calculate proportions of each racial and ethnic category at the regional level; the subsequent analyses essentially compare tract proportions to regional proportions, similar to Menendian and Gambhir's (2019) treatment of tract- and county-level proportions. Population percentages, at the regional level, are provided in the following table. This answers the question: what portion of the *region's population* is Southeast Asian American? These values are then compared to each *census tract's SEAA population* to then calculate the concentration profile. The Southeast Asian American community is extremely small compared to the entire population, never exceeding 3% (see Table 3).⁵

Table 3

Bay Area Regional Population by Select Race and Ethnicity Categories

	Percent of Bay Area Regional Population		
	2000	2010	2019
Southeast Asian	2.5	3.0	3.0
Asian (non-SEAA)	19.0	23.3	26.3
White (non-Hispanic)	58.1	52.5	50.2
Black (non-Hispanic)	7.5	6.7	6.0
Latino	19.4	23.5	23.5

Data is from the 2000 Census, 2010 Census, and 2019 5-Year American Community Survey. From the Census 2000, Census 2010, and ACS 2019, data from "Asian by Specific Origin (Asian with One Asian Category for Selected Groups)" is used, with totals from the categories for Cambodian, Hmong, Laotian, and Vietnamese; this data is found under the category of "Asian and Hispanic Groups." For other groups, "Race," and "Hispanic or Latino" origin is used. The geography of the data is the Bay Area Region, which includes those listed in Endnote 1.

Between 2000 and 2010, some notable changes occurred in the population of the Bay Area. The proportion of Asian, Southeast Asian, and Latino populations increased from 19.0% to 23.3%, 2.5% to 3.0%, and 19.4% to 23.5% of the region, respectively. White and Black populations have proportionally declined, from 58.1% to 52.5% and 7.5% to 6.7%, respectively. 2019 estimates suggest that these trends will continue into the 2020 decennial census, with the exception of relatively stable proportions for Southeast Asian and Latino populations. The concentration profiles (Figure 1) and density maps (Figure 2) for three points in time will provide a look into changes in residential patterns.

The concentration profile graphs essentially summarize how populations at the census tract-level compare to regional populations. The y-axis indicates a *population proportion*, while the x-axis indicates a *threshold level*. Each point on the graph reports the proportion of SEAs (*population proportion*) who live in a tract of a given concentration of SEAs (*threshold level*). The dotted line represents a hypothetical region where each tract has the same proportion of SEAA residents as the region—in other words, perfect dispersal⁶ by census tract. In Figure 1a, the dotted line illustrates that 2.5%⁷ is the threshold level at which a given census tract has the same proportion of Southeast Asian individuals as that of

the region as a whole. Put differently, 2.5% of the region was Southeast Asian in the 2000 Census, so a perfectly dispersed⁸ population would result in each census tract containing 2.5% of the population. This theoretical scenario contrasts with the solid line (actual data), which is the calculated concentration profile.

The intersection of the concentration index (solid line) and threshold level (dotted line) represents the percentage of the Southeast Asian population that lives in a census tract that is at the threshold level of 2.5%. So, approximately 75% of Southeast Asian individuals lived in a census tract in which their proportion of the census-tract level population equaled that of the Southeast Asian proportion of the region as a whole. Approximately 10% of SEAA individuals lived in a tract that is 20% Southeast Asian, and few lived in a tract that is more than approximately 30% Southeast Asian. Next, consider the area to the right of the threshold level within the bounds of the concentration index.⁹ The largeness of this area indicates that there were census tracts with a higher concentration of Southeast Asian residents than if they were dispersed randomly across the region. In other words, there are a large number of census tracts containing a high concentration of SEAA individuals, relative to the region.

In Figure 1, R is a summary statistic ranging from 0 to 1 that indicates the level of concentration for the SEAA population.¹⁰ By the standards of Hong and Sadahiro (2014), the small value of $R=0.08$ in Figure 1a suggests “the group comprises similar proportions of the local population in all census tracts” (Hong & Sadahiro, 2014, p. 217).¹¹ This is consistent with the finding that a large number of census tracts contain a high concentration of SEAA individuals, relative to the region; however, these census tracts are not all necessarily clustered together.¹² This finding presents an interesting issue that is addressed in the sections regarding Figures 2 and 3: although there is concentration (albeit at a low level), one still needs to account for clusters that are visible in density maps (Figure 2). For this, a formal measure of clustering is provided below in a proximity profile (Figure 3). But before examining density mapping and proximity profiles, I will present the 2010 and 2019 concentration profiles.

Calculated from decennial Census data, the 2010 concentration profile suggests an increase in SEAA concentration within census tracts in the Bay Area. Between Figure 1a and Figure 1b, the concentration profile R -value increased slightly from 0.078 to 0.089.¹³ I emphasize that this is an increase in concentration (a *within-tract* measurement) and that we cannot yet tell whether clustering of SEAA (a *between-tract* measurement) has changed. This latter measurement will be considered later in the *proximity profile section*.

Lastly, Figure 1c reports the concentration profile for the Southeast Asian American population using 2019 American Community Survey (ACS) data.¹⁴ 2019 ACS data indicate only modest differences from the 2010 Decennial Census data. Without accounting for margins of error within the ACS data, it appears that there was a modest decrease in concentration within tracts, larger clusters of census tracts, and higher levels of clustering at all threshold levels. These data suggest stability in concentration profiles over the last decade, though it is important to question the influence of statistical noise in these findings.

Previewing the next section, visual inspection of the population map will suggest a more even dispersal of census tracts containing a substantial proportion of SEAA residents; these are clustered mainly in San Jose and the East Bay, and dispersed across San Francisco. This evidence suggests that the remaking of the residential pattern for Southeast Asian American communities was already underway, and a closer look at demographic maps

indicates dispersion and a decrease in the density of SEAA residents. As discussed, a more formal measure of across-tract clustering is provided by the proximity profile (Figure 3).

Figure 1
Concentration Profiles for SEAA Population of the Bay Area

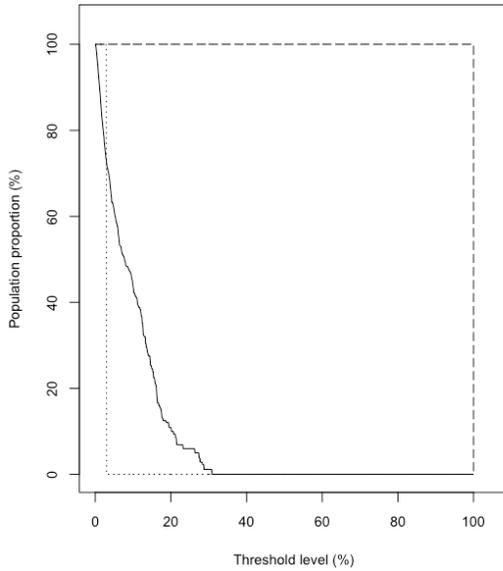


Fig. 1a: Concentration profile 2000. $R=0.0777$

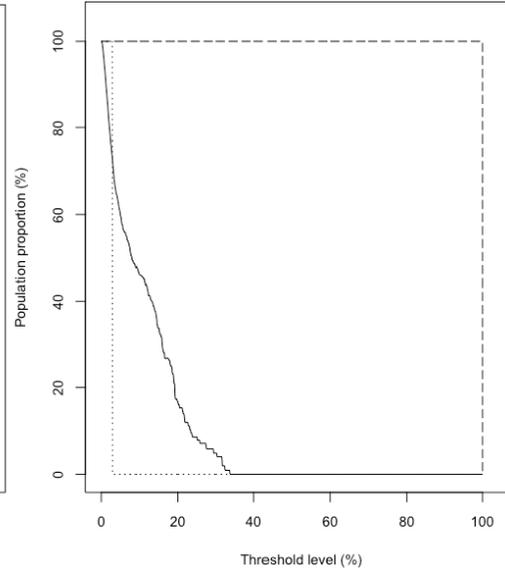


Fig. 1b: Concentration profile 2010. $R=0.0894$

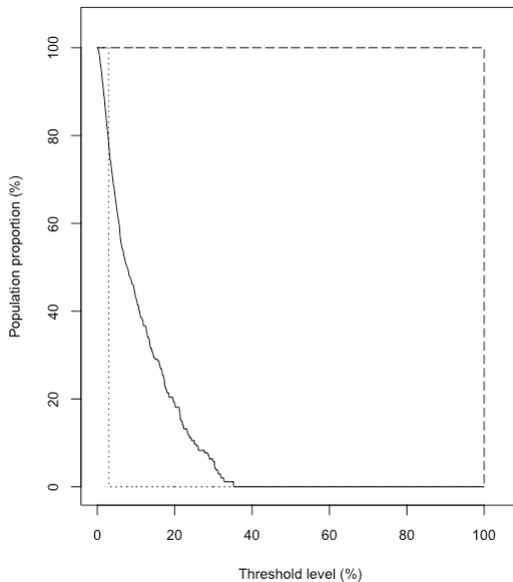


Fig. 1c: Concentration profile 2019. $R=0.0867$

Above: Graphs of the concentration profile for the Southeast Asian population. In each graph, the solid line indicates population distribution, the dotted line marks the regional threshold (which indicates no segregation), and the dashed line indicates complete segregation. This format follows (Hong & Sadahiro, 2014, p. 224). Data are from the 2000 Census, 2010 Census, and the ACS 2019 (5-Year Estimates); data are processed with the R “seg” package.

Density Maps

The density maps in Figure 2 show Southeast Asian American populations by census tracts. Consistent with mapping used in urban planning and related disciplines (Portes & Rumbaut, 2014; Schafran, 2018; Walker, 2018), these visuals illustrate why concentration and proximity profiles are useful in deciphering spatial information. As in Table 1, the data used in these maps are collected through the U.S. Census Bureau, from the Census 2000, Census 2010, and American Community Survey 2019 (5-Year Estimates). The data category is “Asian by Specific Origin Asian with One Asian Category for Selected Groups.” Under this category, sums for the groups Cambodian, Hmong, Laotian, and Vietnamese are used; these four groups are totaled under a broader Southeast Asian American (SEAA) category. This latter is mapped in Figure 2, by census tract.

Tracts with a higher proportion are more darkly shaded, while tracts with little or no SEAA populations are not shaded. Figure 2d shows the San Francisco Bay Area’s location within the State of California, and each map is labeled with sub-regional names (North Bay, East Bay, South Bay, Peninsula) as well as major cities (San Francisco, Oakland, and San Jose). By definition, all census tracts under consideration are nestled within the San Francisco Bay Area region.

A visual inspection of the regional map in Figure 2a suggests a higher concentration of SEAA individuals in several places that I identify as the South Bay, followed by the East Bay and the North Bay, with notable populations in the two metropolitan centers of San Francisco and Oakland.¹⁵ These visual findings are also consistent with my earlier interpretation that there are a notable number of census tracts containing a high concentration of SEAA individuals, relative to the region, and that these census tracts are not necessarily clustered together. While visual inspection suggests some clustering, a more formal measure of clustering, the proximity profile, will give a more precise calculation. Before discussing this profile, a visual examination of Figures 2b and 2c suggests population growth in the East Bay (particularly around Oakland) and the South Bay (particularly in San Jose). San Francisco, though not the epicenter of Southeast Asian American life in the Bay Area, sees growth in clustering over time as well.¹⁶

Proximity Profiles

The proximity profile measures how clustered census tracts are (holding population density level constant). Broadly, the proximity profile is one measure of the density of a given population unit—in this case, units are census tracts of varying concentrations of Southeast Asian Americans within the population. It is simply a statistic expressing whether (and to what extent) census tracts are clustered (on the y-axis as “level of clustering”); census tracts are characterized by their population proportion that is Southeast Asian American (on the x-axis as “threshold level”). For instance, we could look at all census tracts where the Southeast Asian American population is at least 15% (for shorthand, I’ll refer to these *15%-SEAA-tracts*). We are then able to ask whether *15%-SEAA-tracts* are clustered together. The proximity profile graphs summarize this information for census tracts of all concentration levels from 0% to about 30% (there are no census tracts in the Bay Area that are more than about 30% Southeast Asian American). More technically, the proximity profile tells how clustered (on the y-axis as “level of clustering”) tracts of a certain threshold level (on the x-axis as “threshold level”) are for a given population (the SEAA population).

Figure 2
Southeast Asian American Population Density Maps of the Bay Area

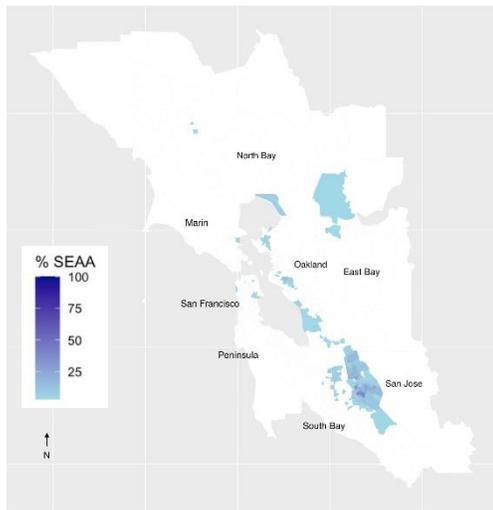


Fig 2a: Density Map for 2000

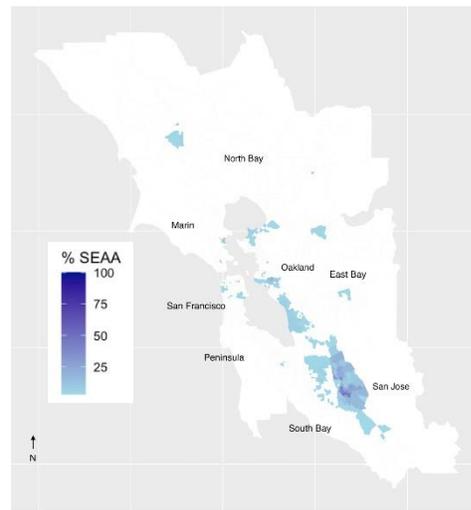


Fig. 2b: Density Map for 2010

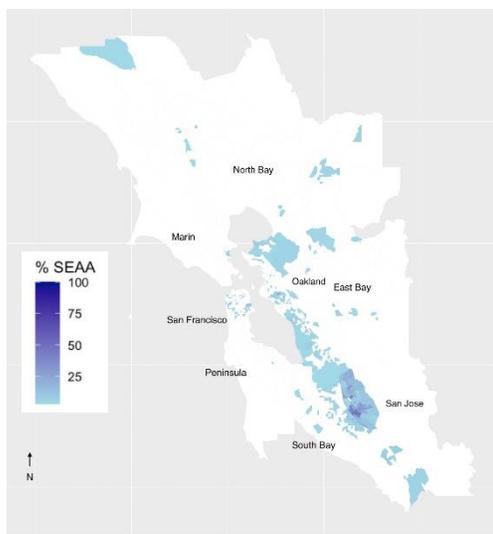


Fig 2c: Density Map for 2019



Fig 2d: Bay Area Location within California

Above: Map of the Southeast Asian population, showing percentage of census tracts that are SEAA. Data are from the 2000 Census, 2010 Census, and 2019 ACS (5-Year Estimates). Maps created through RStudio.

Figure 3a shows the level of clustering (y-axis) against threshold percentage levels (x-axis) for Southeast Asian Americans in Bay Area census tracts in the year 2000, again following the method detailed by Hong and Sadahiro (2014, pp. 218–220). The level of clustering is an index, calculated by dividing a numerator of $k^2 - k$, where k is the number of census tracts, by a denominator that is the sum of distances between census tracts; distances between tracts are calculated as equal to 1 if two census tracts are adjacent (Hong & Sadahiro, 2014, pp. 218–219). The level of clustering ranges from 0 to 1, with 0 indicating that census tracts at a given threshold level are randomly distributed spatially and 1 indicating

complete clustering (meaning tracts are all adjacent to one another). The threshold level refers to the percentage of a given census tract's Southeast Asian population. For example, the first point in Figure 3a falls at (0.18, 5). This indicates that census tracts at the 5% threshold level of SEAA (in shorthand, *5%-SEAA-tracts*) are clustered at a level of 0.18. Notably, at the threshold level of 20% (in shorthand, *20%-SEAA-tracts*), the level of clustering is 0.95. This suggests that census tracts at the 20% threshold level of SEAA were nearly all clustered. I followed Hong and Sadahiro (2014) in constructing confidence intervals using a Monte Carlo simulation, where I sampled and then subset census tracts, after which I calculated the level of clustering for each simulation. The confidence intervals show where the proximity profile graph would lie if the SEAA tracts were randomly dispersed.

The proximity profile graphs in Figure 3 show that the level of clustering is above the confidence interval for each threshold group, with noticeable peaks between 20% and 25% for all three years. The graphs suggest that census tracts between the 15–25% threshold levels of SEAA tend to be more highly clustered for the three years. Lastly, these results fall above the confidence intervals, suggesting statistical significance—more precisely, that the tracts in reality are not randomly distributed and that there is clustering. This result formally measures clustering of higher density SEAA census tracts that can be seen in the map of Figure 1 above. In effect, the proximity profile confirms a visual inspection of clustering.

Between 2000 and 2010 (Figures 3a and 3b), there is a noticeable increase in the proximity profile, which indicates that even though concentration increased only minimally (a *within-tract* measurement)¹⁷, the clustering of higher SEAA density tracts has decreased (an *across-tract* measurement). Note the precipitous decrease in the level of clustering from Figure 3a to Figure 3b, particularly the peak of clustering level in 2000 (~1.00) compared to the peak of clustering level in 2010 (~0.35). Combined with evidence from the concentration profiles and density maps in Figures 1 and 2, the data here suggest that although concentration within census tracts has only modestly increased, the proximity of higher SEAA density tracts has decreased. This illustrates the use of multiple metrics and visualizations in conjunction. Below, in Figure 3b, the proximity profile suggests that the level of clustering of higher SEAA density census tracts in 2010 is lower than that of 2000. At the threshold levels of 20% and 25%, the levels of clustering are 0.31 and 0.34, respectively. Together, the data tell us that in 2010, though SEAA concentration within Bay Area census tracts has increased, these tracts are less clustered together. This supports the notion that SEAA community density has increased within tracts and that regional density has decreased across tracts. In other words, there is higher SEAA density at tract levels, but regionally, there is less clustering.

The 2019 proximity profile in Figure 3c suggests varying levels of clustering of lower SEAA density census tracts (at the 5% threshold level) and the highest levels of clustering above the 20% threshold level. However, statistical noise may account for differences between 2010 and 2019 profiles. Peak clustering here exceeds that of the 2010 Census data only slightly. Together, the data tell us that from 2000 to 2019, SEAA concentration within Bay Area census tracts and clustering between tracts have changed—and that the most drastic change is in between-tract clustering between 2000 and 2010. The results raise a series of questions about spatial assimilation, delayed assimilation, residential mobility, and Southeast Asian American (as well as other immigrants) spaces in general. Further research can explore the causes of major de-clustering between 2000 and 2010. The implications are discussed in the following section.

Figure 3
Proximity Profiles for SEAA Population of the Bay Area

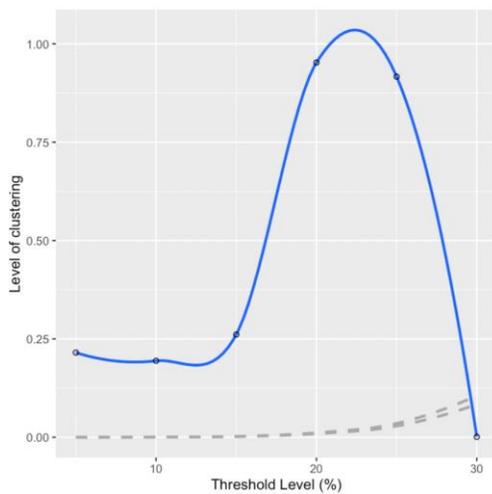


Fig 3a: Proximity Profile for 2000

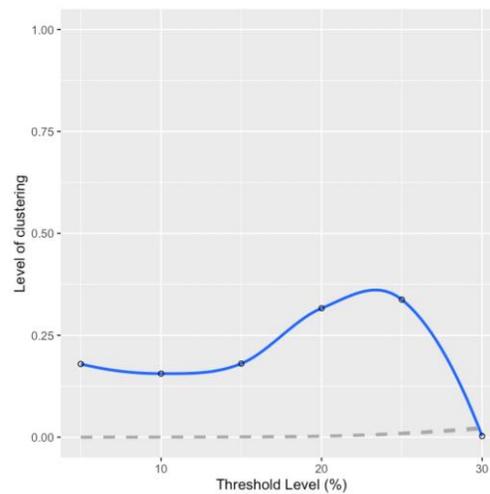


Fig. 3b: Proximity Profile for 2010

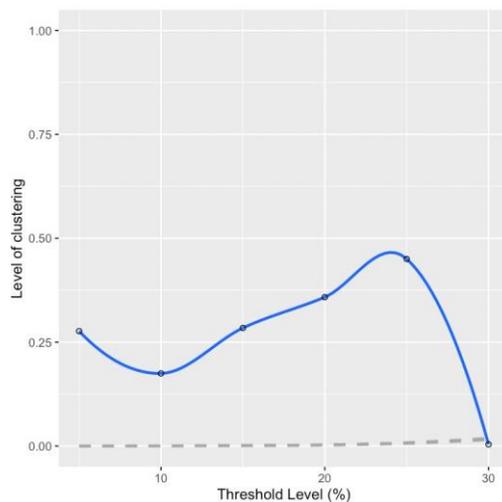


Fig 3c: Proximity Profile for 2019

Above: Proximity profiles for 2000, 2010, and 2019. The solid line indicates the level of clustering for each threshold level, and the dotted lines mark the 95% confidence interval, constructed from Monte Carlo simulations of the data. Particularly interesting is the major de-clustering between 2000 and 2010. The confidence intervals show the proximity profile ranges if the SEAA tracts were randomly dispersed across the region.

Discussion

There is an expansive literature on the residential patterns and spatial mobility of immigrant communities in the United States (Cheng, 2013; Iceland & Nelson, 2008; Miraftab, 2016; Portes & Rumbaut, 2014). These works especially focus on the residential and spatial outcomes of groups from Asia and Latin America. By referencing these works, the Southeast Asian American residential pattern can be seen in the broader context of demographic changes in the United States. There are several salient themes around residential clustering

and patterns in this literature: the role of unique historical circumstances and path dependence in shaping spatial outcomes of immigrant communities (Desbarats, 1985, 1986; Pamuk, 2004; Portes & Rumbaut, 2014); the need for refined theories of spatial assimilation, or even new theories, as patterns may differ from established theories (Miraftab 2016; Pamuk, 2004; Schafran, 2018); the spatial relationship of different groups, such as SEAs and other Asian groups (Cheng, 2013; Iceland, 2009; Iceland & Nelson, 2008); and the general changing demographics of the United States.

Many authors document the effects of history and path dependence on community formation. Portes and Rumbaut (2014) take a broad view on all newer immigrant groups in the U.S. and attribute today's patterns of concentration and diffusion to cohorts who arrived earlier and created clusters that became magnets for later immigrants. The authors find empirical evidence that such path dependence could be found in every major group in the last century, referring to this phenomenon as “the power of pioneer settlement patterns” (Portes & Rumbaut, 2014, p. 49). Of the major immigrant groups¹⁸ studied in the year 2000, virtually all had a plurality in either California, New York, or Florida (Portes & Rumbaut, 2014, p. 46). Each of these groups has a unique story of initial and subsequent settlements. For example, the first of refugees from Vietnam, Cambodia, and Laos were “resettled in 813 separate locations in all fifty states” (Portes & Rumbaut, 2014, p. 63), and most were not placed in their preferred state. Family and community separation brought on a wide set of problems, ranging from psychological to economic. Policymakers and scholars alike were alarmed by the dispersed placement during resettlement. Some of the earliest works on the matter, by Desbarats (1985, 1986), provided spatial studies of the Southeast Asian American population in the 1980s and 1990s. Secondary migration and clustering revealed the will and needs of the Southeast Asian American community at the time. Arguably, SEAA's “pioneering” efforts began with the secondary migration that led to today's major centers of SEAA life—including the San Francisco Bay Area.

The development and longevity of Southeast Asian American communities is the concern of many authors who examine specific places (Aguilar-San Juan, 2009; Hein, 2006; Zhou & Bankston, 1999). Through a case study in New Orleans, Zhou and Bankston (1999) demonstrate how local support networks among the Vietnamese can facilitate assimilation into the American mainstream; the authors support ideas of how community clusters are formed and maintained. On the idea of longevity, Aguilar-San Juan (2009) challenges theories of inevitable spatial assimilation and contributes to a view of long-term forms of new immigrant communities. Through what she refers to as *territorializing*, when groups “put forth symbols that give meaning to the territory and to its attendant community” (Aguilar-San Juan, 2009, p. 137), placemaking for Southeast Asian American communities can be seen as “an attempt not only for the community to survive...[but] as an effort to make the community endure” (Aguilar-San Juan, 2009, p. 141). The work builds on the idea that ethnic clusters and communities follow new patterns and logic. Hein (2006) details the experiences of Cambodian and Hmong refugees in Chicago and Milwaukee. The work foregrounds housing and resettlement agencies' impact on local housing markets, particularly the role of neighborhoods, buildings, and immigrant enclaves as temporary homes for many on the path to more permanent settlement. Hein (2006) argues that community members in these places were to some extent “free from feeling like foreigners and could create enclaves by reclaiming urban space for their ethnic group” (Hein, 2006, p. 124). Hein (2006) addresses theories of ethnic succession from the classic spatial assimilation literature, arguing that residential outcomes are affected by numeric factors: ethnic origins, along with corresponding

worldviews and histories (Hein, 2006, p. 239); specific regional circumstances (Hein, 2006, p. 230); and the role of symbolic place (Hein, 2006, p. 243). These factors have shaped the SEAA experience as much as that of other groups.

Parallels are often drawn between the Southeast Asian American experience of resettlement in the United States and that of other groups during the latter half of the twentieth century—including communities from Cuba, Burma, and Bhutan. On the Cuban American experience, Eckstein (2009) traces major trends in the development of the Cuban communities in Miami, Florida and Union City, New Jersey (Eckstein, 2009, p. 45). Like Southeast Asian American migrants, Cuban Americans resisted federal policies of dispersal and formed long-term communities. In fact, the Little Havana (Miami, FL) and Little Saigon (San Jose, CA) communities often are considered parallel cases of community formation; commonalities are found in transnational trends, the cultural transformation of regions, and political histories. These common themes of international migration, culturally significant places, and the reunion of extended family and centrality of kinship demonstrate the limitations of old theories of spatial assimilation and transnational influences in placemaking. On such influences, Tran and Lara-García (2020) discuss how “premigration characteristics and postmigration integration policies shape early socioeconomic integration in the United States” (Tran & Lara-García, 2020, p. 117). Like other authors, they also show the role of pioneers (Portes & Rumbaut, 2001) in creating an “established coethnic community” (Tran & Lara-García, 2020, p. 132) that in turn affects path-dependent residential formations. On the Burmese American experience, Trieu and Vang (2015) use U.S. Decennial Census data and interviews with the community to find that, although the refugee group was originally dispersed following federal guidelines, a large proportion settled in the South. This dispersion and secondary migration trend echo that of other recent Asian American groups, while the specific locations of settlement are largely determined by circumstantial factors and support organizations. Overall, literature on the topic of residential patterns for newcomers and newer ethnic communities in the United States combines the use of public demographic data and in-depth qualitative work.

As much as we can learn from spatial similarities between new ethnic groups of Americans, we can also learn from groups with different spatial experiences. On this, many studies explore the unique dynamics of different ethnic groups within the same regions. Pamuk (2004) examines the residential clusters of Chinese, Filipino, and Mexican communities—the largest immigrant groups in San Francisco in 2000. Following similar work on residential patterns of Asian and Latino communities, Pamuk (2004) finds that “immigrants are now spatially clustered in ways that may no longer neatly fit theoretical models derived from the settlement patterns of earlier waves of immigrants in the late nineteenth century” and that “new and different forms of spatial ethnic clustering are emerging” (Pamuk, 2004, p. 290, emphasis in original). In exploring possible new clustering, Pamuk (2004) creates a measure of concentration that essentially compares tract populations to the city population (pp. 291–292)—similar in type to the concentration profiles in Figure 1. Like Portes and Rumbaut (2014), this work examines historical settlement patterns as precursors to path-dependent residential patterns. Economic restructuring and urban redevelopment are also identified as drivers of spatial changes. For each of the three groups, the author identifies residential clusters and discusses relevant historical circumstances. In summary, Pamuk (2004) describes the path-dependent development of Chinatown as an ethnic enclave and wealthier Chinese American communities in the western part of San Francisco; the erosion and loss of affordable housing for the Filipino community in

downtown San Francisco that led to clustering on the southern edge of the city; and the Mission District, home to many members of the city’s Mexican American community and famous as an epicenter of gentrification and displacement.

Many works also examine the interrelatedness of ethnic communities, as well the emergence of new mixed communities. Data in this paper, and elsewhere, provide evidence that some Southeast Asian American communities have formed near more established Asian American communities, such as Chinese American communities across the United States. In fact, even the less rigorous dissimilarity index (Table 2) suggests that Southeast Asian American clusters have formed nearer to other Asian American clusters. As Cheng (2013) discusses, residential patterns are further complicated by intra-group dynamics, particularly among different Asian American ethnic groups. Contributing to a “growing body of work that seeks to recover the history of majority nonwhite spaces both within and on the fringes of metropolitan centers” (Cheng, 2013, p. 34), the author finds emerging configurations of multiethnic communities. Other authors have coined terms to describe these new communities and in effect “challenge the dominant view that assimilation is inevitable and the best solution for ethnic minorities” (Skop & Li, 2010, 2021). For Portes and Rumbaut (2014), the fact that residential patterns cannot be explained fully by past theory nor predicted accurately is a hopeful one, and they assert immigrants will continue to contribute to the cultural and economic wealth of the U.S. (Portes & Rumbaut, 2014).¹⁹

The Southeast Asian American experience has been covered extensively since around the 1980s, during massive migration from Southeast Asian to the United States. Subsequent decades have seen the development of a rich literature across disciplines including demography, geography, public health, social welfare, public policy, sociology, and urban planning. It is my hope that this descriptive spatial study contributes to the conversation about the Southeast Asian American experience. Indeed, today’s Southeast Asian American communities face a plethora of issues that may differ drastically from those of past decades. However, a long-term view, coupled with a variety of methods, can help address the needs and concerns of the community, including regional inequality in socio-economic outcomes; visibility and voice in government; and the ability to address issues such as violence, elderly care, and mental health needs. By studying the origins of and changes to Southeast Asian American communities, we can test and develop classical as well as emerging theories, document unique experiences, and say more on the diverse American experience.

My maps and data analysis show a persistent cluster of SEAA communities in San Francisco and around the Bay Area. I ask: what are their origins? Why do they persist? In closing, I offer a few hypotheses and plausible answers. Questions of origin are likely specific and circumstantial. If Portes and Rumbaut (2001) are correct in their assertion about pioneers for each group and the path-dependence of placemaking—such as presented in Aguilar-San Juan’s (2009) documentation of Vietnamese American communities, Pamuk’s (2004) account of San Francisco’s major immigrant communities, and the wealth of aforementioned ethnographic studies—origins are largely circumstantial. My hypothesis here is that it is possible to find additional evidence of these early pioneers of Southeast Asian American space in the Bay Area; in fact, much work has already been completed, such as historical documentation of Laotian Americans in the East Bay by Lee (2012), ethnographic work on the Cambodian Americans of San Francisco by Ong (2003), and Collet’s (2007) work on the Vietnamese American communities of San Jose. With descriptive spatial data,

one can examine aggregate community change, and in doing so, one can triangulate with other methods of inquiry.

To understand the persistence of SEAA places and the perpetual changes acknowledged by scholars, one must also consider internal migration, immigration replenishments, and suburbanization. Internal migration of SEAs within the United States has been studied extensively since the 1980s; these studies have been compiled in several anthological volumes (Bon Tempo 2015; Rumbaut 2006). Secondary migration from the hundreds of settlement locations in the United States to major SEAA communities has contributed to the growth seen in Table 1. At the same time, immigration replenishments largely slowed after the early 1990s, as immediate economic and political crisis subsided in the origin countries (SEARAC, 2020, p. 15); what we see in these data is primarily movement within the United States. Finally, recent scholarship on the ethnoburb, ethnic communities, and the suburbanization of poverty all explain trends affecting SEAA communities. For example, Skop and Li (2010) explore the development of the “invisiburb” and other ethnic communities as reflective of new residential patterns. Indeed, urban and suburban restructuring has coincided with a trend in which “new immigrants settle directly in the suburbs without ever having experienced living in an inner-city ethnic enclave” (Skop & Li, 2010, p. 115).

Theories from sociology and urban planning suggest that the persistence of community clusters is not anomalous. In fact, the density maps of Figure 2 and the profiles in Figures 1 and 3 lend evidence to three arguments: (1) pioneering moments (the establishment of new immigrant communities) can in fact start path-dependent community growth, (2) clustering and dispersion to some extent can be predicted by classic theories of spatial assimilation, but new dynamics are playing out in today’s communities from Asian and Latino origins, and (3) residential clustering cases are circumstantial, dependent on unique local circumstances. Much of the literature suggests that local economic conditions shape residential patterns, and it is likely no coincidence that declustering from 2000 to 2010 (as seen in the proximity index in Figure 3) overlaps with the financial and housing crisis of 2008 that greatly impacted many immigrant communities. Much more can be learned about these communities’ dynamics, and the methods in this paper offer one method of inquiry to explore the Southeast Asian American experience. This paper ends with two appendices on neighborhood-specific studies and notes on the methodologies employed.

About the Author



Minh Q. Nguyen is a doctoral candidate at Columbia University, in the urban planning department. He previously graduated from the University of California, Berkeley with a Master of Public Policy and a Bachelor of Arts degree. Minh's research focuses on how urban planning and public policy shape immigrant and refugee communities. In his research, he combines policy and data analysis with archival and historical data to construct humanizing narratives. In teaching, Minh is dedicated to pragmatic and critical pedagogies and engaged mentorship. He is thankful to his partner and family for their ongoing support and encouragement.

Notes

1. The nine-county region is comprised of Alameda, Contra Costa, Marin, Napa, Solano, Sonoma, San Francisco, San Mateo, and Santa Clara Counties.
2. In their works, Portes and Rumbaut track a diversifying United States population. This diversification began to fundamentally change American society in the latter half of the twentieth century, as newcomers arrived in the United States during the Cold War era; settlement and mobility are components of spatial dynamics that recreate communities, pose challenges to regions, and are primary determinants of integration.
3. As I will discuss in the Concentration Profiles section, Menendian and Gambhir's (2019) treatment of tract-level and county-level proportions is an example of such a more informative metric.
4. In particular, Menendian and Gambhir (2019) note that the dissimilarity index "indicates the number of people of either racial group that would have to move to integrate the community" (Menendian & Gambhir, 2019c) and that it is used to summarize the evenness or spread of two mutually exclusive groups.
5. As discussed above, this is a limitation of other metrics of concentration and segregation. The dissimilarity index measures the population that theoretically would have to move (change location) in order to achieve perfect spatial integration; from a historical and practical perspective, such a metric provides no policy guidance. The spatial proximity measure does not capture the particularities of clustering, and, in fact, it obscures clustering altogether—contributing to rendering important Southeast Asian American communities and places invisible.
6. Or, integration—narrowly defined.
7. Note that for the graphs in Figure 1, the dotted line (regional threshold level) does not fall on 0, but falls right above it. The threshold level is small due to the Southeast Asian American community constituting only a small proportion of the region.
8. I define the geographic unit for dispersal as Census Tracts, based on the geographies of the data. Microdata at the Census Block level is unavailable to the public, while PUMA-level data is not specific enough for neighborhood-level analysis. PUMA data is helpful in studying movement of a population, but the units of analysis do not align neatly with this study.
9. This largest area within the graph is bound by the dashed lines, the dotted line (from ~75 to 100 on the y-axis), the solid line (from 0 to ~75), and the x-axis.
10. Mathematically, R is computed as follows: "calculate the area between the actual concentration profile and the line that represents a uniform distribution...and then divide it by the area above the line of no segregation" (Hong & Sadahiro, 2014, p. 216).
11. In order to benchmark the R statistic values reported here, I refer to Hong and Sadahiro's (2014) R values in their study, which range from 0.11 to 0.32, which constitutes some (but not extreme) levels of concentration (Hong & Sadahiro, 2014, p. 228). On the scale of 0 to 1, 0 indicates low levels of concentration and 1 indicates high levels. In comparison, all R values in the Bay Area SEAA are small.

12. To clarify, there are two questions here. 1) Are SEAA populations concentrated in census tracts? (Which ones and how many?) This is addressed by the *concentration profile*. 2) Are tracts with a high concentration of SEAA population themselves concentrated? This is addressed by the *proximity profile*. Multiple measures are examined, with each providing different information on residential patterns: the former is a within-tract measure, while the latter is an across-tract measure.
13. Please refer to the prior footnote on interpreting and benchmarking these *R* values.
14. Depending on the reliability of 2020 census data and whether the new Differential Privacy policy will allow similar analysis to that of 2000 and 2010 data—specific ethnicity data at the scale of the census tract—I may need to adopt new strategies to create reliable longitudinal statistics and maps. When comparing 2010 and 2019 data in this paper, I am mindful that results can be influenced by margins of error in the data.
15. On a point I expand upon in other works, these latter two clusters around smaller neighborhoods such as The Tenderloin and San Antonio, though proportionally small, are persistent and important cultural centers for a variety of historical reasons.
16. Close-up maps of San Francisco and Oakland are found in the discussion section.
17. Evidence of a minimal increase (of *within-tract* concentration) is shown in Figure 1.
18. The countries of birth for these groups are: Mexico, The Philippines, India, Mainland China, Vietnam, Cuba, Korea, Canada, El Salvador, Germany, The Dominican Republic, and the Former USSR.
19. Prominent scholars in urban planning have examined such contribution, such as Miraftab's (2016) work on the complex revitalization of a town driven by immigrants' labor and settlement.

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Appendix A: Neighborhood-Specific Studies

The maps presented in Figure 2 illustrate SEAA population densities across the San Francisco Bay Area. While it is clear that the centers of SEAA community life in the Bay Area are in the South Bay (particularly San Jose) and the East Bay (including Oakland), I am curious to understand the persistence and growth of SEAA clusters in the city of San Francisco—due to the historical role of resettlement organizations, mutual aid groups, and affordable housing providers. Additionally, the cultural significance of San Francisco’s SEAA institutions have certainly influenced community formation and remaking. Looking at more detail at the San Francisco SEAA density clusters, I will raise some questions about the patterns and futures of the SEAA communities there. Below, I include the same map, but focus on the downtown San Francisco tracts that are home to a high proportion of SEAA residents—see Figure 4. Included is the location of an Oakland neighborhood, also with a high proportion of SEAA residents, for reference.

The notions of pioneering and the path dependent formations of ethnic enclaves and communities from Portes and Rumbaut (2014) lend well to a cursory interpretation of these neighborhood maps. Figure 4 provides some evidence that these community formation patterns had occurred in San Francisco and Oakland, and two specific locations are the Tenderloin neighborhood and the San Antonio neighborhood. From 2000 to 2010 (from Figure 4a to figure 4b, respectively), there is persistence of higher-density SEAA population clusters and increased SEAA populations in the surrounding census tracts. This is evidence that new immigrants, or those migrating from other parts of the United States, do live near co-ethnic communities. The question of pioneering is particularly interesting. For example, the Tenderloin is host to several organizations and institutions. Among them are the Southeast Asian Community Center (SEACC), which has aided refugees from Vietnam, Cambodia, and Laos (as well as other groups in recent years), and the Tenderloin Neighborhood Development Corporation (TNDC), which provided many SEAA refugees with affordable housing early in the settlement period. More research is required on the specifics and histories of these organizations and their role in establishing and protecting SEAs. The spatial analysis presented in the main portion of this paper can provide helpful roadmaps for researchers committed to the advancement and well-being of Southeast Asian American communities.

Appendix B: Notes on Methods

While notes on methods and calculations are interspersed throughout this paper, I will include some general notes on the indexes, statistical profiles, and mapping presented in this article. For a full explanation of the mathematics, Hong et al.’s (2014) work out of Berkeley and Tokyo presents a detailed discussion as well as links to the “seg” R package.

Data was gathered from the United States Census Bureau, using an API run in RStudio software. Details on the data can be found in the footnote to Table 1. For (a) dissimilarity indices and (b) spatial proximity profiles, counts of each race and ethnic group (with SEAA created from four ethnicity categories) were calculated for each census tract, using variables compiled from Census Bureau data. Using the “seg” R package, the `dissim()` and `isp()` functions were used to calculate (a) dissimilarity indices and (b) proximity profiles, respectively. The dissimilarity index is a measure of relative segregation, ranging from 0 (complete inter-dispersal) and 1 (complete segregation) of two groups. The spatial proximity profile gives a single value on segregation and clustering, yet it is unable to capture trends in

small minority groups, of which belongs SEAA communities. Last, (1) concentration profiles, (2) density maps, and (3) proximity profiles were also calculated in RStudio software. The (1) concentration profiles were constructed using population proportions, in that census tracts are compared to the region to assess whether and to what extent the SEAA population is proportionally similarly between the census tract and the region. The (2) density maps were simply created with the `ggplot()` function, with SEAA population density displayed as a color gradient; the maps used census tract geographies that are public data. The (3) proximity profiles use an adjacency matrix to measure proximity and calculates thresholds by subsetting tract-level data equal to or greater than threshold percentage levels. A Monte Carlo simulation using a random sample of 100 tracts was constructed to illustrate profiles for a theoretical population of tracts that are distributed perfectly equally.

Figure 4

Neighborhoods and SEAA Density Maps

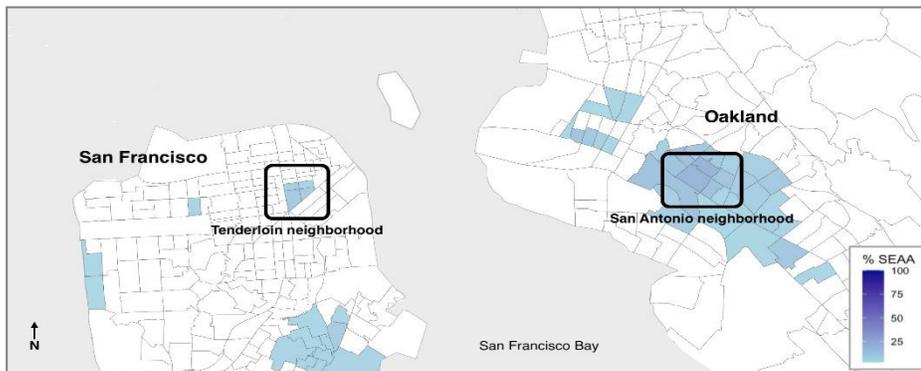


Figure 4a, above: Map for 2000, with neighborhoods labeled



Figure 4b, above: Map for 2010, with neighborhoods labeled

Figure 4 is a close-up of Figure 2, focused on the Tenderloin neighborhood of San Francisco and the San Antonio neighborhood of Oakland. These are two examples of places in the Bay Area that have been consistent centers of SEAA populations. Between 2000 and 2010, for instance, other places are potential sites for further study, such as the development of communities in the rest of the East Bay and the continued growth of the communities of the South Bay; neighborhood maps for these communities can follow the example of Figure 4. Markers on places of origins/pioneers of SEAA, such as notable developments, agencies, or organizations, also tell the story of community development.



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