Using Migration Degree to Distinguish Post-Industrial U.S. Cities

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Abstract

Migration between cities is typically modeled in terms of factors in each city, such as job availability or wages. This framing does not capture the diversity of information flow and social networks within a city. Instead, an "attractive" city (due to wages, etc.) is considered attractive to all potential migrants—regardless personal tacit knowledge and geolocated social capital.

One way to capture the diversity of decisions that may be the result of diverse information flow and values is to measure each city's migration network degree. Given this notion, we explore the use of migration network degree to distinguish attractive cities for migrants. We use a network of U.S. CBSA-to-CBSA migration flows for more than 200 million people from 1990-2011. We find that certain derivations of network degree, i.e. variety of flow origins and destinations, can successfully distinguish economically-declining Post-Industrial region cities from U.S. cities at large.

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1. Introduction

1.1 Human Migration

Inter-place migration is typically examined in the aggregate: movers from city *i* to city *j* are most often modelled as a function of distance between *i* and *j*, as well as population and economic factors at both *i* and *j* (e.g. Greenwood and Sweetland 1972, Treyz et al. 1993). This approach resembles the Neoclassical Model of migration that describes how labor flows from poor to wealthy areas (for a review, see Greenwood 1975 and Greenwood 1985), where the flow of people moves freely to sources and sinks, and produces an equilibria, reverse flows and symmetry (Tobler 1995). Based on this notion, economic opportunity is the main factor for predicting how attractive a place will be for potential migrants, though these flows are also guided by sociological factors (Mangalam and Schwarzweller 1970) demographic factors such as age and gender (e.g. Joseph 1975 and Franklin 2003) as well as climate and moving costs (Carrington 1996).

These types of models differ do not always consider human interpersonal relationships. Instead human capital models (Greenwood 2005), which enlist theories of chain migration and increasing returns provided by one's contacts, actually facilitate migration. Perhaps more so than wages, personal push and pull factors (Dorigo and Tobler 1983), given a lack of intervening opportunities (Stouffer 1940), could illustrate how humans make decisions to migrate to a certain location, not given the economic conditions at both locations, but the personal social benefits of moving to a certain location—which are harder to generalize.

1.2 Flow Data and Economic Viability

Instead of modeling aggregate place-to-place flows, we argue that examining the *diversity* of flows in and out of a city provide a salient alternative to traditional migration gravity model analyses. A city's ability to attractive flows from diverse places may be the result of diverse social networks (referred to as human capital in the migration modeling literature (Greenwood 2005). Although flows have been rarely used to explore a place's variety in connectivity, the incoming and outgoing currents of a city are integral for understanding its nature (Batty and Cheshire 2011). These channels of research have shown, for instance, that cities with diverse communication patterns tend to have higher socio-economic characteristics than those with insular communication (Eagle et. al 2010).

Transmitting information between places helps link those places together (Fawcett 1989, Rojas 2010), as migrants tend to follow information, and vice versa (Castells 2009). Methods that define the *variety* of information and social ties that exist in a city, such information entropy (Shannon 1948), should be applied more to understanding the composure of information flow in and out of cities. Consider the following example: perhaps a neighborhood of 50 people might have, collectively, 500 social contacts who can offer opportunities (jobs, temporary lodging, and introduction to specialized social circles) in 100 different U.S. cities. Another neighborhood of 50 people might have 500 social contacts who can offer jobs in only 5 different U.S. cities. Residents in the first neighborhood may have many attractive destinations that offer increasing social returns--fringe benefits, opportunities, jobs, etc.-- (Granovetter 1973) while others may not, but may also reap the benefits of a close community (Fischer 1982). This theory of flow variety can be applied to a city's migration flows, so that a city that has few migration origins or destinations (for example) may indicate that there are homogenous veins of information flow to, from and within that city.

We recommend that a city or region's economic characteristics may be better correlated with the number of places with which a city exchanges migrants (its migration degree), than the city's net migration rates, which are typically used as such an indicator. The reasoning behind these personal decisions are not well-captured by a neoclassical model or by raw migration statistics such as net-gain and net-loss of migrants (Andris et al. 2011). For instance, prominent cities like Boston, San Jose, San Francisco and Los Angeles are intermixed with post-industrial declining cities Buffalo, Cleveland and Detroit in a list of net migrant loss as a function of city population (Table 1). It is challenging to distinguish prospering cities from "declining" cities with these statistics.

Table 1. Top U.S. metropolitan areas ranked by net migrant loss as a fraction of population

Metropolitan Anchor City	Net migrant loss (1995-2010)	2004 population	Loss as fraction of population
New Orleans, LA	-178,225	1,342,875	-0.132
San Jose, CA	-232,979	1,787,468	-0.130
Los Angeles, CA	-1,447,486	12,889,807	-0.112
New York, NY	-1,724,003	18,770,041	-0.092
San Francisco, CA	-287,747	4,261,797	-0.067
Buffalo, NY	-70,818	1,167,173	-0.061
Cleveland, OH	-125,259	2,132,298	-0.059
Boston MA	-259,585	4,464,336	-0.058
Detroit, MI	-257,650	4,532,482	-0.057
Chicago, IL	-503,129	9,457,619	-0.053

Source: U.S. Census and U.S. Internal Revenue Service. Population growth rate accessed from Frey, W. (2012) "Population Growth in Metro America since 1890: Putting the Volatile 2000s in Perspective", Washington, DC: Brookings Institution.

To capture the variety of flows a city can attract or repel, we look at the *number of origins and destinations* of in and out migrants moving in and out of a city. We develop a set of statistics that resemble *derivations of network node degree* and apply these statistics to a case study whose goal is to distinguishing a region of post-industrial cities from all U.S. cities (described further in 2.1). These new derivations of degree can serve as viable as a statistical features of "attractive" or "unattractive" places, based on agent behavior and individual decisions to move to a place. This mindset is notably different than past methods that define cities by their demographic and economic characteristics.

1.3 New Statistics

We describe three new statistics derived from network degree, for analyzing cities. First, we find the number of origins (in-degree), destinations (out-degree) for U.S. cities. *Degree* is divided into **outgoing degree (D_o)** and **incoming degree (D_i):** for each city *c* with population *P* and migrants *M*.

We theoretically distinguish D_o from D_i so that high values of outgoing degree indicate that a city's residents seek connection and information from a multitude of places; high levels of incoming degree indicate that a wide variety of places seek information and opportunities inherent to a place.

Since larger cities produce more individuals and variety of pull and push factors, we expect degree to correlate with population size of the city. Thus, we use city population as a normalizing factor to create **outgoing** and **incoming propensity** (***PR_o and PR_i***) as the degree over city population [D_o / P_o] and [D_i / P_i]. In migration studies, propensity refers to the probability of a resident migrating (Greenwood 2005), here we indicate that a city's propensity is correlated with its population size.

As population accounts for a place's potential to produce flows, not the actual magnitude of flows, we also expect degree to correlate with number of migrants. Since a city's population does not always account for the number of actors that are in- or out-migrating, we use the **outgoing** and **incoming variety (*V_o and V_i*)** as the degree over number of migrants [D_o / M_o] and [D_i / M_i].

Finally, we create the **degree ratio (R),** a ratio that measures the incoming degree / outgoing degree **[**D_i / D_o**]**. Lower degree ratios should be a signal of economic health, as people from many areas are pulled to a city, but not pulled away from the city.

We hypothesize that migration degree and its derivations: ***propensity, variety,*** and ***degree ratio*** will be significantly lower for post-industrial cities than for the U.S. at large. We will interpret these findings indicators of a place's ability to attract people from multiple places. We next describe our case study and methods for discovering the variety of migrant origins and destinations cities, and our results.

2. Case Study and Methods

2.1 Case Study

The concern on the economic viability of industry and manufacturing is not a nationwide concern, but has been focused on certain regional shifts (Harris and Todaro 1970, High 2015). In the U.S., this area has been a recent concern, due to the lack of industrial productivity in the later art of the 20th century vs. the productivity in the earlier part of the 20th century (High 2015).This regional community includes the Appalachian region and Midwest as an area referred to as the "Rust Belt" (see High 2015 for a review). This region has seen a loss of population in the past 30 years, and has struggled with urban blight, industrial closure, unemployment and increased poverty (High 2015). Notably, a lack of economic productivity leads to lower wages for families, fewer educational opportunities, reduced purchasing power and household income. We choose this region because of its distinct heritage in the U.S. and the rapid changes imposed on the American family by the closure of manufacturing and industrial sectors, i.e. factories (regional characteristics are outlined in Isard 1960). By-products include a lower tax base, and thus dilapidated infrastructure, the inability for 'blue-collar' workers to find new jobs with their current skill-set and domestic issues at home (Vedantam 2011). This case study is not unique to the U.S. but has applications worldwide. For instance, economically-declining regions are found parts of Central Europe and the U.K., where post-industrial culture and economic decline is also a prominent issue (Flynn and Taylor 1986).

2.2 Data and Study Region

We define our study region as a set of U.S. Core Based Statistical Areas (CBSAs) (according to 2010 Decennial U.S. Census metropolitan and micropolitan regions) in Pennsylvania and selected neighboring cities (Figure 1). We remove the Philadelphia and New York City CBSAs, as although both claim Pennsylvania counties as part of their cities, these cities are tied more to the eastern seaboard economic system than that of the post-industrial region. In total, our study area has 47 cities ranging in size from Pittsburgh, PA (population: 2.4 million) to St. Mary's PA (35,223) (Table 2). Although CBSAs (henceforth, city) refer to a city and its metropolitan area, we truncate these names and write the anchor city ("Pittsburgh, PA") in the document.

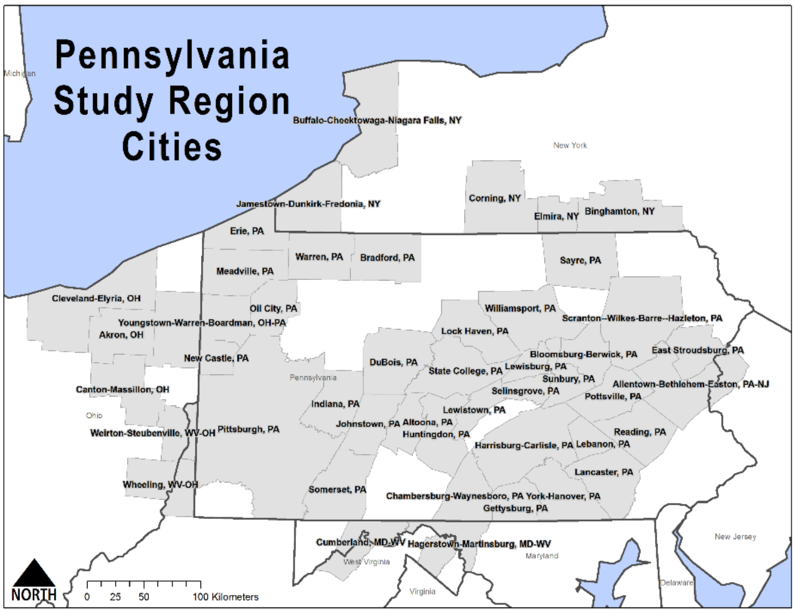

Figure 1: Pennsylvania study region cities.

Table 2. Pennsylvania region anchor cities and 2004 population (in thousands)

Anchor City	Pop.	Anchor City	Pop.	Anchor City	Pop.
Pittsburgh	2,414	East Stroudsburg	158	Meadville	93
Cleveland, OH	2,132	Pottsville	154	Indiana	91
Buffalo, NY	1,167	Wheeling, WV	149	Elmira, NY	91
Allenown/ Beth-lehem	769	Johnstown	149	DuBois	85
Akron, OH	701	State College	141	Bloomsburg	84
Youngstown, OH	592	Jamestown, NY	139	Somerset	81
Scranton/Wilkes-Barre	558	Chambersburg	134	Sayre	63
Harrisburg	521	Weirton, OH	129	Oil City	57
Lancaster	487	Altoona	129	Lewistown	47
Canton, OH	402	Lebanon	124	Huntingdon	46
York	399	Williamsport	120	Bradford	46
Reading	390	Morgantown, WV	113	Warren	44
Erie	281	Cumberland, MD	103	Lewisburg	43
Binghamton, NY	251	Gettysburg	96	Lock Haven	39
Hagerstown, MD	241	Sunbury	95	Selinsgrove	38
		New Castle	94	St. Marys	35

'Pop.' indicates population in thousands via ESRI. All cities are in Pennsylvania unless otherwise noted as Maryland (MD), New York (NY), Ohio (OH) or West Virginia (WV).

We explore the uniqueness of this region's migration patterns in comparison to those of the all U.S. cities. We use migration data from the U.S. Internal Revenue Service (IRS) for tax years ranging from 1990-2011 (U.S. IRS 2014). To estimate migrants, we use the number of tax exemptions (i.e. the sum of filers and dependents) listed as living in one U.S. county a given tax year, and another U.S. county in the following tax year. A pair of counties must have at least 10 migrants to be considered in the network. We aggregate counties to the CBSA level to create a network of CBSA-to-CBSA migrants.

We sum the number of migrants and degrees for our time frame. Counties and their populations that do not belong to a CBSA are not included in this analysis, although these represent a relatively small population. Each year, there are on the order of 2-3 million tax filers, and 5 million exemptions and 80–150 billion dollars in income traveling between counties. Each value tends to increase with time.

The top six origins and destinations for large cities Pittsburgh, Cleveland and Buffalo for 2010 serves as intuition for degree (Table 3). Here, we see that Cleveland exchanges on average 20% of its migrants with Akron through the years. In another example, Buffalo sends 20% (1990), 22.5% (2000) and now 25% (2010) of migrants to its top two destinations: Rochester and New York City, indicating a growing concentration of out-migrant destinations. Over time, the dynamics of degree change for each large example city (Table 3).

Table 3. Top U.S. metropolitan areas ranked by net migrant loss as a fraction of population

Year		Intercept	Slope	Mean of Residuals	R^2
1990	Penn Region	-0.057	1.02	-0.030	0.942
	ALL	-0.148	1.04		0.924
2000	Penn Region	-0.037	1.00	-0.066	0.929
	ALL	-0.286	1.07		0.936
2010	Penn Region	-0.089	1.02	-0.053	0.932
	ALL	-0.189	1.05		0.943

2.3 Statistical Tests

We first examine migration rates through the use of the following three Ordinary Least Squared (OLS) regression lines: P_o vs. M_o, P_i vs. M_i, and M_i vs. M_o, as well as propensity (*PR*), variety (*V*) and degree ratio (*R*). We perform the following tests using the statistics described in 1.3. For each test, we distinguish the correlations found using the Pennsylvania region "PR" cities to those found using all of U.S. CBSAs, ("ALL"). Correlations are defined by OLS regression, and the average of the residuals for each group (PR and ALL). We assess statistical significance at the 0.05 level. Due to the non-normality of our data, all results are found on the log base ten scale. In all figures the Penn Region is represented with colored points and a dashed trend line. The ALL data is represented with grey points and a dotted line.

In section 3.1, we correlate the number of a city's migrants vs. city population. In section 3.2, we calculate migration *propensity* (Pr_i, Pr_o), i.e. determining whether a city's degree is correlated with its population. In section 3.3, we calculate *variety*: whether a city's degree is correlated with its total migration rates (V_i, V_o). In section 3.4, we determine the *degree ratio* (*R*) for each city by comparing ratio of in-degree vs. out-degree for each city. We also show the spatial autocorrelation of these variables using Getis-Ord Gi* hot spot test as implemented in the ESRI ArcGIS environment. In section 3.5, we describe the temporal dynamics of the degree and migrants of our three most populous cities: Pittsburgh, Cleveland, and Buffalo (1990-2011). We conclude in section 4.

3. Results

3.1 Migration Rates

We find a strong positive relationship between the number of people moving in and out of a city (Figure 3a). The slopes are significant and approximately one (Table 4) with correlation coefficients ranging from .93 to .94. As out-migration increases by one unit, in-migration increases by one unit or slightly more. OLS regression lines are not significantly different for the Penn Region vs. all cities. Penn Region residuals are negative on average (Figure 3b, Table 4), indicating that the Penn Region has less migration on average. However, we note that East Stroudsburg, Pennsylvania in both 1990 and 2000 has a large positive residual and in fact has more incoming migrants than outgoing, while Buffalo consistently has a large negative residual with more out migration than in.

Table 4. Migrants, propensity and variety for in and out going migrants for 1990, 2000 and 2010

Year	Type	Out				In			
		Int.	Slope	Resid.	R^2	Int.	Slope	Resid.	R^2
Migrants: Migrants per population									
1990	Penn.	-2.0	1.026	-0.169	0.901	-2.2	1.069	-0.169	0.833
	ALL	-1.9	1.045		0.877	-1.9	1.032		0.835
2000	Penn.	-2.1	1.056	-0.146	0.920	-2.0	1.026	-0.146	0.833
	ALL	-1.8	1.028		0.897	-2.2	1.098		0.856
2010	Penn.	-2.0	1.027	-0.139	0.912	-2.3	1.074	-0.139	0.878
	ALL	-2.2	1.089		0.894	-2.2	1.081		0.879
Propensity: Degree per population									
1990	Penn.	-3.3	0.873	-0.159	0.887	-3.3	0.867	-0.195	0.851
	ALL	-2.8	0.820		0.806	-3.0	0.845		0.769
2000	Penn.	-3.1	0.848	-0.100	0.855	-3.2	0.851	-0.175	0.846
	ALL	-2.7	0.799		0.810	-3.0	0.856		0.789
2010	Penn.	-3.0	0.834	-0.083	0.871	-3.3	0.869	-0.141	0.871
	ALL	-2.8	0.805		0.825	-3.0	0.841		0.802
Variety: Degree per migrant									
1990	Penn.	-1.2	0.749	-0.033	0.822	-1.3	0.755	-0.069	0.812
	ALL	-1.0	0.700		0.832	-1.2	0.751		0.862
2000	Penn.	-1.1	0.725	0.012	0.784	-1.3	0.745	-0.057	0.816
	ALL	-0.9	0.674		0.811	-1.2	0.749		0.849
2010	Penn.	-1.1	0.716	0.025	0.841	-1.2	0.743	-0.030	0.834
	ALL	-1.1	0.709		0.849	-1.3	0.759		0.868

Population	Symbol
0-49,999	X
50,000-95,949	O
95,950-241,119	Δ
241120-999,999	+
>999,999	□

Figure 2: Key for Figures 3-7.

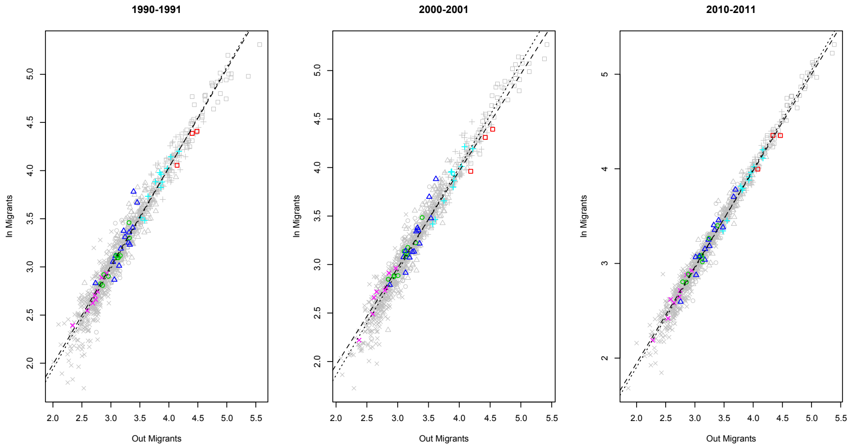

Figure 3a: **Incoming vs. Outgoing Migrants** Total out migration vs. total in migration on log scale for tax years beginning in 1990, 2000, 2010 shows an upward trend.

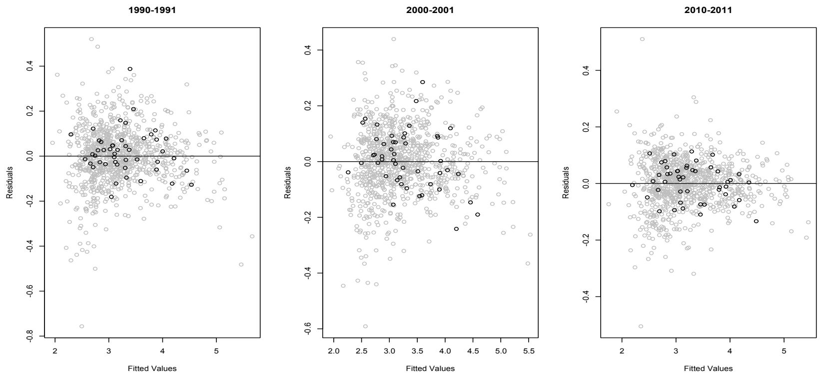

Figure 3b: **Incoming vs. Outgoing Migrants Residuals** Residuals vs. fitted values of outgoing migrants Penn Region cities (black points) are distinguished from other cities (grey points) and exhibit both negative and positive values.

Next, we expect to see migration increase as the population increases, and find that Penn Region cities typically have *both* fewer incoming and outgoing migrants per city size than the typical city. This is counter to our expectation that many people were moving from the region. The regression equations are each statistically significant (Table 5), and the Penn Region has significantly lower out and in migration over all time periods (Table 5, Figure 4a). The Penn Region cities are below the trend line, as the population increases, and cities move further away from the trend line (Figure 4b). This suggests that on average; as the population increases the PA regional cities tend to have less migration than other cities with similar sizes.

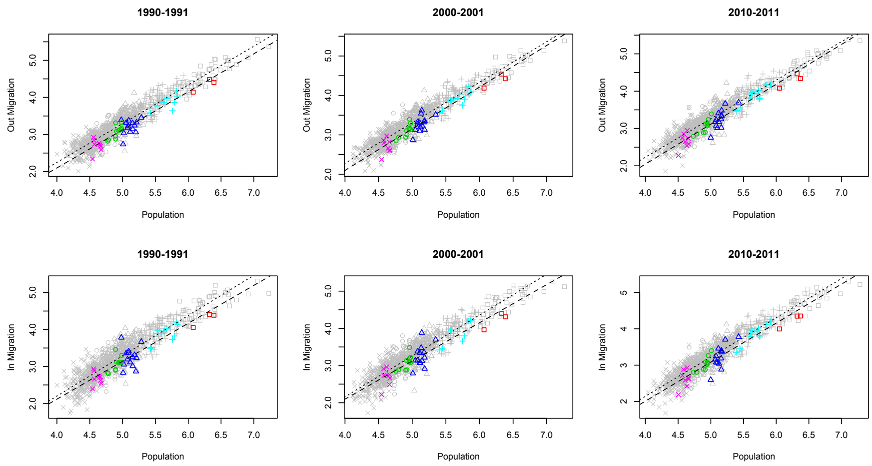

Figure 4a: **Migrants per Population** Total out/in migration vs. total population on log scale for tax years beginning in 1990, 2000, 2010 shows a positive trend that is slightly less correlated than the trend found in 3a.

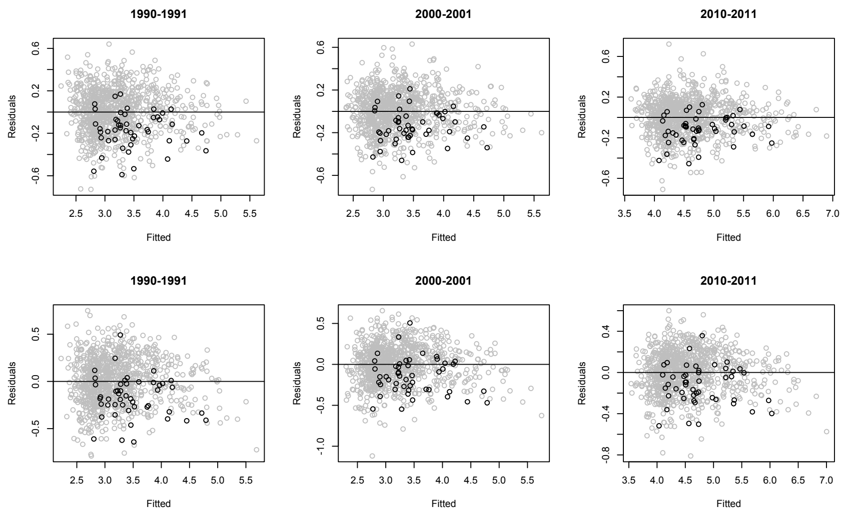

Figure 4b: **Migrants per Population Residuals** Residuals vs. fitted values of out-migration degree (top) and in-migration degree (bottom). Penn Region cities (black points) are distinguished from other cities (grey points), and exhibiting negative residual values more often.

3.2 Migration Propensity

We define population increases in tandem with incoming and outgoing degrees, as evidenced by statistically significant differences between the Penn Region and ALL cities (Figure 5a, Table 5). In the Penn Region, population and degree are highly correlated, in comparison to the ALL cities. The Penn Region is statistically below the trend line in terms of both in and out migrants over all time periods. These cities also exhibit negative residual values, indicating that for the city's population size, both migration in-degree and out-degree are less than predicted (Fig. 5b, Table 5). One city, State College, PA, consistently over-performs with more incoming and outgoing migrant degrees than expected given population. This city is home to a large university, and thus, sees a more transient population from more locations than is typical. This anomaly does not arise in number of migrants per city, necessitating the use of degree to discover non-typical observations.

Table 5. Correlation features of incoming degree vs. outgoing degree

Year		***Intercept***	***Slope***	***Resids.***	R^2
1990	Penn.	-0.032	0.984	0.018	0.964
	ALL	-0.038	1.013		0.955
2000	Penn.	-0.078	0.972	0.008	0.963
	ALL	-0.115	1.051		0.962
2010	Penn.	-0.099	1.006	0.005	0.987
	ALL	-0.074	1.028		0.981

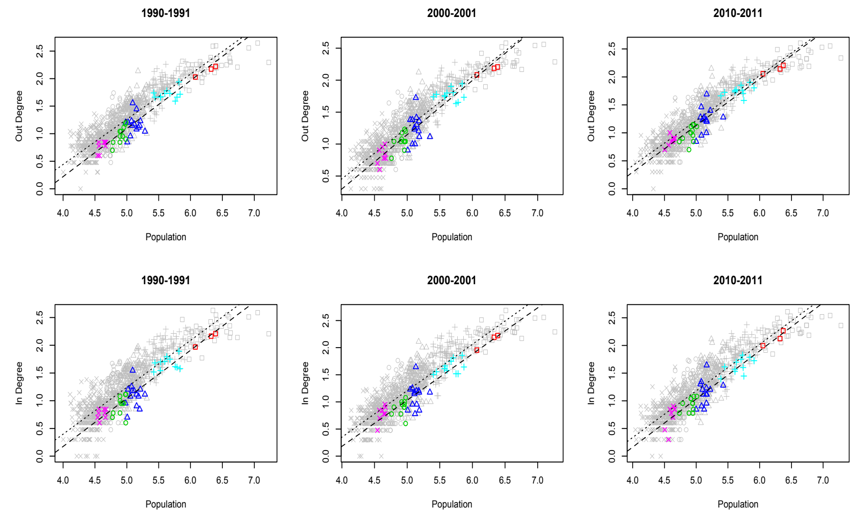

Figure 5a: **Migration Propensity** Total outgoing (top) and incoming degree (bottom) vs. total population on log scale for tax years beginning in 1990, 2000, 2010 shows a positive upward trend that is not as predictable as the correlations found in 4a (in and out migrants vs. population).

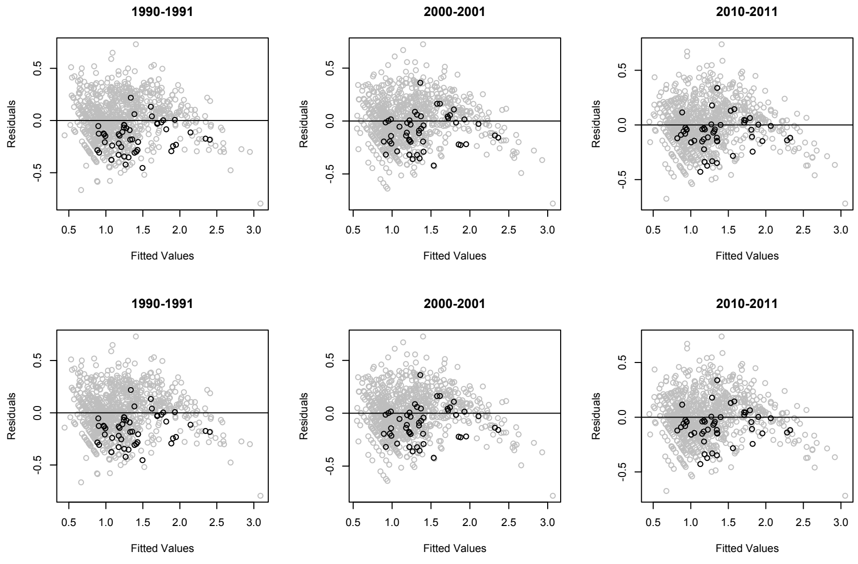

Figure 5b: **Migration Propensity Residuals** Residuals vs. fitted values of out-migration degree (top) and in-migration degree (bottom) as predicted by number of origin and destination city populations. Penn Region cities (black points) are distinguished from other cities (grey points).

Another artifact of the residual values created by predicting in and out degree by total population is a two-parameter “elephant” trend (Figure 5b), where a point cloud emerges for small and medium city sizes. Regarding residuals (Figure 5b), in and out degree are discrete rather than continuous variables, producing a lingering pattern left in the residuals, particularly with the smaller fitted values.

For largest cities, those with fitted values of 2.0 and higher, the number of possible origins and destinations seems to saturate, so that a high population cannot command higher corresponding degree values. As the largest cities grow, more incoming and outgoing propensity is unlikely, unless more cities are formed. Population can increase without bound, yet the number of possible degrees is 932. At some point, the degree saturates.

3.2.1 Incoming Propensity

In all time periods, the largest cities consistently fall below the baseline. In both 1990 and 2000, only State College, PA is found above the regression line. In 2010, State College, Morgantown, WV and Williamsport are above the line. State College and Morgantown are well-known university towns which are able to attract a larger variety of people than other cities of similar populations, while Williamsport has attracted new wealth due to the hydraulic fracturing (fracking) industry.

3.2.2 Outgoing Propensity

PR cities have lower than expected outgoing variety. In fact in 1990, there are only three cities that lie above the baseline: Binghamton, NY, State College, PA, and Jamestown, NY. In 2000 there are several cities above the baseline, but State College, PA, Binghamton, NY, Erie, PA, and Lancaster, PA are the highest. While in 2010, there are five cities to lie above the baseline: State College, PA, Binghamton, NY, Erie, PA, Morgantown, WV, and Selinsgrove, PA. State College and Morgantown not only have a large variety of people coming in, they also send people to a large variety of places. However, the rest of the cities listed here are only sending people to a large variety of places.

3.3 Migration Variety

We expect to see similar results when regressing the total number of degrees against the total migrants (Figures 6a, 6b). As migration increases, the degree also increases. Although all of the lines are significant, Penn Region is not statistically different from the ALL distribution, as it was with propensity. We again see similar patterns in the residuals because degree is a finite discrete value. However, the Penn Region average residuals are positive and approximately zero (Figure 5).

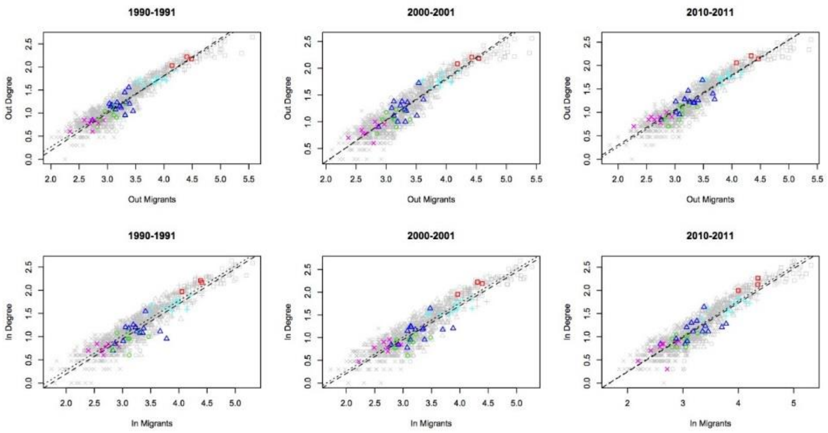

Figure 6a: **Migration Variety** Total outgoing (top) and incoming degree (bottom) vs. total number of in or out migrants for either the origin or destination city for tax years beginning 1990, 2000, 2010. This positive upward trend is not as predictable as the correlations found in 4a (in and out migrants vs. population).

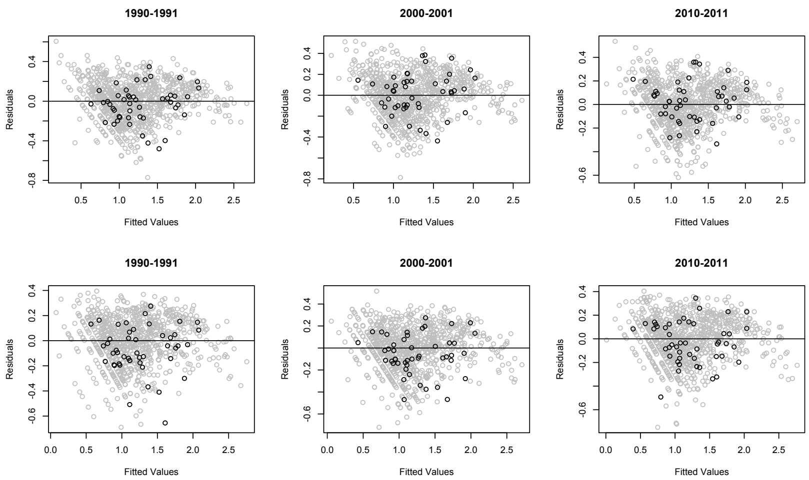

Figure 6b: **Migration Variety Residuals** Residuals vs. fitted values of out-migration degree (top) and in-migration degree (bottom) as predicted by number of in and out migrants. Penn Region cities (black points) are distinguished from other cities (grey points) and do not show a significant pattern. The lowest residual for outgoing values is East Stroudsburg, as many out migrants may travel to neighboring New York City.

3.3.1 Incoming Variety

For all cities, on average, as in-migration increases by one log-scale unit, .75 degrees will follow. Especially for incoming degree, the ALL cities have a better correlation than the Penn Region cities (Table 5). In 1990, East Stroudsburg, PA serves as a negative outlier in the residuals. For its population size, East Stroudsburg has higher than expected in-migrants. But for cities with a similar in-migration, East Stroudsburg has a smaller than average degree—perhaps due to its proximity to New York City. Unlike propensity, where the Penn Region's largest cities have lower than expected degrees given population, in terms of variety, the largest cities are now consistently above the baseline. For the number of in migrants, these cities are able to pull people from a larger than expected number of places. This may be due to the large number of cities in close proximity.

3.3.2 Outgoing Variety

As in-migration increases by one unit, the in-degree increases by approximately 0.7 in all years. The Penn Region stays resembles the ALL trend line with very little deviation and no extreme or influential outliers. In essence, the migrants that leave Penn Region cities have a typical number of destinations.

3.4 Degree Ratio

Degree ratio D_r is defined as (D_i/D_o). The incoming degree and outgoing degree are the most highly correlated features in the study (Figure 7a, Table 6). As out degree increases by one unit, the number of in degrees will also increase by approximately one unit in all time periods. The Penn Region is not statistically different from all data points, but does fall below all cities. The cities tend to be clustered by population. This clustering is exact for the largest two population groups and only slightly follows the pattern for the smallest three groups. There is one extreme exception in 1990 and 2000, with State College, PA in population group three appearing at the tail end of population group four. We note that the residuals show heteroskedasticity. The average of the PA residuals (Figure 7b) are approximately zero and positive for all years. Both Pittsburgh and Cleveland fall along all the cities OLS line, but Buffalo falls below.

The degree ratio is visualized first using hot spot detection for 1995-1996, which indicates high degree ratio in the southern states, Oklahoma and Kansas and low degree ratio in New York State and the Penn Region (Figure 7). In figure 8 (top), the degree ratio is visualized for 1996-2010 (summed values), indicating a clear pattern of rust belt and sun belt (as discussed in Harris and Todaro 1970), while plotting the in-migrants over out-migrants does not produce such a clear pattern (Figure 8, bottom).

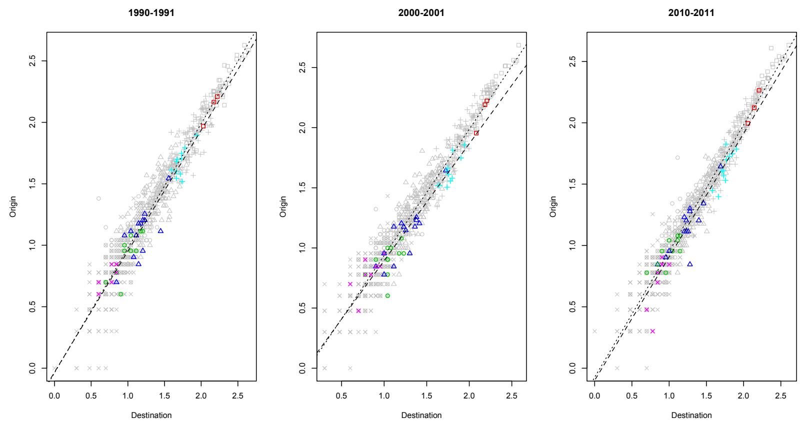

Figure 7a: An upward correlation of out degree vs in degree for each city for tax years beginning in 1990, 2000, and 2010 is heteroskedastic.

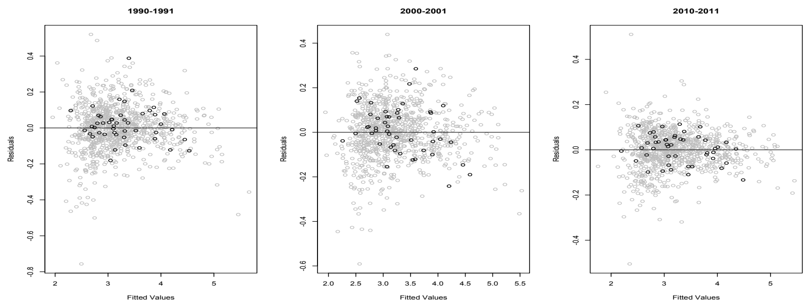

Figure 7b: Residuals vs. fitted values of out-migration degree vs. in-migration degree (bottom). Penn Region cities (black points) are distinguished from other cities (grey points) and do not show a significant pattern.

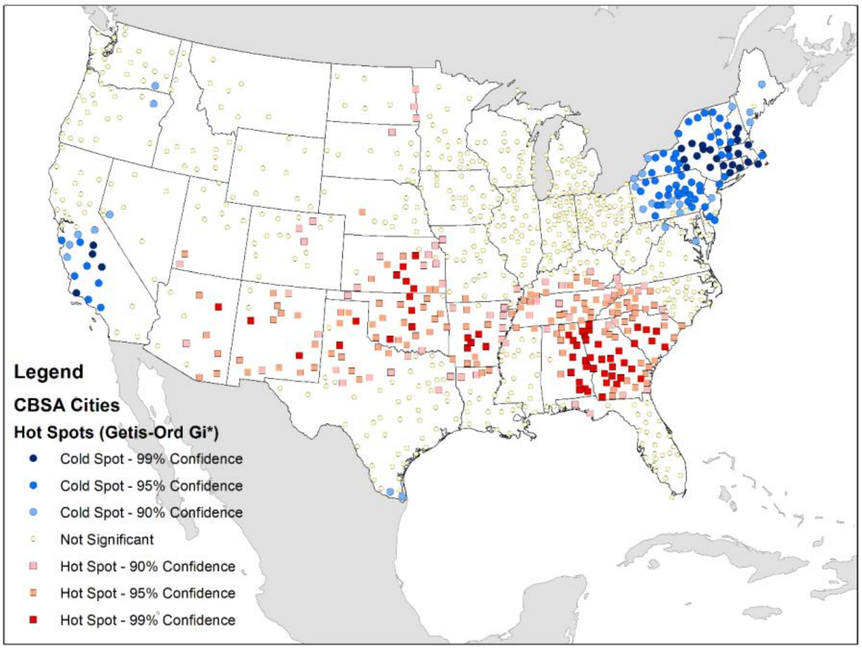

Figure 7c: Hot spot analysis of high and low degree ratios for 1995-1996 show significant regional trends in New England and the South, as well as California and Oklahoma, Kansas and Arkansas.

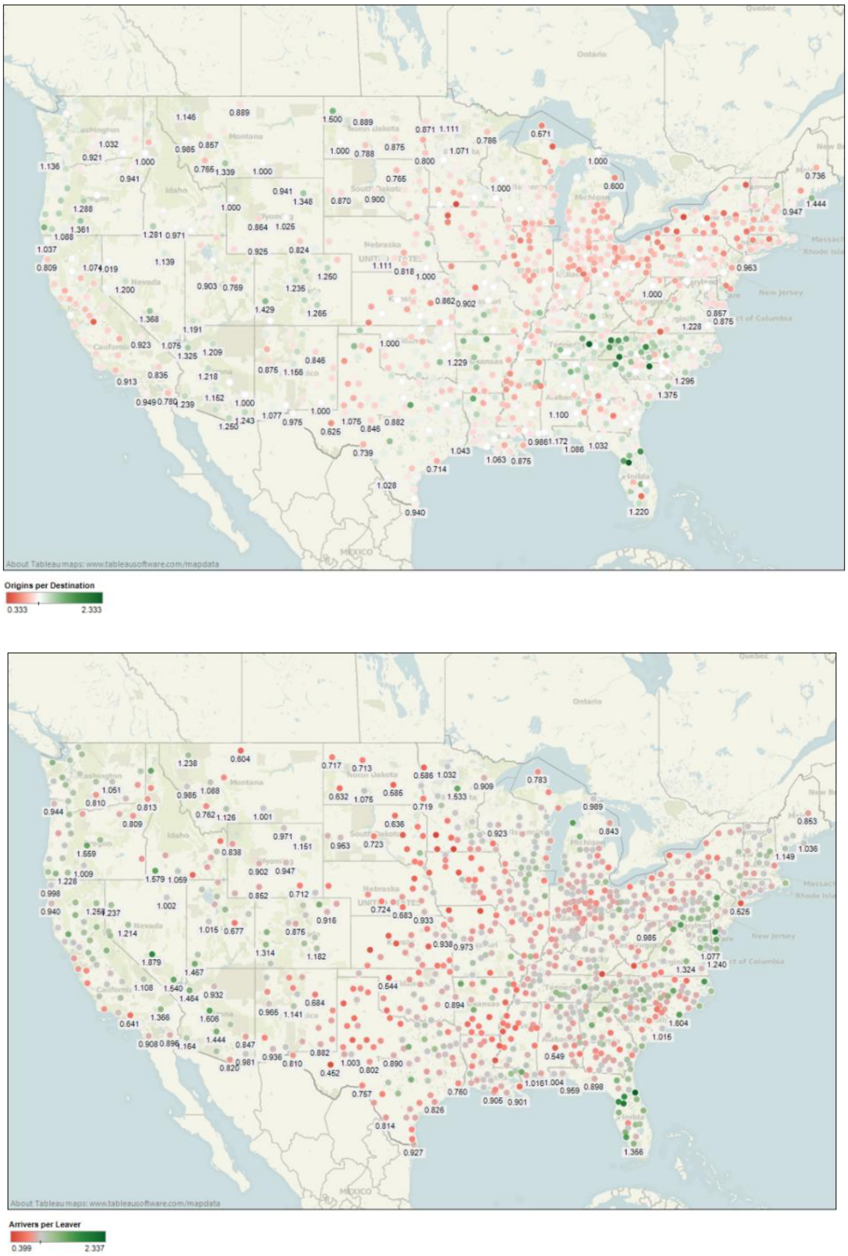

Figure 8: Degree ratio, i.e. origin degree / destination degree for years 1996-2010 (summed values) (top) elicit clearer spatial patterns than the display of out-migrants per in migrant (bottom) summed for 1996 – 2010.

4. Conclusions and Discussion

In summary, we find that migration degree is an important consideration when looking at certain aspects of a city's behavior in a larger network. We also find that this method is more telling than a single measure of total migrants, net-migrants or ratio of in-migrants to out-migrants. We also find that degree can be visualized more easily than flow data, and still represents the anisotropic 'spread/reach' of people migrating from different kinds of locales.

Our experiment illustrates that the migration degree of a city may be an indicator of how "well-connected" people are, what the range of their geographic social capital might be, and how this differs from city to city. Social capital is a type of 'wealth' that is often overlooked, and the degree helps us better understand the variety of social ties, individual decisions in sub-communities, neighborhoods, cities and regions. Although more exploration is needed, by using degree, we may better predict and detect promising cities or cities at risk.

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