Where are the Legacy Cities? Framing Urban Growth and Decline within the Regional Economy*

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Abstract

In comparison with healthy top-tier cities and those in abject decline, legacy cities are typically characterized as a middle ground where a complex mixture of assets and challenges provide the city with a unique variety of opportunities and hurdles. Proponents of legacy cities have constructed the term in an attempt to change the existing narrative around deindustrialized cities as a places of blight and poverty, instead re-framing the discussion around their unique challenges and distinct competitive advantage. In this paper, we interrogate the construct of "legacy cities" by examining how closely the original framework is captured by the operationalization of legacy cities used in recent literature and advocacy. To accomplish this, we use a technique called cluster-discriminant analysis, which groups metro areas according to their shared position on a number of theory-driven dimensions. This paper contributes to the literature surrounding legacy cities by 1) putting economic content behind the analytical framework by changing the geography from city to region, 2) demonstrating an improved method to better distinguish clusters of legacy regions according to the theoretically-rooted variables that drive them, and 3) structuring this method in such a way that places can shed their legacy status when revitalization occurs (an acknowledgement of successful recovery).

Keywords: urban decline, revitalization, clusters, legacy cities.

1. Introduction

The decline of US industrial cities has puzzled urban planners, geographers, policymakers, and economists for over half a century. Once home to stable manufacturing empires of steel and automobiles, such cities have experienced dramatic shifts in their economic prominence and civic relevance. Due to the population loss and economic distress that dominated the late twentieth century, older industrial cities became practically synonymous in the eyes of many with blight, unemployment, violent crime, drug addiction, and poverty. However, after decades of continual decline, the outlook for many struggling American cities has finally begun to improve.

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The term "legacy city" is a product of recent scholarship and advocacy to paint older industrial cities in a favorable light, at a time when national demographic patterns indicate a "revival" of the desirability of urban life. Proponents of legacy cities have constructed the term in an attempt to change the existing narrative around deindustrialized cities as a places of blight and poverty, instead re-framing the discussion around their unique challenges and distinct competitive advantage. In this paper, we call into question how closely the original framework of "legacy cities" is captured by the operationalization of legacy cities used in recent research and advocacy. Our model identified over 30 variables—representing a range of assets and challenges pertaining to U.S. cities—which were used to separate metropolitan areas into homogeneous clusters and then identify the role of said variables in shaping each cluster.

2. Background

Throughout the latter half of the twentieth century, older industrial cities in the U.S. received scholarly and political attention on account of the many challenges they faced. As jobs left cities, so too did wealth, investment, and national economic relevance. This depletion of capital—not just of the financial variety, but human and social capital as well—from the urban core led to a proliferation of scholarship focused on the "ills" of the city (Downs, 1970; Dye and Hurley, 1978), such as concentrated poverty, rampant crime and drug addiction, hyper-segregation, unemployment (or low-wage service and retail jobs), and municipal budget shortages. The result of these problems was a decentralized urban center, "spatially cut off from education and employment opportunities" (Vey, 2007), whose bifurcation from the suburban periphery led to an enduringly negative connotation of "inner-cities," a term often used as a euphemism for the poor, jobless, and mostly minority urban cores. This outlook—of treating declining cities as aberrant epidemics of "stagnation and decay" (Jacobs, 1984)—reflected a common attitude of scholars and city practitioners during this era.

The urban growth of the late 1990s and early 2000s gave hope to policy analysts and urban economists who had patiently waited for the policy window (of urban revitalization) to open. However, due to a turbulent decade of global conflict and economic volatility—including the post-9/11 recession and the Great Recession—claims of a widespread urban revival may have been premature (Frey, 2012), as growth had begun to decelerate in many cities. Kingdon (1984) defined a policy window as an opportunity "for pushing pet proposals or conceptions of problems." Such windows require "compelling events" in order to be opened, acting as "catalysts for the adoption of policies" (Zahariadis, 2015). Despite the questionable evidence of urban regrowth, the policy window had opened nonetheless, providing an opportunity for advocates and scholars to amend the discourse concerning America's older industrial cities.

3. Legacy Cities

The word *legacy* can be defined as either "a gift by will especially of money or other personal property" or as "something transmitted by or received from an ancestor or predecessor or from the past." Note that in both definitions, is it unclear whether the thing gifted or transmitted is inherently good or bad. This definitional ambiguity highlights the innate tension of the term "legacy city." On one hand, many U.S. cities are heirs to the valuable endowments of a bygone era of industrial prosperity. On the other hand, the decline of domestic manufacturing employment and nationwide economic prominence has left the very same cities with several not-so-great reminders of their now-distant heydays. This intersection of assets and challenges is what makes the word "legacy" such a fitting descriptor.

As opposed to "shrinking cities" or even "older industrial cities," the term "legacy cities" carefully utilizes politically charged language to control the narrative. Prior to what (Glaeser and Gottlieb, 2006) called the "urban resurgence," the narrative around large, older cities tended to resemble a cartoonish caricature, centered around the decaying cesspools of crime, drug addiction, and poverty popularized in film and TV. Because "linguistic cues evoke pre-structured beliefs in people's minds" Edelman (1974), such words with negative connotations—decay, shrinking, decline—are not optimal for use in advocacy. Furthermore, because language allows people to "read their wishful thinking into an ambiguous phrase in a policy pronouncement" Edelman (1971), the term *legacy city* is well suited to subvert the traditional social construction of said cities.

The term originated at the 2011 meeting of the American Assembly (2011) as a "discursive framework" to help struggling cities "manage their realities in new ways that lead to reinvention rather than decline." Since then, its conceptual foundation has been strengthened by recent scholarship (Mallach, 2012b; American Assembly, 2012; Mallach and Brachman, 2013). At its core, the term is meant to convey both the *dilemma* and the *opportunity* housed within each legacy city. The dilemma is that older industrial cities have unique assets whose value is being limited by the wider urban context of decline and social problems. However, within legacy cities also lies the opportunity for reinvesting in those assets, allowing them to meet a set of demands that the current economy is generating.

3.1. Legacy City Assets

The overarching benefit of legacy cities is their competitive economic advantage (Porter, 1990). In some form or another, cities possess a combination of assets that both attract business and spur growth (cost advantage) and set them apart from bland, automobile era development (differentiation). Most of these assets are unevenly distributed throughout the country, but tend to be concentrated in older industrial cities (Schwarz, 2012). These include:

- *Traditional downtowns.* Younger cohorts "increasingly prefer downtown living and work options" (Brachman and Hollingsworth, 2016) and urban amenities typically "attract the next generations' economic change agents" (Piiparinen and Russell, 2013). *Operationalization in the model*: land use mixture index, MSA age.
- *Anchor institutions.* Commodities such as higher education are "nontraded sectors" of the regional economy and their primary institutions are relatively immobile (Hill et al., 2012). Investment in research also tends to spill over to the skill-level of the workforce (Mallach and Brachman, 2013). *Operationalization in the model*: top-tier research universities, state capitals.
- *Historic industrial clusters.* Although Detroit and Pittsburgh eventually lost their stronghold on the automobile and steel industries (Chinitz, 1961), their respective metropolitan regions are still home to technological expertise in the auto-making and metallurgic processes. The ability to transition from a production-based economy to a technology-based economy (Treado, 2010) is one of the positive legacies of an industrial heritage. *Operationalization in the model*: location quotient of MSA's gross metropolitan product (GMP) in manufacturing.
- *Large nonprofit organizations, arts institutions, and foundations.* Due to their heritage as former centers of industry and growth, legacy cities typically possess a wealth of "philanthropic institutions based on bygone industrialists' generosity" (Brachmann, 2012). These provide a social safety net that can help remedy the budget shortfalls that often plague legacy cities. *Operationalization in the model*: total assets of tax-exempt charitable organizations within MSA boundaries.
- *Extensive transportation networks.* Building a new rail system is so costly that approval to do so requires years of feasibility studies and heavily-subsidized tax incentives. However, legacy cities possess "billions of dollars in sunk infrastructure investment" in roads and transit networks (Mallach, 2012a). Furthermore, a city's economic prosperity at the time of the birth of the airline industry is a good predictor of the prominence of its airport in present-day air travel **(CITATION NEEDED)**. *Oper-*

ationalization in the model: number of intermodal transit and rail facilities (stations, depots, etc.) in the MSA, number of enplanements from all airports in the MSA.

- *Historic neighborhoods and architecture.* Because historic neighborhoods have proven to be an attractive commodity for young professionals and developers and a significant contributor to urban economies (Mason, 2005), a city with a large stock of historic properties is prone poised to reap the benefits of likely investment (Kinahan, 2016; Gao, 2014; Mallach, 2011). *Operationalization in the model*: Percentage of housing units in MSA's principal city designated as historic properties, median age of housing stock in MSA's principal city.

3.2. Legacy City Challenges

The challenges facing legacy cities are reminders of the decades of decline mentioned above. Legacy cities are faced with the disadvantage of having several weaknesses which must be mitigated if revitalization is to take place. These include:

- *Population and employment decline.* Despite the rebound in urban population mentioned above, many legacy cities are "still losing population and jobs" (American Assembly, 2011). Moreover, the erosion of the manufacturing sector led to a "bifurcation in terms of job quality" (Slack, 2014), wherein service jobs came to dominate. As such, within the service sector, the 'good' jobs increasingly are located in the central business district and suburbs, while not-so-good jobs abound in disadvantaged neighborhoods. *Operationalization in the model*: decades since census year in which MSA's central city population peaked, percent decline since peak, change in the size of each MSA's population from 2000 to 2010.
- *Vacancy, blight, and low property values.* In 2009, over one quarter of Detroit's residential lots were either vacant or "had structures awaiting demolition" (Bergelin et al., 2012). A similar pattern is present in legacy cities, in which the aging housing stock lacks proper upkeep. Ultimately, vacancy and neglect are a gateway to several other problems, including "a reduced tax base, reduced property values for remaining homes, and increased crime" (Heckert et al., 2015). *Operationalization in the model*: vacancy rate of housing units in MSA, Percent of housing units older than 1940 in MSA, percentage of total housing units in MSA designated as Section 8 or low-income housing units, median value of owner-occupied housing units.
- *Crime.* One study found crime rates to be strongly associated with population decline, noting that cities which have "reduced their crime rates below those of shrinking cities" should see an economic-turnaround (Hill et al., 2012). *Operationalization in the model*: property crimes per 1000 people.

- *Poor health.* A study found that babies born to women living in Michigan legacy cities were "much worse off than those born in the out-county areas" (Zehnder-Merrell, 2014). Health is a complex, multi-dimensional factor which interplays with several other challenges faced by legacy cities. *Operationalization in the model*: infant mortality rate, obesity rate, adult smoking rate.
- *Poverty and inequality.* Even though localized revitalization has taken place in many urban neighborhoods, poverty still abounds in most inner cities (Goldsmith and Blakely, 2010). Furthermore, small-scale revitalization attempts can often exacerbate inequality by attracting wealthy professionals and displacing the incumbent residents. This process is often referred to as gentrification (Palen and London, 1984; Smith, 1996) and tends to create a false buzz, clouding the true situation of a struggling inner city. *Operationalization in the model*: poverty rate, Gini coefficient, civilian labor-force participation rate.
- *Deteriorating infrastructure.* When low property values combine with an increasingly poor tax base, a cities' "ability to provide services and maintain their infrastructure deteriorates" substantially (Brachmann, 2012). These deficiencies tend to compound upon themselves, as budgetary constraints preclude municipal government efforts to remedy them. *Operationalization in the model*: percent of all bridges in MSA deemed "poor" or "structurally deficient."
- *Brownfields and environmental distress.* Centuries of heavy manufacturing has rendered a large portion of city land unusable. Urban "greening" and sustainability initiatives are needed to make such areas livable again (Heckert et al., 2015; Bergelin et al., 2012), but are often out of reach due to their high costs. *Operationalization in the model*: number of "superfund" waste sites, number of drinking water violations in MSA.
- *Education and human capital deficiencies.* Poor performance and funding of public schools encourages new residents to locate in better school districts (Tiebout, 1956). This inhibits growth in the tax base, ensuring that the lagging schools remain underfunded and under-performing. Consequently, because "graduation rates among city schools lag significantly behind suburban counterparts" (American Assembly, 2012), the city's unskilled workforce is usually not attractive to firms planning to locate in the region. Thus, an inequitable distribution of opportunity "serves as an economic and social brake on the entire community" (Lambe et al., 2017). *Operationalization in the model*: percentage of 25-and-older population with a bachelor's degree or higher, percentage of 25-and-older population whose highest level of education is below a HS diploma.

3.3. So what?

According to Markusen (1999), "The researcher or scholar has an obligation to be clear in proposing and defining a new concept, to answer the question, 'how would I know it when I see it?"' A poorly constructed criterion for how legacy cities are defined can undercut their potential as a policy construct. Popularly branded concepts can become trendy rhetorical tools for policymakers, philanthropic investors, and advocates but are not useful (and can even be harmful) when they remain too fuzzy.

Our objective in this paper is to add an empirical backbone to the construct of legacy cities by concretely distinguishing them from their peer cities throughout the US. While much of the literature refers to specific legacy cities—such as Syracuse, Detroit, or St. Louis—there have been few, if any, empirical mechanisms whereby the universe of U.S. cities can be differentiated in terms of "legacy" status. Attempts by policy advocacy groups to generate a list of legacy cities has fallen short of capturing the richness of the conceptual framework, leading to apparent measurement error. Using only a single criterion—such as population loss since peak—fails to capture many other elements of what a legacy city theoretically should be, and due to the stickiness of population, would create a classification that cities typically cannot "graduate" from.

4. Methods

The weakness of a single-measure criterion for distinguishing legacy cities is that it only captures *one* of the many components that make up the construct. Such a component, while an important feature of legacy cities, alone is prone to produce false-positives and false-negatives when determining which cities fit the description of legacy cities. To overcome this shortcoming, we implement a cluster-discriminant analysis (Hill et al., 1998; Hill and Brennan, 2000), which assembles a population into distinct groupings and tests the statistical validity of those groupings. On its own, cluster analysis can only go so far as to reduce the variance of squared Euclidean distances between observations. Discriminant analysis, too, is insufficient on its own, and requires a set of 'priors' which help identify[1] independent variables that influence discrete outcomes. In cluster-discriminant analysis, said priors are provided by the cluster grouping assignment. Thus, cluster analysis allows us to identify homogeneous units (cities, counties, regions, etc.) and discriminant analysis helps to identify *why* those units were grouped together. When combined, the benefit of using cluster-discriminant

[1] According to Hill et al. (1998) : "For readers who are unfamiliar with discriminant or factor analysis, but use regression techniques, it may be useful to think of discriminant analysis as being analogous to a multinomial logit or probit equation, where linear combinations of two or more independent variables are used to describe the behavior of a single, multiple-category, dependent variable" (Hair et al., 1987).

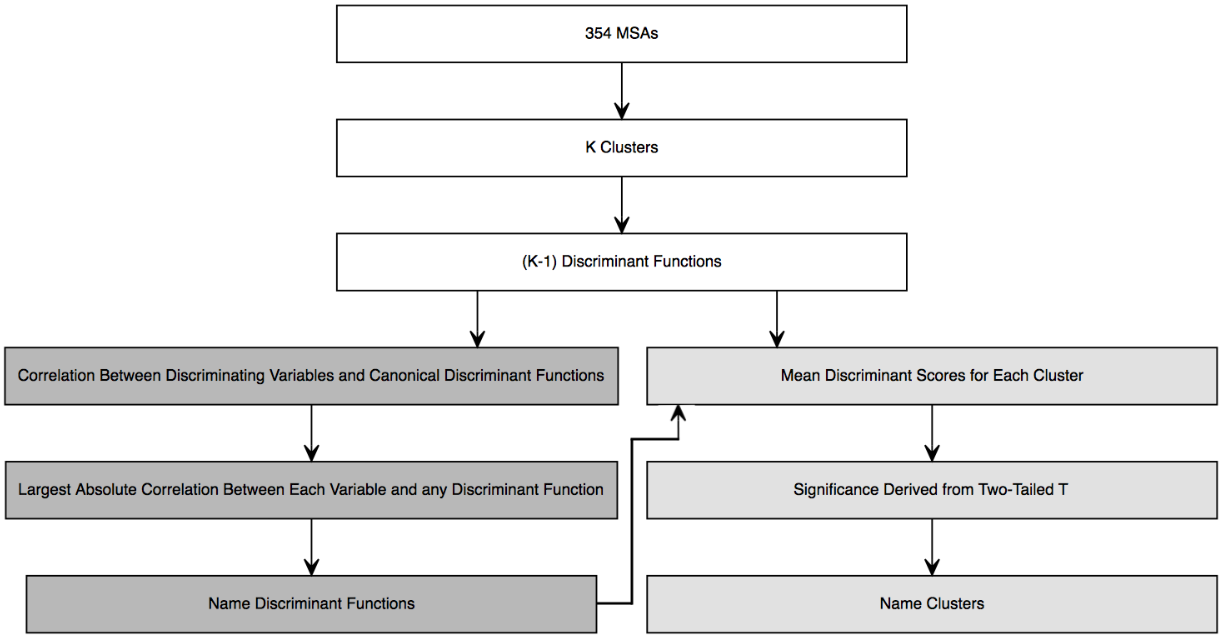


Figure 1: Step-by-Step Workflow of Cluster-Discriminant Analysis

analysis in urban and regional research is that it provides a two-step classification system, wherein 1) the assumption of homogeneity across cities is tested and 2) each cluster's "drivers"—which are the variables that significantly affect cluster formation—are identified.

5. Data

Since its inception, the legacy city construct has aptly been framed according to its namesake: the city. One of the contributions of this study is to argue in favor of abandoning the arbitrary jurisdictional boundaries of cities, instead framing the analysis around a new construct: the legacy region. In doing so, however, there is an inherent trade-off. On one hand, measuring assets and challenges at the city level improves one's ability to capture the true state of affairs in an urban municipality. Because suburbanization has made it possible for a struggling city to be located an otherwise healthy labor market, variables like poverty or population change might be muted by healthy suburbs if measured at the metro level. On the other hand, cities are inextricably situated within labor markets, and the health of a region cannot be omitted from the analysis. Thus, in this study, we measure *most* assets and challenges at the metropolitan level, save for a few instances in which it is theoretically justified to measure a variable for the MSA's principal city. The codebook (see Appendix) is clear as to whether each variable is given at the city or the regional level.

Metropolitan statistical areas (MSAs) are "less artificial geographic units" (Glaeser, 2000) than traditional municipal boundaries, as they are an amalgam of counties that constitute a region's labor and housing markets. The number of MSAs constantly fluctuates, as smaller urban areas grow large enough to become recognized as MSAs and as shrinking regions drop out of the classification (Farley, 2007). For this analysis, we use the 354 labor markets whose MSA status remained unchanged between 2003 and 2015.[2] Between one and four variables were selected to represent each of the assets and challenges as dimensions in the cluster model. It is worth re-emphasizing that "the theoretical justification for the interactions that are being modeled in cluster-discriminant analysis is key" (Andreason, 2015), and that these variables were chosen carefully as proxies for the assets and challenges outlined in the literature.

The variables chosen to operationalize the assets and challenges pertaining to legacy cities are listed at the end of each asset and challenge in the above section. Four additional variables were included in the model to control for demographic or geographic heterogeneity among metro areas. They are as follows:

- *Population density* . Accounts for relative differences in metro-wide suburbanization (or lack thereof).
- *Percent non-citizen or not foreign-born* . Accounts for relative differences in immigration levels between metro areas. This variable provides a crucial control for identifying regional labor forces
- *Percent over age 65 and percent under age 18* . Accounts for relative differences in age structure between metro areas.

6. The Model

The cluster analysis yielded thirteen groupings of metropolitan areas. These cluster assignments were then used to generate discriminant functions, which—when interpreted carefully—help to meaningfully *name* the clusters according to the key variables driving group membership. However, to interpret the results of the cluster-discriminant analysis, it is first necessary to understand how the cluster and discriminant analyses are employed and combined. To minimize the confusion of the reader, the entire process is mapped in Figure 1.

[2] 2003 is the year that the Core-based Statistical Area (CBSA) system was established by the Office of Management and the Budget for use by the Census Bureau and other agencies (OMB, 2015). The system divided urban counties into metropolitan and micropolitan statistical areas. A full list the 354 MSAs used in this paper is available upon request.

Table 1: Partial agglomeration schedule for cluster analysis

Stage	Clusters	Agglomeration Coefficient	1st Derivative (%)	2nd Derivative (%)
334	20	13.761		
335	19	14.99	0.09	
336	18	15.299	0.02	-0.77
337	17	15.773	0.03	0.5
338	16	17.077	0.08	1.67
339	15	17.954	0.05	-0.38
340	14	18.035	0	-0.91
341	13	18.06	0	-0.69
342	12	19.315	0.07	**48.81**
343	11	21.758	0.13	0.82
344	10	22.027	0.01	-0.9
345	9	23.059	0.05	2.79
346	8	23.082	0	-0.98
347	7	25.236	0.09	**94.94**
348	6	27.898	0.11	0.13
349	5	28.047	0.01	-0.95
350	4	30.393	0.08	**14.7**
351	3	33.964	0.12	0.4
352	2	41.762	0.23	0.95
353	1	48.198	0.15	-0.33

6.1. Interpreting the Clusters

A cluster analysis is a mathematical operation that minimizes the squared euclidean distance between a 'universe' of observations, each plotted according to several[3] variables. A *hierarchical* cluster analysis—which we use here—starts with as many clusters as there are observations (in this case, n = 354) and iteratively combines clusters until only one cluster remains (after n–1 stages). This process is called "agglomerative" clustering and produces a coefficient at each stage which corresponds to the level of heterogeneity that is lost when clusters are combined. Because agglomerative clustering will thus produce anywhere between 1 and 354 clusters, the question becomes *where to stop* in order to reach an optimal cluster solution.

In line with Hill et al. (1998), the agglomeration coefficient is used to determine the ideal number of clusters (K) to use in the discriminant analysis. In Table 1, the fourth and fifth columns serve as "derivatives" to track the change in the agglomeration coefficient. Column four tracks the rate of change in the agglomeration coefficient, and column five tracks the rate of change in column four.[4] A large, positive value for a given stage's "second derivative" indicates that the previous stage's agglomeration wiped out a

[3]In this analysis, there is no concern about such a liberal quantity of variables, as our N of 354 MSAs provides a comfortable starting point of degrees of freedom.

[4]Table 1 is a *partial* agglomeration schedule, and as such only displays coefficients for the final twenty stages of the analysis. Also of note, Andreason (2015) suggested more intuitive names for the first and second derivatives, respectively naming them the *slope* and *acceleration* of the agglomeration coefficient.

significant amount of heterogeneity between clusters. Each stage of a hierarchical cluster analysis can be depicted as a row in a table. Using Table 1 as a reference, it is clear that the "second derivatives" of stages 342, 347, and 350 (shown in bold) are much higher than the other values in the column. The number of clusters (column 2) for the stage *prior* to each of these is the number of clusters that existed before the between-cluster heterogeneity was dispersed. This means that the ideal candidates of selecting K could be either five, eight, or thirteen. Opting for more granularity and nuance, we elect to use a 13-cluster solution in the discriminant analysis.

Table 2: Cluster Names and Hit Ratios

Number	Cluster	% of Total	% Correctly Predicted
1	Young Central City, Growing Metro	20.1%	88.7%
2	Old Central City, Declining Metro	12.4%	79.5%
3	Weak Assets, Low Human Capital	13.6%	89.6%
4	State Capitals, Undiversified Economic Base	1.7%	100.%
5	Low Economic Distress	11.6%	87.8%
6	Old Central City, Declining, Weak Assets	8.8%	90.3%
7	Unconnected College Towns	6.8%	91.7%
8	Connected, with Strong Anchors	4.%	100.%
9	Younger Central City, Growing Metro, Connected State Capitals	7.6%	100.%
10	Low-Skill, Low Nativity, Younger Central City	6.5%	95.7%
11	Retirement and Vacation Communities	3.1%	100.%
12	Poster Child Metros	1.7%	100.%
13	High Human Capital, Young, Migrant (California)	2.3%	100.%

Cluster	1	2	3	4	5	6	7	8	9	10	11	12	13	Total
1	63		4		2		2							71
2	1	35	1		2	4			1					44
3	5		43											48
4				6										6
5	1	2			36	1	1							41
6		1	1		1	28								31
7	1		1				22							24
8								14						14
9									27					27
10	1									22				23
11											11			11
12												6		6
13													8	8
Predicted Total	72	38	50	6	41	33	25	14	28	22	11	6	8	354

6.2. *Combining Cluster with Discriminant*

When the universe (of 354 MSAs) is cut into K clusters, each MSA belongs to a grouping which acts as a sort of categorical outcome variable (a prior) for the discriminant analysis, which produces a series of 'discriminant functions' (numbering one less than K, to be precise). These functions—which are linear combinations of features that summarize between-cluster variation (Fisher, 1936)—are then used to classify each cluster according to the variables originally specified prior to the cluster analysis. Simply put, the discriminant analysis uses cluster membership as a 'prior' and transfers the dimensionality of metropolitan conditions from 33 different variables to 12 functions (which are each unique *combinations* of those variables).[5] The key difference between the two analyses is that while cluster analysis is nothing more than a *descriptive* technique (which separates observations into homogeneous groups), discriminant analysis is a *statistical* procedure that "tests the goodness of fit of...group assignments" (Hill et al., 1998). In other words, cluster analysis identifies similar groups of metro areas, but discriminant analysis is needed in order to meaningfully identify the variables that significantly drive cluster membership.

6.3. Interpreting the Discriminant Functions

A key question surrounding the results of a discriminant analysis is how well each discriminant function separates cases into groups, otherwise known as discriminatory power (Kinahan, 2016). The Wilks' Lambda for the 13-cluster discriminant analysis is extremely small (<0.0001) and significant at the 99.9% level, which indicates that group means differ from one another (Klecka, 1980), a high level of discriminatory power. This is illustrated in Table 2, which consists of 13 columns—which correspond to the assignments produced in the cluster analysis—and 13 rows—correspond to the assignments predicted when the discriminant functions.[6] The two assignments only 'disagree' with one another in 33 of 354 cases: a 'hit ratio' of 90.7%. The amount of total variance (of the universe) explained by each discriminant function is highest for Function 1 (21.8%)[7] and gradually declines for each function after that (the final function, Function 12, only explains 0.7% of the total variance).

The penultimate step of the cluster-discriminant analysis is to identify *which* variables contribute to each function's discriminatory power. This is done by analyzing the pooled within-group correlations between the 33 discriminating variables and the 12 discriminant functions. The functions can then be 'named' by associating them with the variables with which they are most correlated. This step, illustrated in Table 3, can at times be more of an art than an exact science. For instance, Function 1 is associated with pre-war housing

[5]This type of dimensionality reduction is not unique to discriminant analysis and can be seen in techniques such as factor analysis or principal component analysis.

[6]According to Hill et al. (1998): "There are two ways to think about the off-diagonal elements. One is to consider these to be cases in which the cluster technique made mistaken assignments. This would be appropriate if the clusters were mutually exclusive objective categories and, in this article, they are not. However, it is also possible that these off-diagonal cases are the makings of latent or emerging clusters."

[7]See bolded values in Table 3.

Table 3: Correlations between the discriminating variables and discriminant functions*

Functions	Correlation Coefficient*
Function 1: Old Central City, Prolonged Decline	**21.8**
Decades Since Peak	0.577
Number of Housing Units older than 1940	0.496
Decline Rate Since Peak	-0.493
Median Age of Housing Stock [a]	0.473
Population Change from 2000 to 2010	-0.288
Age of MSA's Principal City	0.281
Percent of Bridges Labeled Poor or Structurally Deficient [a]	0.264
Function 2: Connected and Strong Anchors	**18.4**
Total number of enplanements per-capita from all airports in each MSA	0.466
Size of Intermodal Transportation Network	0.463
Number of Top-Tier Research Universities	0.404
Population per square miles of MSA land area	0.375
Function 3: Low High School Dropouts, Few Kids, High Nativity	**13.9**
Percentage of the MSA population age 25+ with no high school diploma	-0.544
Percentage of the MSA population foreign-born	-0.531
Percent of population under age 18	-0.315
Function 4: State Capitals	**11.4**
Indicates that state capital is in MSA	0.641
Number of Section 8 Units & Low Rent Units per 1000 people	0.303
Function 5: College Educated [b]	**8.8**
Function 6: Older Residents, Vacant Homes	**6.3**
Percent of population age 65 and over	0.439
Percent of housing units which are vacant (in principal city)	0.295
Function 7: Anchored Philanthropy	**5.7**
Total assets per-capita of tax exempt charitable organizations	0.419
Function 8: Low Educational Attainment, Poor Health	**4.9**
Percentage of the MSA population age 25+ with a bachelor's degree or higher	-0.6
Percent of Adults who are Obese	0.501
Percent of Adults who Smoke [a]	0.399
Infant Mortality Rate	0.369
Property crimes per 1000 people	0.339
Function 9: Poverty, Low Labor-force Participation, High Inequality	**4.1**
Percent population with income below poverty level	0.584
Civilian Labor Force Participation Rate	-0.426
Gini coefficient	0.4
Neighborhood-level diversity of land use types [a]	-0.162
Function 10: Expensive Central City Homes	**2.6**
Median Value of Housing Units in the Principal City	0.547
Location Quotient of gross metropolitan product in manufacturing sector	0.205
Drinking water violations	-0.176
Function 11: Superfund Sites	**1.4**
Number of National Priority List (NPL) "superfund" Waste Sites per thousand square miles	0.276
Function 12: Historic Preservation	**0.7**
Number of historic properties per housing unit (in principal city)	0.429

* Percentage of total variance explained by each function displayed in bold in column 2
[a] This variable not used in the analysis (due to collinearity)
[b] Function 5 did not have the highest absolute correlation coefficient with any variable (but was the 2nd highest for research universities and percent of adults with a bachelor's or higher)

units, populations which have long-since peaked, and principal cities which came of age very long ago. It can be difficult to assess the overall "meaning" of this amalgam of variables, especially if their direction or magnitude appear to conflict with one another. However, the naming of the discriminant functions is of secondary importance to the naming of the clusters themselves, and as such, the names themselves are only meaningful if carefully used in the final step. As an example, Function 1 was given the name "Old Central City, Prolonged Decline," a name which is only as useful as long as each of its correlated variables are considered in the next step.

6.4. Naming the Clusters

The final step of this paper's analysis is to name each cluster. This is done by generating an individual discriminant score (the predicted value $\hat{Y}$) for each observation and across each function. The "group centroid" is then calculated by averaging the discriminant scores for each cluster group. A simple two-tailed T-test is used to determine whether each group centroid (mean) is statistically nonzero. Table 4 displays the results and significance of cluster mean discriminant scores. This table represents the key output of the cluster-discriminant analysis, and is what we used to name the clusters, each according to the significance, direction, and magnitude of its mean score at the discriminant functions.

For instance, the previously-unnamed "Cluster 3" can now be named "Weak Assets, Low Human Capital" due to its high (and statistically significant) association with low education, poor health, and high property crime rates (which were key components of Function 8). Conversely, Cluster 13 is named "High Human Capital, Young, Migrant" because of its *negative* association with Function 8, along with its low poverty rates and younger, less native-born population. As with the discriminant functions, assigning meaningful names to each cluster group is a subjective process and requires some discretion. The names chosen for the thirteen clusters in this analysis (represented in the leftmost column in Table 4) are imprecise distinctions, but nonetheless they sufficiently reflect the "statistically significant descriptors of each grouping" (Hill and Brennan, 2000).

6.5. Cluster-Discriminant Analysis: Recap

Cluster-discriminant analysis is a combination of two relatively straightforward techniques which, when combined, generate a set of results which can be complicated to interpret. Following along with Figure 1, the universe of 354 MSAs was divided into 13 clusters using 33 *conceptually-driven* variables, each of which was included because of the assets and challenges they represent. The resulting 13 cluster groupings were used as 'priors' (akin to a categorical dependent variable) in the linear discriminant analysis, which produced 12 discriminant functions (akin to a factor in a factor analysis). Each function was named according to the variables with which it was most highly correlated, after which point the clusters themselves were named according to the *function(s)* they were most associated with. In short, the multi-stage method of cluster-discriminant analysis:

- groups similar metro areas together,
- "assesses the appropriateness of the defined clusters" (Mikelbank, 2004), and
- "identifies which (of the numerous) variables drive those [groupings]" (Andreason, 2015).

7. Results

The output of the model includes several components (see Table 4), but the meaningful results of this study are the 13 clusters produced by the cluster-discriminant analysis. What follows is a brief overview of each cluster, followed by a general discussion of the findings.

7.1. Cluster-by-cluster Overview

When using the agglomeration coefficient (see Table 1) to decide on an optimal K, it appears that the eight cluster solution could be an optimal stopping point in our hierarchical cluster. However, we decided on a K of 13 for two reasons. First, the hit ratio of the cluster and discriminant analyses is highest when K=13 and *lowest* when K=8.[8] This is not an end-all decision rule for determining K, but it is preferable to find a solution where each MSA's true cluster assignment is also accurately predicted by the discriminant functions. Second, it is not a surprise that most of the 354 MSAs in the U.S. don't exactly fit the description of legacy regions, not to mention prosperous "poster child" regions. Thus, for the median group—on either side of economic extremes—a higher K allows us to divide "middle America" into more specific categories. The following are brief overviews of each cluster (or set of clusters), including a specific example or two of which MSAs fell into each group.

Growth and Decline The first two clusters are explained by only one discriminant function, and fortunately, it is the function with the highest 'explained variance' in the model. Function 1 is associated with older central cities and an older housing stock, further complicated by a decrease in overall MSA population

[8] It is somewhere in the middle when K=5.

Table 4: Scores of the discriminant functions evaluated at centroids (group means)

Cluster	Function 1: Old Central City, Prolonged Decline	Function 2: Connected & Strong Anchors	Function 3: Low High School Dropouts, Few Kids, High Nativity	Function 4: State Capitols	Function 5: College Educated	Function 6: Older Residents, Vacant Homes	Function 7: Anchored Philanthropy	Function 8: Low Educational Attainment, Poor Health	Function 9: Poverty, Low LFPR, High Inequality	Function 10: Expensive Central City Homes	Function 11: Superfund Sites	Function 12: Historic Preservation
1. Young Central City, Growing Metro	-1.41**	-0.08	0.32	-0.77	0.09	-0.46	0.32	0.12	-0.37	-0.6	-0.76	-0.28
2. Old Central City, Declining Metro	3.41**	-0.82	-0.06	0.02	-1.07	0.14	-0.38	-0.96	0.24	-0.38	-0.42	0.58
3. Weak Assets, Low Human Capital	-1.13	-1.33***	0.09	-0.31	0.68	-0.09	0.17	1.91***	0.19	0.53	0.08	0.51
4. State Capitals, Undiversified Economic Base	4.36	1.69	-0.59	7.34***	2.71*	1.94	5.86***	0.55	-0.18	-0.24	-0.31	-0.22
5. Low Economic Distress	0.78	-0.73	0.17	-0.03	0.2	-1.21	0.15	-0.44	-1.82**	-0.18	0.92	-0.06
6. Old Central City, Declining, Weak Assets	2.63**	-2.74***	0.38	0.06	-0.96	0.71	-0.64	0.63	0.82	0.66	0.2	-0.8
7. Unconnected College Towns	-1.19	-0.89*	-0.19	0.04	3.73***	-0.43	-0.61	-1.81	1.66	-0.01	0.29	-0.03
8. Connected, with Strong Anchors	1.21	5.43***	0.88	-1.45	-1.54	-3	1.61	-0.35	1.45	1.61	0.1	-0.07
9. Younger Central City, Growing Metro, Connected Capitals	-1.92**	2.74**	2.69***	3.26***	-0.67	0.49	-1.97**	0.07	-0.14	0.05	0.05	0.02
10. Low-Skill, Low Nativity, Younger Central City	-2.93***	0.54	-4.95***	0.97	-2.11**	0.25	0.14	-0.09	0.83	-0.67	0.54	-0.03
11. Retirement and Vacation Communities	-2.64**	0.9	3.97***	-3.58***	-1.28**	3.98**	2.19**	-1.1	0.42	-0.45	0.96	0.15
12. Poster Child Metros	6.55***	8.79**	-3.30*	-3.71*	3.45	2.35	-2.27	2.48	-0.5	-1.26	0.34	-0.26
13. High Human Capital, Young, Migrant (California)	-1.82**	0.82	-3.77**	-0.66	0.65	2.71*	-0.48	-2.07***	-2.53***	3.37	-0.95	0.02

*p <.05; **p <.01; ***p <.001 (two-tailed)

Read cluster scores from left to right (across the row), rather than by columns from 2000 to 2010. Cluster 2's positive discriminant score on Function 1 is a reflection of urban decline, while Cluster 1's *negative* score on function one indicates the inverse. They are named as such. Cluster 1 included MSAs such as San Antonio, TX and Portland, OR, and Cluster 2 included MSAs such as Dayton, OH and Providence, RI. Similar to those in Cluster 2, the metros in Cluster 6 are closely associated with decline. However, their decline is compounded by a significant weaker portfolio of assets. Cluster 6 included MSAs such as Wheeling, WV and Saginaw, MI.

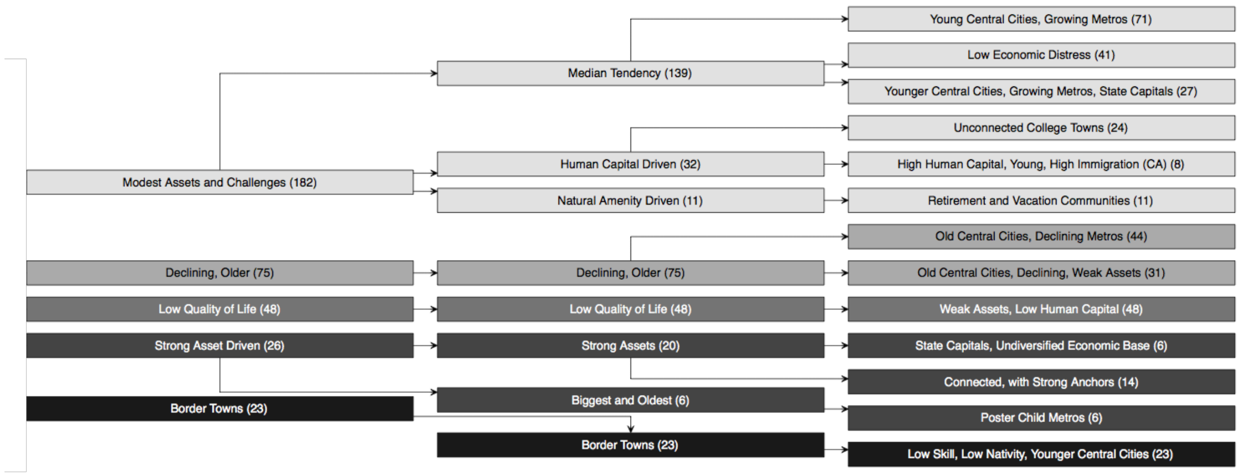
All challenges, no assets Cluster 3 was comprised of those places with high challenges yet very little assets. They face all the problems of poor education, poor health, and crime *without* the anchor institutions or transportation networks that might help to mitigate such challenges. Cluster 3 included MSAs such as Macon, GA and Joplin, MO.

Two types of capitals Clusters 4 and 9 were mostly comprised of state capitals, but there are a few notable differences between the two. Cluster 9's MSAs are much better equipped with transportation and university assets, but Cluster 4 is home to the highest level of philanthropy of any cluster. Cluster 4 included MSAs such as Albany, NY and Tallahassee, FL, and Cluster 9 included MSAs such as Phoenix, AZ and Nashville, TN.

Low Economic Distress In Cluster 5, poverty and inequality are relatively low, while labor-force participation is high. It included MSAs such as Cedar Rapids, IA and Manchester, NH. Because the 41 metros in this cluster are associated with neither growth nor decline, they stand in a league of their own.

(Un)Connected College Towns Cluster 7 scored well on discriminant Function 5, which was associated with high concentrations of college educated residents. However, it scored poorly on Function 2, which was associated with transportation connectedness. Thus, metros in Cluster 7—which included MSAs such as State College, PA and Blacksburg, VA—are what most would consider "college towns," as they are strengthened by higher education but little else. Cluster 8 was also home to several research universities. However, while it did not have a significantly high score on Function 5 (college educated population), Cluster 8 scored extremely high on the Function 2 (transportation networks). Almost the inverse to Cluster 7, the metro areas in Cluster 8—such as Seattle and the Twin Cities, MN—are large enough and possess sufficient transportation infrastructure to harness the economic benefits of a higher-education sector.

Poster Child Metros Cluster 12 was home to the "outliers" in the U.S. metropolitan landscape. These are metro areas with extremely old central cities, but—despite experiencing some decline over the last half-



Cluster Solution (K)	5	8	13
Second derivative from the cluster analysis	14.7%	94.9%	48.8%
Hit ratio from the discriminant analysis	89.3%	87.3%	90.7%

Figure 2: Simplified Dendrogram Illustrating 2, 5, and 13 Cluster Solutions

century—are unmatched in their level of assets. Also home to high concentrations of foreign-born residents, Cluster 12 included the New York, Boston, Philadelphia, Chicago, San Francisco, and Los Angeles metro areas.

Geography Matters Clusters 10, 11, and 13 each fit within a unique and relatively cohesive set of geographic boundaries. Metros in Cluster 10 (with the exception of two in GA and another in WA) are all located in states along the US-Mexico border. Central cities are younger and growing, but education levels are quite low, and the labor pool is largely foreign-born. In Cluster 11, the pairing of high vacancy rates and high philanthropy is explained by the high concentration of retirees living along the Atlantic coast. Finally, in Cluster 13 all 8 MSAs are in a single state, which suggests the uniqueness of California in its ability to match a high quality of life with immigrant labor and high concentrations of young (under 18) people. Cluster 10 included MSAs such as Las Cruces, NM and El Paso, TX; Cluster 11 included MSAs such as Ocean City, NJ and Daytona Beach, FL; and Cluster 13 included MSAs such as San Diego and San Jose (both CA).

7.2. *Overall Findings*

Similar to the legacy cities construct itself, the names chosen to fit each cluster are "fuzzy" at best (Markusen, 1999). However, such fuzziness is actually a feature—not a bug—of using cluster-discriminant analysis. The trade-off between a construct's theoretical complexity and its marketability for use in policy advocacy will always exist. More to the point, the model does a good job of 1) creating relatively homogeneous clusters and 2) identifying why each cluster's members belong together, which is, after all, the central goal of cluster-discriminant analysis.

The key difference between conceiving of legacy cities as a binary construct and as a *multi-dimensional set of clusters* is that subsets of clusters pertain to some policy issues but not all of them. This makes theoretical sense, as it would be illogical to assume that every legacy city has the exact same combination of assets and challenges. Instead, it is better to think of subsets of legacy cities according to their most pressing policy issues; perhaps there are 'housing legacy' cities that differ greatly from 'economic legacy' cities. Both groups of cities might possess the same assets—such as a healthy nonprofit sector, a dense walkable downtown, and so forth—but simultaneously are experiencing very different challenges.

The initial goal of this study was to put the "legacy city" construct to the test. From our analysis, it looks like the metropolitan areas belonging to Cluster 2 most closely align with the conceptual framework outlined in the early sections of this paper. We used a two-by-two matrix to crudely approximate how each cluster loaded in their overall levels of assets and challenges. Figure 3 plots out these scores, which were calculated by summing the z-scores of each asset variable and dividing by the number of variables.[9] Again, this is a crude estimation of each cluster's relative asset and challenge loading, but it provides a decent ex post confirmation of the cluster discriminant analysis. The MSAs in Cluster 2 belong to a cohort of "legacy regions" with both the benefit of industrial-era assets and the drawback of *post-industrial era* challenges.

8. Discussion

The purpose of this paper has been to propose three refinements to the construct of "legacy cities" as it currently exists. Going forward, these improvement should serve as guidelines for how older industrial

[9]This process was repeated for the challenge variables to produce a challenge score. Attention was paid to ensure the proper sign (positive or negative) was assigned when summing z-scores. For instance, when summing variables related to challenges, variables such as 'infant mortality rate' or 'vacancy rate' were summed as true challenges, while the 'median value' variable—while belonging in the challenge index—needed to be subtracted, as MSAs with higher property values were consider *less* challenged.

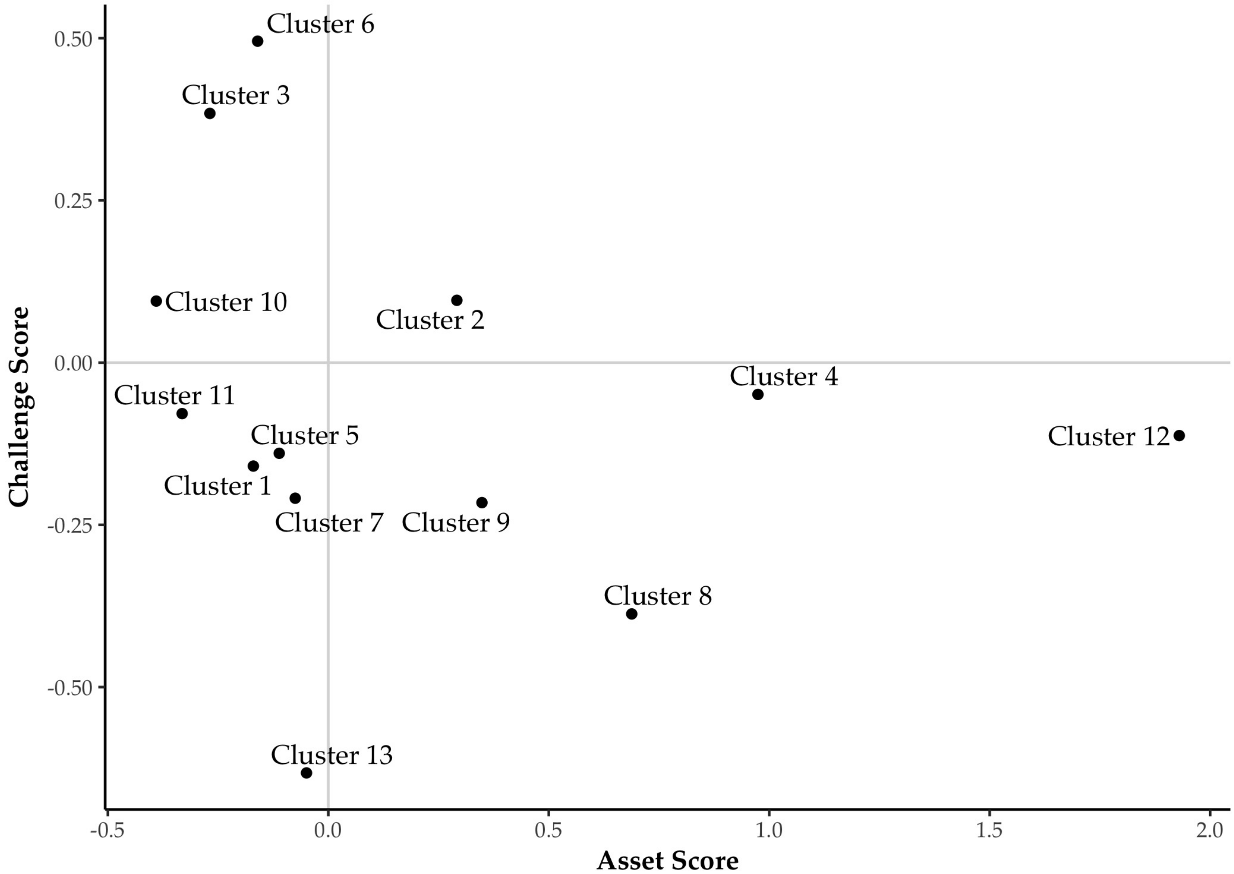


Figure 3: Plotted Asset and Challenge Scores

cities—housed within "legacy regions"—should be studied and discussed. These refinements are discussed as follows.

8.1. Capturing multidimensionality

First, the implementation of a cluster-discriminant analysis provides a more comprehensive means of capturing the theoretical construct of the "legacy city." This construct—as laid out in (Mallach, 2012b) and other supporting literature—involves the presence of both assets and challenges and cannot be accurately identified using just one variable. Because population growth "captures the quantity side of popular demand to live in a city." (Glaeser and Gottlieb, 2006), it is the most commonly used measure or indicator of urban vitality (Wolman and Lee, 2018). As such, it is probably the best *single* indicator to use in determining legacy city status, yet our contention in this paper is that a single measure could not possibly capture the multi-dimensional complexity of the legacy city construct.[10] To remedy this shortcoming, over 30 variables—

[10] According to Trochim et al. (2015), the single-measure criterion of *population loss since peak* would have 'face validity' but not 'content validity,' as it only meets one of the criteria for "the relevant content domain for the construct."

representing a range of assets and challenges identified in the literature—were selected and included in the analysis, which *separated* metro areas into homogeneous clusters and *identified* which of those variables were key in driving the membership of each cluster.

The resulting cluster groupings allow for a wider net to be cast. Because the assets and challenges of legacy cities are much more than simple population loss, it is possible that cities failed to meet that criterion's threshold but in several other dimensions do indeed fit the bill. The cluster-discriminant analysis helped to identify such places. Furthermore, the 13 clusters allow the careful analyst to cities with more nuance than a simple binary 'legacy' or 'non-legacy' designation. The clusters identified in this paper encompass a wide mixture of urban characteristics, ranging from extensive regional transportation networks to adult obesity rates. As mentioned above, a non-binary construct requires more critical analysis and might become so fuzzy that it hinders effective policy advocacy. However, a binary construct—especially one which is operationalized poorly—can be just as counterproductive. This study's analysis simply provides a starting point by which a more nuanced understanding of urban decline and resurgence can be had.

8.2. *Preventing tautology*

Second, we have suggested that using a single parameter of legacy cities—such as population loss—tends to create a dilemma in which places deemed as legacy cities cannot 'graduate' from that classification. Accordingly, if a legacy city's status is determined by population loss then the only way to successfully shed that status is to grow again. This implies that a revitalizing city would have to regain a significant portion of its former population—rather than simply experience new growth—in order to no longer be a "legacy" city. Such an operationalization of legacy cities is inherently flawed, as "urban decline is not the mirror image of growth" (Glaeser and Gyourko, 2005).

Ignoring this reality about urban population change risks committing a tautological fallacy wherein the status of a legacy city is merely a descriptor of past outcomes rather than an indicator of present economic and demographic conditions. The cluster-discriminant analysis employed in this paper is a first step toward poking a hole in this circular logic, allowing for dynamic (changing) cluster groupings that account for path-dependencies[11] (historically-influenced levels) *and* current momentum (direction of year-over-year performance).

[11]See Myrdal (1957) and Arthur (1994). The theories of cumulative causation and path dependence both deal with how historic success (or failure) breeds future success (or failure). Because of regional economic path dependencies, it is unreasonable to expect present-day performance to *only* reflect present-day circumstances. Rather, it is vital that any assessment of urban/regional 'conditions' takes into account both past *and* present factors.

8.3. Regions, not cities

Finally, in this paper we have suggested the need to modify the legacy city conceptual framework to account for the assets and challenges of an entire *region* rather than solely considering those of its central city. An example of this this need is demonstrated by the Legacy Cities Partnership (2017) list of legacy cities (discussed in detail in the following section), which included a diverse cohort of urban areas, ranging from Washington, D.C. to Pontiac, MI and Springfield, OH. When analyzed as *cities* , all three places might appear to behave similarly according to various metrics of decline. However, when viewed as part of the Washington-Arlington-Alexandria *labor market* , it is apparent that Washington D.C. belongs to a metro area with very different assets and challenges than the other two cities. The Washington D.C. example is probably the most extreme case, as indeed many of the LCP's designated legacy cities do indeed belong to clusters 2 and 6 (which are highly associated with population loss). A more modest case is that of Chicago, which was *not* designated by the LCP as a legacy city, but whose two Indiana suburbs—Hammond and Gary—did make the list. The Chicago-Naperville-Elgin MSA was assigned to Cluster 12—the "Poster Child" metros—alongside with New York, Los Angeles, and others. By virtue of belonging to the Chicago labor market, Gary and Hammond are bolstered economically in a way that a similar city with no such economic adjacency (such as St. Joseph, MO or Altoona, PA) would not be.

Even if a city like Gary, IN meets several of the legacy city criteria on its own, it cannot be overlooked that such cities are members of larger metropolitan areas, and as such, they have access to the "forward and backward linkages" (Hirschman, 1958; Krugman, 1991)—the circular supply and demand of work and workers—generated by the overall economic performance of that larger labor market to which they belong. Even for a relatively *isolated* city, a failure to account for the region as a whole introduces an enormous risk of bias. The Binghamton, NY and Lubbock, TX MSAs had respective populations of 251,725 and 284,890 in 2010, but the *cities* themselves had populations of 47,376 and 229,573 (which respectively accounted for 19% and 81% of their MSA's population) that same year. If such stark disparities are possible between the city and the metro in terms of population, it is quite reasonable to assume that similar disparities exist in terms of jobs, property values, demographics, and several other dimensions. In this paper, the variables input into the cluster-discriminant analysis were carefully chosen to avoid allowing the aggregate performance of the MSA to wash out the condition of the principal city. For instance, when measuring the age of the housing stock, it would be unwise to aggregate such a statistic across the entire region, as predominantly-suburban housing market would mask the *asset* of historic properties and districts. However, when measuring the infant mortality rate or housing vacancy rate, it would be imprudent *not* to aggregate across the entire

Table 5: Legacy Cities Partnership, List of 48 "Legacy Cities"

CITY	CBSA	CLUSTER	Principal City?
Louisville, KY	Louisville/Jefferson County, KY-IN	1	1
Akron, OH	Akron, OH	2	1
Baltimore, MD	Baltimore-Columbia-Towson, MD	2	1
Birmingham, AL	Birmingham-Hoover, AL	2	1
Buffalo, NY	Buffalo-Cheektowaga-Niagara Falls, NY	2	1
Canton, OH	Canton-Massillon, OH	2	1
Cincinnati, OH	Cincinnati, OH-KY-IN	2	1
Cleveland, OH	Cleveland-Elyria, OH	2	1
Dayton, OH	Dayton, OH	2	1
Detroit, Ml	Detroit-Warren-Dearborn, MI	2	0
Erie, PA	Erie, PA	2	1
Fall River, MA	Providence-Warwick, RI-MA	2	0
Hartford, CT	Hartford-West Hartford-East Hartford, CT	2	1
Milwaukee, WI	Milwaukee-Waukesha-West Allis, WI	2	1
New Bedford, MA	Providence-Warwick, RI-MA	2	0
New Haven, CT	New Haven-Milford, CT	2	1
New Orleans, LA	New Orleans-Metairie, LA	2	1
Niagara Falls, NY	Buffalo-Cheektowaga-Niagara Falls, NY	2	0
Pittsburgh, PA	Pittsburgh, PA	2	1
Pontiac, Ml	Detroit-Warren-Dearborn, MI	2	0
Providence, RI	Providence-Warwick, RI-MA	2	1
Reading, PA	Reading, PA	2	1
Richmond, VA	Richmond, VA	2	1
Rochester, NY	Rochester, NY	2	1
St. Louis, MO	St. Louis, MO-IL	2	1
Syracuse, NY	Syracuse, NY	2	1
Utica, NY	Utica-Rome, NY	2	1
Warren, Ml	Detroit-Warren-Dearborn, MI	2	0
Macon, GA	Macon-Bibb County, GA	3	1
Albany, NY	Albany-Schenectady-Troy, NY	4	1
Schenectady, NY	Albany-Schenectady-Troy, NY	4	0
Trenton, NJ	Trenton, NJ	4	1
Washington, DC	Washington-Arlington-Alexandria, DC-VA-MD-WV	4	1
Norfolk, VA	Virginia Beach-Norfolk-Newport News, VA-NC	5	0
Charleston, WV	Charleston, WV	6	1
Flint , Ml	Flint, MI	6	0
Huntington, WV	Huntington-Ashland, WV-KY-OH	6	1
Saginaw, Ml	Saginaw, MI	6	0
Scranton, PA	Scranton–Wilkes-Barre–Hazleton, PA	6	1
Springfield, OH	Springfield, OH	6	1
Youngstown, OH	Youngstown-Warren-Boardman, OH-PA	6	1
Minneapolis, MN	Minneapolis-St. Paul-Bloomington, MN-WI	8	1
Camden, NJ	Philadelphia-Camden-Wilmington, PA-NJ-DE-MD	12	0
Gary, IN	Chicago-Naperville-Elgin, IL-IN-WI	12	0
Hammond, IN	Chicago-Naperville-Elgin, IL-IN-WI	12	0
Newark, NJ	New York-Newark-Jersey City, NY-NJ-PA	12	0
Philadelphia, PA	Philadelphia-Camden-Wilmington, PA-NJ-DE-MD	12	1
Wilmington, DE	Philadelphia-Camden-Wilmington, PA-NJ-DE-MD	12	0

region, as historically confounding elements such as racial redlining and 'white flight' create a situation in which it would be careless to generalize about the labor market from its principal city (a potential ecological fallacy).

8.4. Policy advocacy and the allure of tidy lists

A report by the Lincoln Land Institute identified 18 of the 50 largest U.S. cities as legacy cities, defined as those with "a minimum population of 50,000 in 2010 and a loss of 20 percent or more from peak population levels" (Mallach and Brachman, 2013). The report's authors are explicit in stating that their sample of 18 cities is not an exhaustive list. However, a policy advocacy group has created an actual list of legacy cities, which are defined as cities which "have lost between 20–7% of residents since their mid-century population peak" (Legacy Cities Partnership, 2017). Of the 48 places listed by the Legacy Cities Partnership (LCP) as legacy cities, only 33 are the principal city of their respective metropolitan statistical area. Of those 33, almost 8% belong to either Cluster 2 or Cluster 6, both of which represented urban decline. Of the non-principal cities in the LCP list, 8 of 15 belonged to Clusters 2 or 6 (see Table 5).

While the LCP's list does a reasonable job of identifying cities within declining regions, its success—and that of *any* method employing a single-measure criterion—pales in comparison to a model which accounts for the multidimensional richness of the legacy city framework. In this study, we have sought to demonstrate a preferable means of testing the legacy city construct. In such a test, the likelihood of detecting false-positives and false-negatives (and thus eliminating them as such) is much higher when the analysis is 1) based on the geographic unit of the *region* and 2) accounts for a multiplicity of relevant variables.

9. Future Directions and Limitations

This paper provides a good start toward a multi-dimensional understanding of legacy cities and the use of the region as their basic unit of analysis. However, there are a number of further improvements that could take this study to the next level going forward. Most imperative among these is the need to more thoroughly interrogate the claims of the latter contribution, namely that the region (or labor market) is truly a preferable unit of analysis in measuring and discussing legacy cities. If a cluster-discriminant analysis were to be performed on, say, the 1,500 most populous cities, how would it compare to this paper's analysis of 354 MSAs? It would certainly differ in many regards, but would the resulting *city-based* clusters be able to provide a more granular portrayal of the urban condition? This is a question for a future analysis.

Another improvement that could be made to this study is the inclusion of more spatially-derived variables. A refined adaptation of this paper's analysis could better account for things like political and jurisdictional boundaries, border-spanning regions (such as the Cincinnati MSA, which encompasses Ohio, Kentucky and Indiana), access to natural resources and amenities, and the "circular causation" that causes agglomeration economies to be sticky (Fujita and Krugman, 1995). Furthermore, certain statistical operations—such as calculating the Moran's I or SaTScan statistic (Kulldorff, 1997)—might prove useful in identifying patterns of autocorrelation or clustering across space. Finally, GIS might be used to calculate more complex variables, such as the minimum time required to drive from one region to the next nearest region (or simply the number of regions which are reachable within a certain drive or flight time-horizon).

One of this study's significant limitations is the true importance (or lack thereof) of the "legacy city" construct itself. It is true that studying the "urban condition" (whether positive or negative) has been a stable practice for economists, geographers, and planners for more than half a century. However, the idea that urban vitality is not a binary condition (or that incorporating the entire labor market produces a more holistic view of a city) is nothing new. This paper's analysis and findings are not the result of questions begged by the academic community, but rather, they are glaring holes in a theoretical construct which is (reportedly) finding use by policy advocacy groups. As such, this paper's contributions might appear remedial in comparison to the body of literature it belongs to, but this limitation is a necessary one if it is to influence policy decisions involving taxpayer dollars.

Another shortcoming of this paper is the temporal inconsistency of data used as variables in the analysis. By this, we mean that there were significant limits posed by the availability of administrative data. Most, if not all, of the variables were collected from governmental institutions with a very strong reputation for reliability. However, some variables originated from the 2010 decennial census, while many others were *averaged* from the 2011-2015 range in the American Community Survey. Still other variables were collected from the year 2012, 2014, or even 2007. The aggregation of data from different years creates a number of well-known problems, principal of which is the fact that a major macroeconomic event (the Great Recession) occurred from 2007 until 2010, and its recovery took place in a spatially and temporally uneven fashion. Especially for those variables collected as 5-year ACS averages, the recession poses a nontrivial threat to data reliability.

10. Conclusion

The legacy city construct is one that, by design, acts as a "discursive framework" to help struggling cities "manage their realities in new ways that lead to reinvention rather than decline" (American Assembly, 2011). In this paper, we have reviewed the construct of legacy cities and applied a statistical analysis to improve the process of identifying places that match the construct's definition. Rather than identifying what is—and is not—a legacy city, the results of this study's analysis are something more akin to a taxonomy: a process whereby metropolitan areas were divided into relatively homogeneous clusters and can be identified according to the assets and challenges most associated with legacy cities. This approach lends a stronger theoretical backbone to an already useful construct.

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