Using a Network-based Framework to Measure and Inform Regional Entrepreneurial Ecosystem Investments: A Case Study of 20 Economic Zones in the state of Michigan

Author information

Dr. Daniel Romero, Associate Professor, University of Michigan, Schools of Information and Computer Science, Ann Arbor, Michigan, USA, ORCID ID: 0000-0002-8351-3463

Dr. David Brophy, Professor Emeritus, University of Michigan, School of Business, Ann Arbor, Michigan, USA

Thomas Jensen, Managing Director, ICatalysts, and Entrepreneur Futures, San Francisco, California, USA, tjensen@icatalysts.net, ORCID ID: 0000-0002-6510-1983

Dr. Mary Shepard Spaeth, Associate Professor, University of Wisconsin-Stout (retired); President, Transmera AB, Linköping/Stockholm, Sweden

Abstract

Federal policy-makers prefer an ecosystem building approach to high-tech entrepreneurial-driven economic development (Mason, et al, 2014). Examples are the National Science Foundation's Regional Engines and the Department of Commerce's Tech Hubs programs.

Entrepreneurial ecosystem approaches emphasize a "connected network" contextualization (Stangler, D., Bell-Masterson, J., 2015), whereby entrepreneurial organizations, institutions, investors, and entrepreneurial processes are interconnected and share resources and knowledge (Feldman, M., 2020:pg. 2 citing Mason, et al, 2014). How, why, when and where these connections produce results is important for policy-makers and researchers to understand.

Academic researchers use social network analysis (SNA) as a primary method to study and measure entrepreneurial ecosystems (Ancona, A. et al, 2023, Cavallo et al, 2019). However, despite their interest in building ecosystems, policy-makers have not adopted this method because of its complexities, and prefer outputs such patents, startup creation, funds raised, and jobs created to plan and evaluate their investments.

This paper presents a novel model that indicates if a region's ecosystem is underperforming or overperforming based on network density and applies the model to analyze over 12,000 organizations in 20 economic zones in the state of Michigan over 13 years. Zone by zone comparisons are made.

The authors show a strong correlation between regional network density and startup funding rates. Our research is important to inform entrepreneurial policy and investment decisions where billions of dollars are at stake. Further, this research will help lay the groundwork to increase the adoption of network science in governmental entrepreneurial policy and investment decisions.

Keywords

Social Network Analysis, Entrepreneurial Ecosystem, Economic Development, Regional innovation benchmarking metrics

Statements and Declarations

We wish to confirm that there are no known conflicts of interest associated with this publication and there has been no significant financial support for this work that could have influenced its outcome. The authors formally declare that the content of this paper is the original work of themselves. It is not being reviewed by any editorial office of publishers. All cited materials have been properly credited with citations in the contexts and the References section. We further confirm that the order of authors listed in the manuscript has been approved by all of us. We confirm that we have given due consideration to the protection of intellectual property associated with this work and that there are no impediments to publication, including the timing of publication, with respect to intellectual property. In so doing we confirm that we have followed the regulations of our institutions concerning intellectual property.

JEL Codes

G11	Portfolio Choice, Investment Decisions
O25	Industrial Policy
P41	Planning, Coordination, and Reform
P51	Comparative Analysis of Economic Systems
R11	Regional Economic Activity: Growth, Development, Environmental Issues, and Changes
R58	Regional Development Planning and Policy

Literature Review

The entrepreneurial ecosystem concept originated with practitioners in the mid-1990s. Colin Mason and Ross Brown offer what has become the generally accepted definition of ecosystems:

> “a set of interconnected entrepreneurial actors (both potential and existing), entrepreneurial organizations (e.g. firms, venture capitalists, business angels, banks), institutions (universities, public sector agencies, financial bodies) and entrepreneurial processes (e.g. the business birth rate, numbers of high growth firms, levels of "blockbuster entrepreneurship," number of serial entrepreneurs, degree of sell-out mentality within firms and levels of entrepreneurial ambition) which formally and informally coalesce to connect, mediate and govern the performance within the entrepreneurial environment.” (Feldman, M., 2020:pg. 2).

What we call entrepreneurial ecosystems today will continue to be redefined contextually to reflect changing externalities including ideologies, policies, and practices common to geographic regions, or to extend academic and public conversations in the search of improved practical outcomes based on theoretically conceived ideas. The defining concepts that reflect our understanding of how social, economic/financial, and social-intellectual activities intersect to support economic and entrepreneurial outcomes that communities find desirable is not necessarily a journey along disappointment nor of "broken dreams” (Lerner, 2009).

As reported by the Kauffman Foundation, a global leader in entrepreneurial research and action, "Innovation thrives in dense networks of people, built on a culture of trust, collaboration, and helping each other (Kauffman Foundation, 2018). In the Foundation’s 2015 study on Measuring an Entrepreneurial Ecosystem the authors wrote, "connections matter, and a dense network of connections, among a small number of programs, is arguably more important than a sparse network among a larger number” (Stangler, D., Bell-Masterson, J., 2015).

The exponential growth in research and articles about innovation systems and entrepreneurial ecosystems, by practitioners and academics alike, remains punctuated by seminal material from the US, Scandinavian countries, Netherlands, Spain, and Britain. In the early 1980s, Lundvall (2007) describes the first 20-year evolution of our defining, understanding, and practice of innovation systems, and more specifically ‘national innovation systems’. He suggests that “the ‘system’ terminology may have had a negative impact on the use of the concept in public policy. Certain policy-makers have interpreted the “system” in a mechanistic way assuming that the system can be easily constructed, governed and manipulated” (Lundvall, 2007)

Over the last 15+ years since Lundvall’s 2007 paper, the broadening and narrowing of terms that utilize ‘system’ concepts have led to understandably deeper and richer understanding of the possible and even necessary parts and players needed in a community, state, or nation to drive for some form of a successful economy. Lundvall (2007) cautions us, however: “How we define innovation is of course important for how we end up defining and analyzing innovation systems.” pg. 101. These entrepreneurial players are key to the entrepreneurial ecosystems that are a subset of Lundvall’s national innovation systems.

For many decades, particularly since the last mid-century, economic developers, political scientists, economists, and policy influencers have strived to understand and describe the interrelated cooperations and interactions of system players as a means to measure and optimize impactful outcomes related to innovation, technology transfer, and forms of successful commercialization, all ideally benefitting a community's, regions, or nation's economic well-being.

It is the intent of this paper to uncover ways of utilizing longitudinal network analysis to provide comprehensive and comprehensible information to policy-makers so that their understanding of efficient resource allocation and potential returns on investments is improved and their interpretations better reflect the possibilities and intents of the entrepreneurial ecosystems they help fund.

When civic and academic leadership in cooperation often with public policy-makers aim to improve the economic success of a community, their ability to do so is contingent on factors that may or may not be within their full control. The systems are not, as Lundvall 2007, pointed out, "constructed, governed and manipulated" in any sort of mechanistic way. They are fluid, unpredictable, and open to uncontrollable forces and market inefficiencies.

Leydesdorff (2000:pg., 245) refers to the "complexities and flexibilities of a triple helix network system" as interacting players from academia, industry and government face dynamics that reflect the challenges inherent to the collisions of innovation, culture, competition, and capitalism. Razak and White (2015) went further to identify not only the enablers of these potentially beneficial innovation catalyzing systems, but also the barriers. Delgado et al (2010), Swords (2013) and Moretti (2018) extend and apply Porter's cluster theory to innovation ecosystems as a means to further Leydesdorrf's (Leydesdorff, 2000) argument against the creation of what he described as "an engineering model of society" where local feedback loops support local development and seek to obviate expectations for successes implied through globally understood generalizations regarding ecosystem outcomes.

This paper considers the evolutionary theorization of concepts and motivations related to entrepreneurial ecosystems and their metrics vis a vis social network analysis (SNA) from a multi-regional perspective within the state of Michigan. The literature surrounding SNA as it relates to entrepreneurial ecosystems is relevant to understanding the ways in which it may be used to generate data based on ecosystem complexities to produce simpler forms of communication regarding an ecosystem's anticipated and real outcomes. Network density is a key metric in entrepreneurship and innovation. "Highly connected individuals, such as serial investors, play an outsized role in building a dense network and increase economic outcomes, such as investments, sales, and jobs" (Pittz, T., 2019).

Also, network density and centrality have been shown as leading contributors to network measurement in other fields such as health, economics, finance, law enforcement and other fields. (Light, R., Moody, J, 2020, Liu, E., 2023).

The literature points to several network-based principles and metrics that help shed light on the structure and dynamics of regional entrepreneurial ecosystems. Density, connectivity, and diversity (Stangler, Bell-Masterson, 2015, Brüderl & Preisendörfer, 1996) are commonly cited metrics whereas other metrics are fluidity, stability, intermediaries, leadership, and feedback loops (Ancona, Cinelli, Ferraro, & Lovanella, 2023). But overall, the literature is lacking in entrepreneurial ecosystem measurement methods and metrics, particularly those that are quantitative (Johnson, Hemmation, Lanahan, & Joshi, 2022).

Several studies have provided cases that illustrate the importance of quantitative network metrics (Ancona et al, 2023, Kemeny et al, 2015). Often these studies quantify the influence of individuals and organizations that connect entrepreneurs to mentors, investors, and other resources (e.g., R&D grants) to develop their technologies and businesses (Pittz et al, 2019). Researchers usually use social network analysis as a methodology to quantify network-based metrics such as density and connectivity in regional entrepreneurial data because it is well-suited to study complex systems (Cavallo et al, 2019).

Network density is a function of connectivity and cohesion (Light, R., Moody, J, 2020, Borgatti. S. et al, 2009). In entrepreneurial networks, the most central players exchange or facilitate the exchange of resources, such as R&D grant funding, training, mentoring, and financial capital. Especially in R&D stage startups, intermediaries, such as accelerators and universities drive this resource exchange.

Network centrality is a primary metric to understand the relative influence of actors in a social network (Bhattacharya, S. et al, 2023, Borgatti. S. 2009, Light, R., Moody, J, 2020).

Network density is the degree to which the actors - people and organizations - in a social network are connected to each other (Haythornthwaite, 1996). It is measured by the number of existing contacts (links) divided by the potential number of contacts among the network members (Cross and Parker, 2004, pg. 159). This number is typically very small because few organizations and people are connected to many others in a network. Network density can also reflect the level of connectedness among the actors in a social network (Coleman, 1990). The stronger the connections between individuals in a network, the stronger the social norm is through mutual influence and reinforcement. This reduces uncertainties and creates a sense of belonging and is likely to enhance trust (Chua and Morris, 2006).

Majumdar and Venkataraman (1998) propose that the density and variety of the user population will be positively related to levels of new technology adoption at all times. These interconnections between actors inform and influence one another to create a shared meaning and a sense of common purpose (Tenkasi and Chesmore, 2003).

A stronger density in a social network, as a result of many and strong ties, may help the actors to cope with change and ensure that the change succeeds (Tenkasi et al., 2003). With less access, historically, to the dense agglomerative networks of urban areas, rural counties have lower business startup rates (Renski, 2008), and the startups that do emerge experience lower growth (Lee and Xu, 2020), though firm survival rates are higher in rural communities (Yu et al., 2011, Deller and Conroy, 2017).

“Entrepreneurship policies, and innovative entrepreneurship ones in particular, are widely used at different governmental levels throughout the world” (Audretsch, D, et al., 2020). Policy-makers will likely be more effective if they understand ecosystems better. Audretsch’s research evaluated 39 policies in 29 countries. Twelve of the policies are related to “access to capital”, 18 pertain to “access to skills”, 9 are related to “immigration”, 25 to “access to networks” and 12 to “fiscal policy and tax incentive”.

With the largest category being “Access to Networks” and the “Access to Capital” tying for the third largest category, our network density: startup funding framework should be very helpful to policy-makers. Increasingly, policy-makers prefer an ecosystem approach to innovation and entrepreneurship (Mason, et al, 2014).

As such, to illustrate the importance of our findings on density to policy-makers interested in better understanding where and when capital access policies catalyze startups, we correlate density performance to the percent of externally funded startups.

Methodology

We chose Michigan for our analysis because we could study its entrepreneurial ecosystem within the context of the State's policy to build regional ecosystems. The State of Michigan established its SmartZone program in 2002. From 2005 until today, the Michigan Economic Development Corporation (MEDC) has made regular grants of a few million dollars every five or six years to local accelerators who manage the 20 SmartZones. Counties that the zones reside also contribute funds. The program only funds zones that are anchored by one or more research universities because policy-makers believe that technologies invented at universities are necessary to seed or grow an entrepreneurial ecosystem.

The purpose of the program is to build up Michigan's technology sectors to diversify the industries beyond more traditional industries, such as automotive. Also, these areas leverage this funding to win other state and federal R&D and startup funding. The MEDC's thinking about only investing in areas with universities is that invention at local universities, even in very rural areas, is fundamental to technology product development and startup production.

The SmartZone program is viewed by Michigan policy-makers as successful. For example, after being decimated by the financial crisis of 2008, the Detroit region has strengthened its ecosystem. In 2023, Pitchbook ranked Detroit (including Ann Arbor) as the World's second fastest-growing VC ecosystem and Startup Genome ranked Detroit as the World's No. 1 Emerging Ecosystem in 2022.

To conduct our ecosystem analysis in the state of Michigan, we collected and analyzed county specific business and investment data from CrunchBase from 2009 to 2022. Data on 12,618 organizations including startups, investors, universities, accelerators, and corporations was cleaned and parsed. We used Neo4j, a widely used graph database, to organize the data by industry, location, company funding stage (e.g., grant, angel), funding amount, and links between organizations (e.g., financial and non-financial links).

We used NetworkX, a widely accepted Python package for the creation, manipulation, and study of the structure, dynamics, and functions of complex networks, to calculate network metrics including density, centrality, and modularity. Then, we loaded the full data set, including the company data and network links from Neo4j and the metrics data from NetworkX, into a web-based software platform we developed for this research.

The software has two views: A network view and a map view. Exhibit 1 depicts the network view. Exhibit 2 shows the map view.

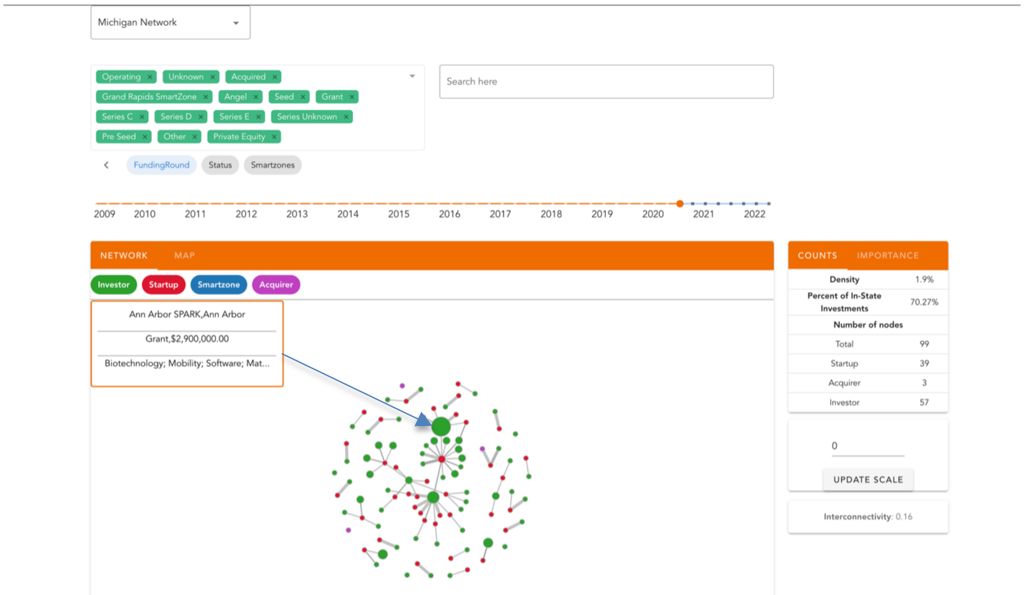


Exhibit 1: Network View of Software

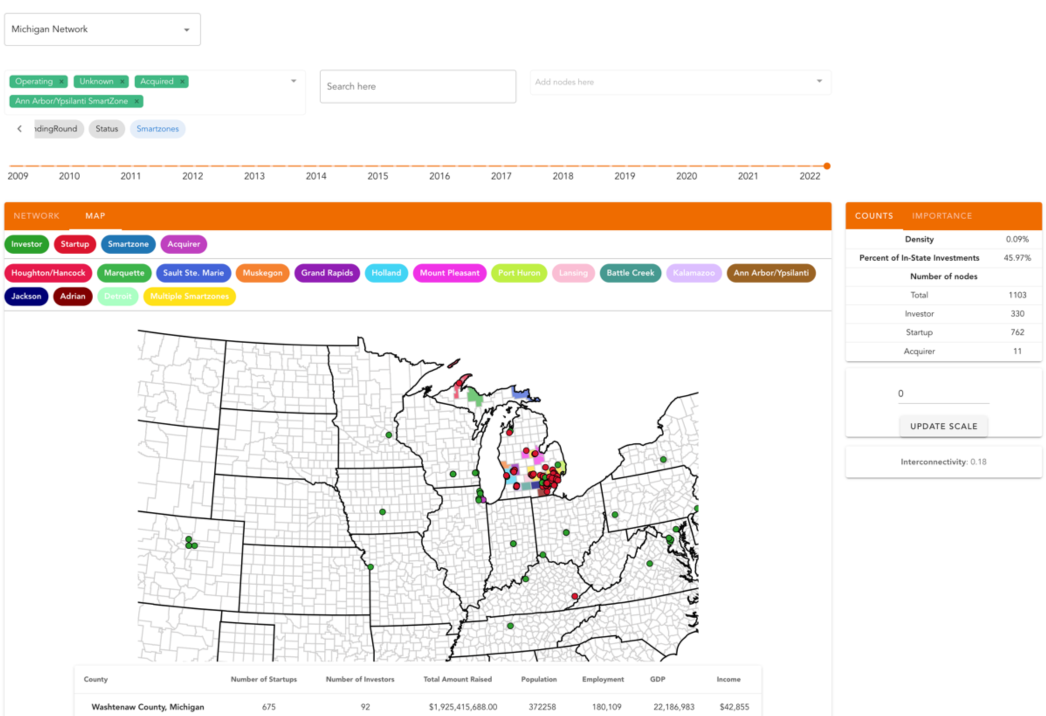


Exhibit 2: Map View of Software

Based on Crunchbase data, from 2009 to 2022, the total organizations increased from 10,193 to 12,618.   Over this time period, the total funded startups in Michigan grew from 95 to 519.

Exhibit 3 is a map of the state's SmartZones.

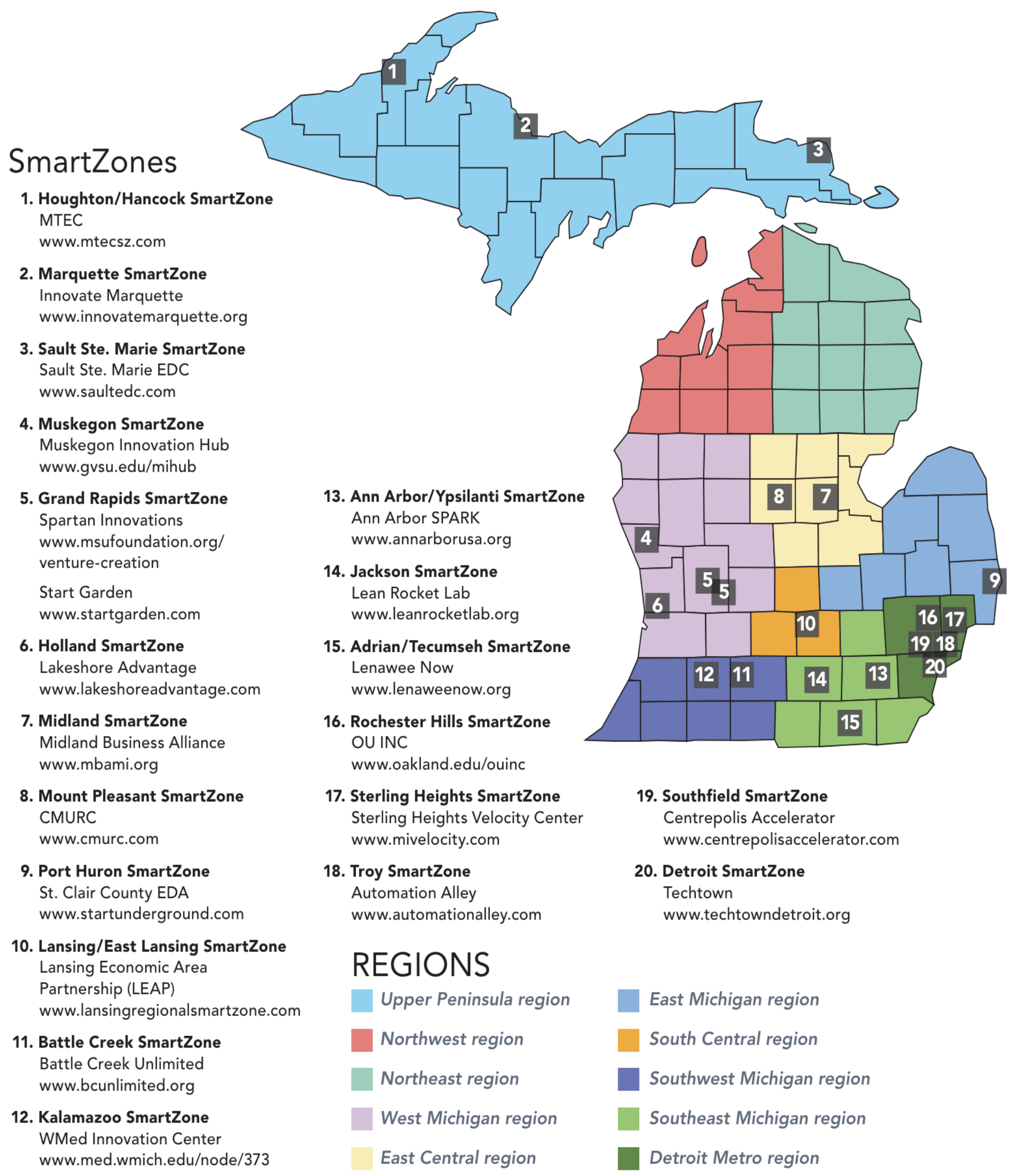


Exhibit 3: Michigan SmartZones

To gather feedback on our methodology from policy-makers, investors and ecosystem experts, we conducted 20 interviews.

Density is not the only measure of entrepreneurial ecosystem quality. Clearly the quality and influence of connections (i.e., network centrality) is important.

However, we found in our interviews and in our review of the literature that setting density as a first order metric will allow for easier and clearer comparison from region to region at least in our Michigan study (Dempwolf, C. S., et al 2012).

This decision is reinforced by that strong correlation that we have found in our analysis in the state of Michigan between regional network density and the incidence of externally funded startups.

Network Density

First, we used regression analysis to develop a predictive model using data on 12,618 organizations from 2009 to 2022 for SmartZone performance in terms of network density using a statewide average. Second, we quantified SmartZones based on whether they over or under-performed based on the density factor given their size.

The regression analysis defines a connection as a link (e.g., an exchange of resources between startups and other organizations that provide support and funding, such as mentoring, technical assistance, research grants, an equity investment or loan). Out of the 5442 startups in the nine SmartZones analyzed below, 1016 or 18.6% had at least one link.

Our team developed and ran regressions in R using two basic approaches using both predictor and response variables in order to evaluate alternative approaches. We first tried the model shown in Exhibit 4 that did not use a log transformation, whereas the second model we used depicted in Exhibit 5 did. The first model yielded only a 35% accuracy. The second model using the log transformation produced a

Exhibit 4

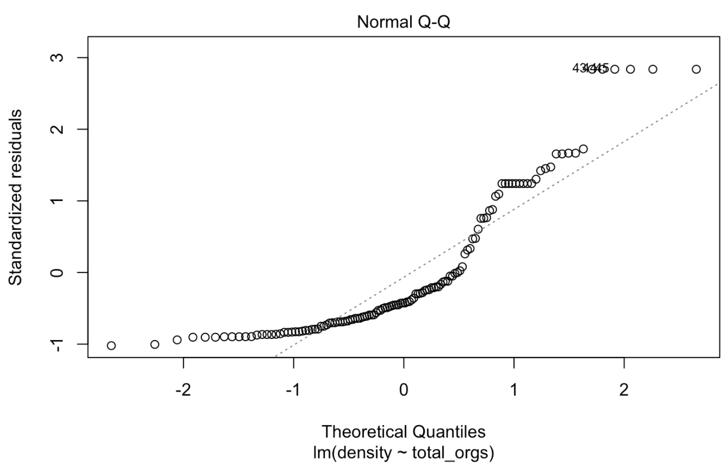
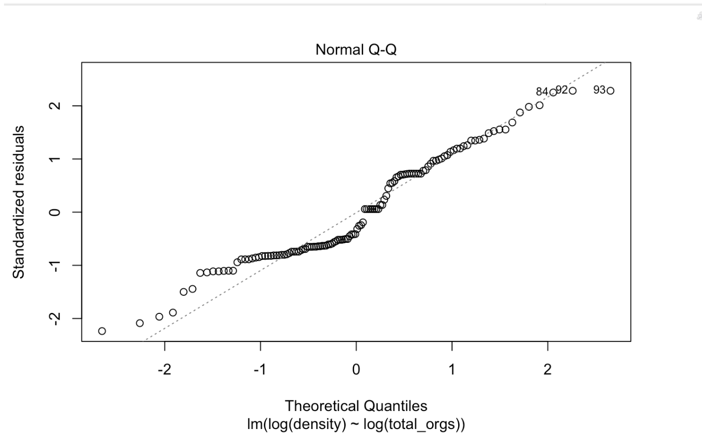


Exhibit 5



96% accuracy compared to actual connectivity data reported by Crunchbase. We used this model.

Key characteristics of this model/results are:

- The multiple R squared is 0.961 which means the model accounts for 96% of the variance of the predicted density values - this is very high.
- For every 10% increase in total organizations, there is a 9.03% decrease in density.
- The two graphs shown above illustrate if the model meets the Ordinary Least Squares (OLS) assumptions.

Correlating Network Density and Funded Startups

In order to evaluate to what extent under or over performing density influences an economic outcome, we correlated density performance (variance between observed and predicted density) with the percentage of funded startups by zone by year.

The Spearman correlation initially provided a measure of the monotonic relationship between variation and the percentage of funded startups. To further investigate, we applied a spline-based approach to explore potential non-linear relationships specifically between observed density and the percentage of funded startups.

A degree 4 spline was selected to capture non-linear patterns in the data while mitigating overfitting. The spline model indicated an overall positive correlation between observed density and the percentage of funded startups. Correlation coefficients across smart zones ranged from 0.773 to 0.998, suggesting a generally strong positive association across different regions. For example, Ann Arbor displayed a correlation of 0.957, highlighting a high consistency in the observed density's impact on funded startups across zones.

We chose the percent of externally funded startups (e.g., with grants, angel and VC funding, loan, etc.) as the entrepreneurial ecosystem (EE) output to measure. We selected percent of funded startups because new startup creation is widely recognized by policy-makers as an important goal of ecosystem development.

This is for a good reason (Audretsch, et al, 2020). According to the OECD report, “No Country for Young Firms?: Start-up Dynamics and National Policies,” startups and young firms in member countries account for nearly half of all new jobs created over time, despite making up only around 20% of total employment. This demonstrates the profound impact startups have in driving job growth and reducing unemployment rates. (Calvino, F, et al, 2016).

Among startups in the US, “venture capital-backed companies account for 41% of total US market capitalization and 62% of US public companies’ R&D spending. Among public companies founded within the last fifty years, VC-backed companies account for half in number, three quarters by value, and more than 92% of R&D spending and patent value.” “VC-backed companies have had an impact on other measures commensurate with their market values. For example, VC-backed companies employed 6 million people, had $3 trillion in revenue, made $300 billion in profit, and paid $55 billion in taxes in 2020.” (Gornall, W, et al, 2021:pg., 3). Also, Lerner (2000) found that venture capital is associated with higher levels of innovation.

Findings

SmartZones

An exhibit is presented for each SmartZone we analyzed. We chose to examine the more populous zones but included a couple of smaller zones for comparison, such as Marquette and Kalamazoo, which are more rural. The exhibit shows SmartZone observed vs. predicted density, and percent of funded startups from 2009 through 2022. The data only includes organizations with connections that exchanged resources. This means that other organizations where linkage data was not available are not presented in the network.

Each exhibit shows:

- Number of organizations
- Network density - Scale is depicted on the left side of each graph
  - Observed Density (in blue)
  - Predicted Density (in orange)
- Percent of Funded Startups (green line) - Scale is depicted the right slide of each graph

The observed density is what it actually is based on Crunchbase data. SmartZones that lose density less than the average across the state (9.03% for every 10% increase in the number of organizations), will be more connected and over perform in our model. Detroit and Ann Arbor are examples of SmartZones that maintain relatively higher density than other SmartZones.

Ann Arbor

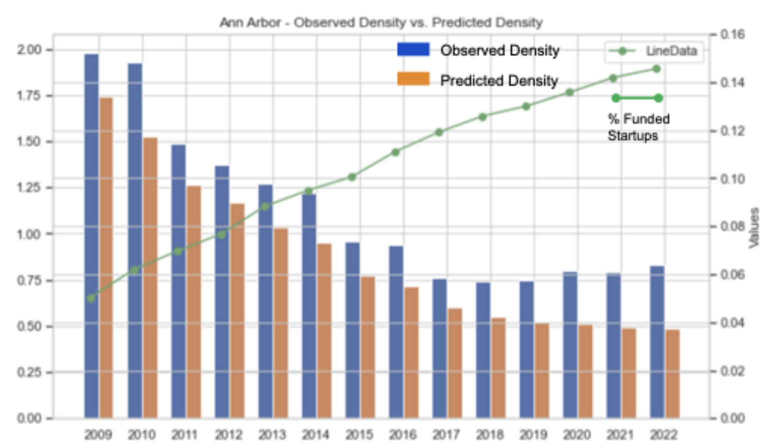
Ann Arbor is a medium-sized community of approximately 120,000 people. It's not a larger city, like Detroit, that has a population of approximately 620,000. But it still is big enough to have a lot of interaction in its ecosystem and it also has a strong startup culture. And of course, it has the University of Michigan, which is America's 4th ranked university in annual research funding and boasts a top three global business school with a high caliber entrepreneurship program and tech transfer arm. Also, the region hosts top performing accelerators, such as Ann Arbor Spark, which runs a SmartZone. This SmartZone has 797 startups and 370 investors that play in this vibrant ecosystem (not all have links in the dataset). This highly interactive environment lends itself to this relatively high network density.

As shown in Exhibit 6, this SmartZone has a consistent positive density variance; meaning that it outperforms the predicted density for a SmartZone of this number of organizations. The left scale of this exhibit is density, and the right scale is the percentage of funded startups.

The observed density is always greater than the predicted density from 2009 to 2022.   In terms of growth of the number of organizations over time, Ann Arbor almost triples in size over the 14 years but yet continues to maintain a relatively high density.

Looking at the percent of funded startups, we can see that it has a pretty consistent growth over time. It starts at around five percent and goes up to about 15%. And when we look at this, compared to the other SmartZones, we'll see that that's very high. And we can see this consistent growth.

As indicated with a 9.57 correlation factor, Ann Arbor's density correlates very closely with the percent of funded startups over the 13-year study period (2009-2022).



Ann Arbor

Year	SmartZone	density	total_orgs
2009	Ann Arbor/Ypsilanti	1.98	99
2010	Ann Arbor/Ypsilanti	1.93	113
2011	Ann Arbor/Ypsilanti	1.49	137
2012	Ann Arbor/Ypsilanti	1.37	148
2013	Ann Arbor/Ypsilanti	1.27	167
2014	Ann Arbor/Ypsilanti	1.22	182
2015	Ann Arbor/Ypsilanti	0.96	224
2016	Ann Arbor/Ypsilanti	0.94	243
2017	Ann Arbor/Ypsilanti	0.76	290
2018	Ann Arbor/Ypsilanti	0.74	316
2019	Ann Arbor/Ypsilanti	0.75	332
2020	Ann Arbor/Ypsilanti	0.80	338
2021	Ann Arbor/Ypsilanti	0.79	351
2022	Ann Arbor/Ypsilanti	0.83	356

- Ann Arbor's observed density is greater than predicted density each year
  - Ann Arbor is doing better than the model predicts → has a higher density given size compared to other SmartZones percent

Exhibit 6: Ann Arbor

Detroit

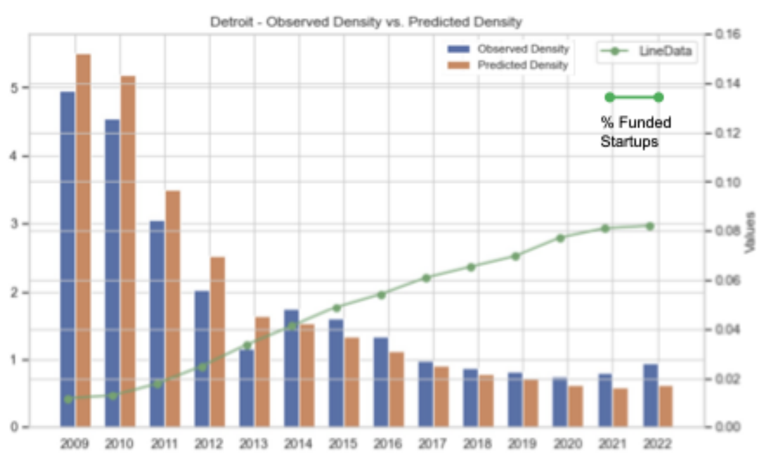
Detroit is a fascinating case because it underperformed from 2009 to 2013 then turned itself around as a strong, emerging globally significant ecosystem from 2014 to this very day.

Looking at Exhibit 7, there was a large variance between observed and predicted density in these early years. This is understandable given that Detroit was hit harder than almost every other American city by the “great recession” of 2008-2009 which was the worst economic downturn in the US since America’s Great Depression.

The network triples in size from 2012 to 2017 and this is a factor in the overall density significantly dropping year over year. So, what Ann Arbor did over the 13 years, Detroit did over four years. This plays a major role as to why density is rapidly decreasing from almost five to just above one. Then, however, in 2014 it shifts, and the observed density becomes greater than the predicted density as the network size continues to increase. It is interesting to ponder how Detroit was able to increase its size so much yet be above what was expected of it. What happened in 2014? Was there an infusion of R&D and entrepreneurship government grants from the federal government and state? What other external factors were at play before the turn around in 2012, such as the Obama Administration’s bail out for Detroit’s fabled automotive companies?

With respect to the percentage of funded startups, Detroit was under 5% in 2009 but they reach 8% in 2022. While subtle, the increase in the line’s slope from 2012 to 2020 is very apparent but flattens out in the last two years, perhaps influenced by the COVID-19 pandemic.

As shown with a 9.34 correlation factor, Detroit’s density correlates very closely with the percent of funded startups over the 13-year study period (2009-2022).



Detroit

	Year	SmartZone	density	total_orgs
0	2009	Detroit	4.95	31
1	2010	Detroit	4.55	33
2	2011	Detroit	3.06	49
3	2012	Detroit	2.02	68
4	2013	Detroit	1.15	105
5	2014	Detroit	1.74	113
6	2015	Detroit	1.61	129
7	2016	Detroit	1.34	153
8	2017	Detroit	0.98	190
9	2018	Detroit	0.88	219
10	2019	Detroit	0.83	244
11	2020	Detroit	0.75	279
12	2021	Detroit	0.80	291
13	2022	Detroit	0.94	275

- Detroit's density is under performing from 2009 to 2013: predicted density > observed density
- Large decrease year over year (YOY) density → total orgs tripled in this time span.
- 2014 density increases, while network increases. What happened in 2014? Grants? Programs? External economic factors?
- 2014 to 2022: observed density > predicted density; Detroit's density given its size is better than expected.
- Starting in 2012 the slope of percent of funded startups gets steeper until about 2017
- Coincides with change from negative to positive density error.
- Large increase in % of funded startups, less than 0.5% to 8%

Exhibit 7: Detroit

Rochester, Troy, and Southfield

Each of these SmartZones located in the greater Detroit metropolitan area, is average size. Together, they underperform from 2009 to 2022 as shown in Exhibit 8. So, what is going on here? Is there a lack of community present? Did the State of Michigan underinvest in accelerators or are their research universities producing less fundable technology then their peers? What could be done to improve the level of connection and resource exchange in these communities?

Regarding the percent of funded startups, this metric also lags most of the other SmartZones. With a 9.94/9.95 correlation factor, Rochester, Troy and Southfield's density correlates very closely with the percent of funded startups over the 13-year study period (2009-2022).

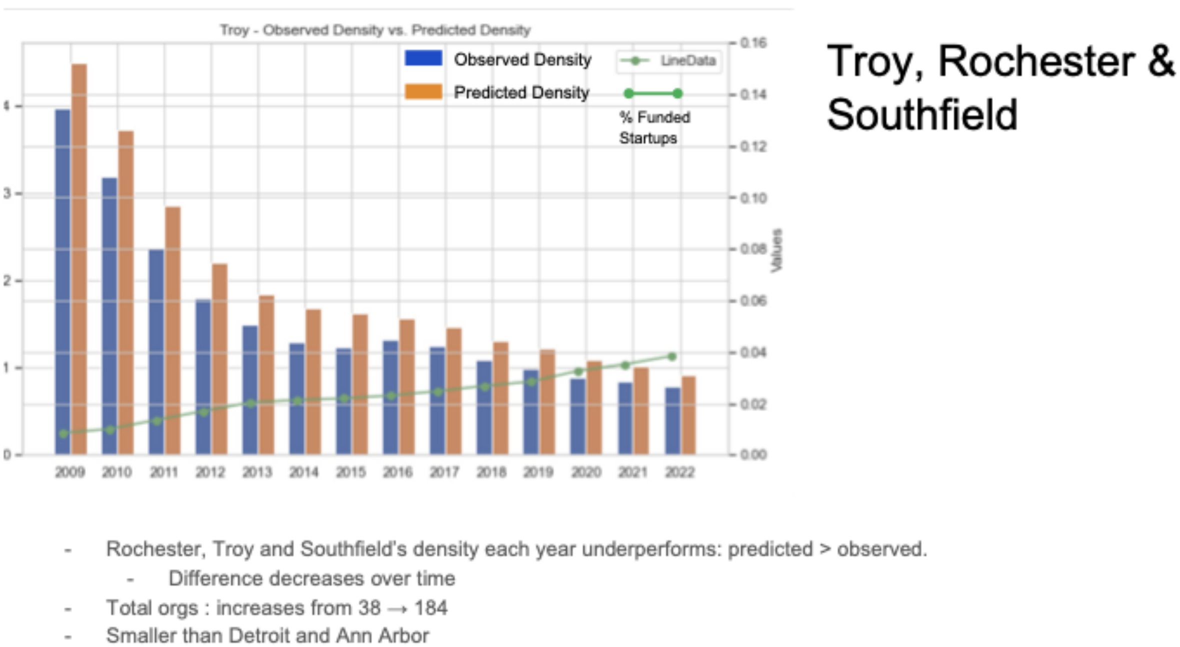
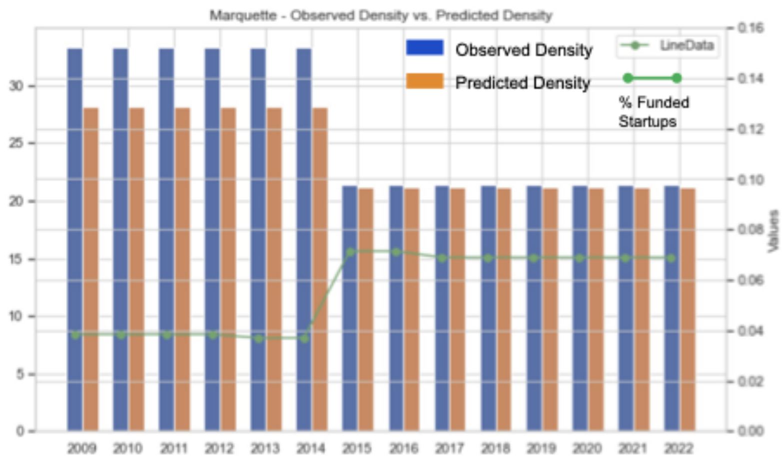


Exhibit 8: Rochester, Troy, and Southfield

Marquette

This SmartZone is somewhat of an outlier because it is such a small, rural network. Therefore, an increase of one or two connections or startups in the mix has a major effect on density. As one can see in Exhibit 9, the network begins with six connections between one startup and five investors. By 2015, there was an addition of one more investor and one more startup. The funding deals were big, however. Both startups are life science companies. One startup received $20 million and the other received $30.5 million. Density is overall much higher here due to the small scale of the network.



Marquette

Year	SmartZone	density	total_orgs
2009	Marquette	33.33	6
2010	Marquette	33.33	6
2011	Marquette	33.33	6
2012	Marquette	33.33	6
2013	Marquette	33.33	6
2014	Marquette	33.33	6
2015	Marquette	21.43	8
2016	Marquette	21.43	8
2017	Marquette	21.43	8
2018	Marquette	21.43	8
2019	Marquette	21.43	8
2020	Marquette	21.43	8
2021	Marquette	21.43	8
2022	Marquette	21.43	8

- Marquette is relatively small
- Increase of 1 org, leads to a large change in density
- Higher density than expected, until 2014, 2 more orgs added and did not maintain such a high density given size.

Exhibit 9: Marquette

This situation in Marquette could be valuable for small and rural communities and their researchers. In this case, it's not about the quantity of organizations but it's providing the training, mentoring, available talent, and research facilities at Northern Michigan University to attract a few promising startups that may match the needs of local angels and other investors.

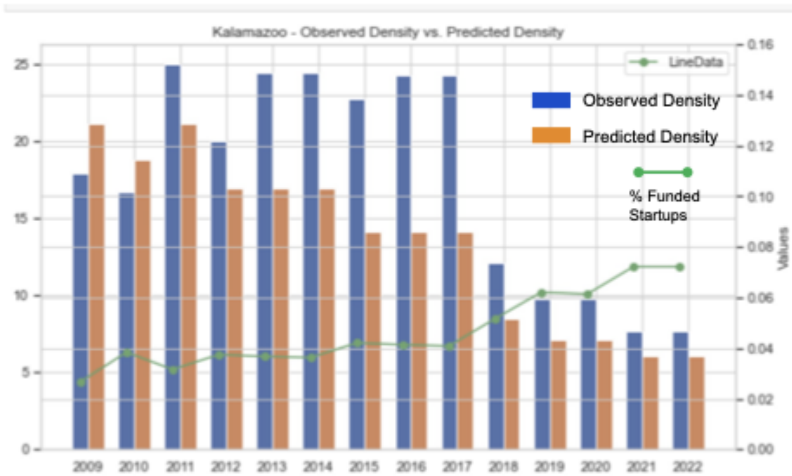
As indicated with a 9.98 correlation factor, Marquette's density correlates very closely with the percent of funded startups over the 13-year study period (2009-2022).

Kalamazoo

Kalamazoo has a very unusual trajectory compared to the other SmartZones. In 2009, and 2010, its predictive density is greater than the observed, which means it's underperforming. But from then on, it shifts, and the observed density is greater than the predicted density. From 2011 to 2016 there is this huge difference, and in certain years, the density is just substantially higher than expected. What is their funding looking like? What are their different programs? And how are they able to kind of catch up with their density?

Looking at the left of the chart in Exhibit 10, after Pfizer left this area in 2007 a lot of the people working for Pfizer created startups in Kalamazoo. This and the State of Michigan's investments in life science R&D in the wake of the company leaving may explain the solid activity in the early years of 2010's as these life science startups began to leave their labs, raise more VC funding, and add jobs.

As illustrated in Exhibit 10, as a result of this activity after Pfizer's collapse and general startup development activity, one can see steady growth in funded startups. A dynamic that is quite interesting is that there is a visible jump in funded startups from 2017 to 2022, even as the network density declines. Could this jump be a product of the strong group of investors locally and the public investments made in the preceding years? Could Kalamazoo be a good example of what the Kauffman Foundation researchers theorized -- that a dense network among a smaller number of programs is arguably more important than a sparse network among a larger number of programs (Stangler, D., Bell-Masterson, J., 2015). With a 9.8 correlation factor, Kalamazoo's 's density correlates extremely closely with the percent of funded startups over the study period.



Kalamazoo

Year	SmartZone	density	total_orgs
2009	Kalamazoo	17.86	8
2010	Kalamazoo	16.67	9
2011	Kalamazoo	25.00	8
2012	Kalamazoo	20.00	10
2013	Kalamazoo	24.44	10
2014	Kalamazoo	24.44	10
2015	Kalamazoo	22.73	12
2016	Kalamazoo	24.24	12
2017	Kalamazoo	24.24	12
2018	Kalamazoo	12.11	20
2019	Kalamazoo	9.78	24
2020	Kalamazoo	9.78	24
2021	Kalamazoo	7.67	28
2022	Kalamazoo	7.67	28

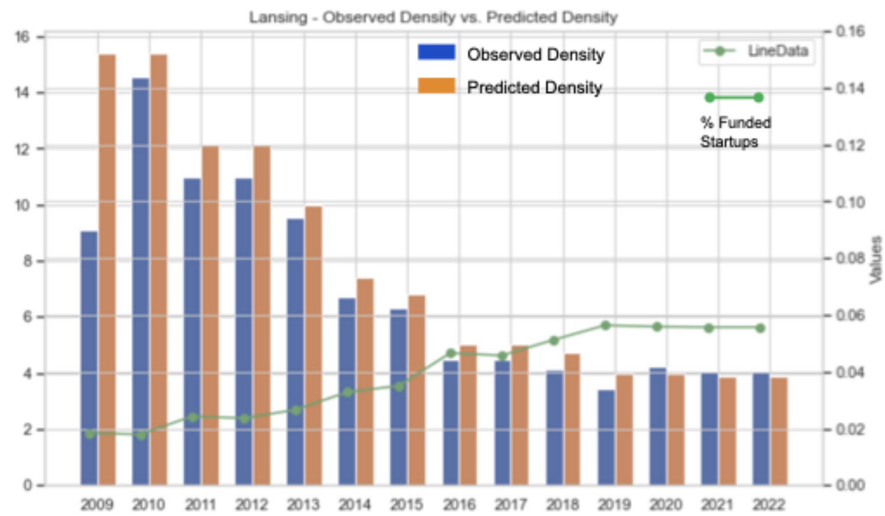
- 2011 and on: observed density > predicted density
  - 2011 to 2016 huge positive difference. Maintains similar size, very high density given size
  - 2018, size of network increases from 12 to 20
- Questions: looking at 2012 to 2013, how did they increase density? Funding? Programs? E.g., starting in 2008 state investments to retain Pfizer assets and people after plant closures in Kalamazoo and Ann Arbor

Exhibit 10: Kalamazoo

Lansing

Lansing is Michigan's capital and Michigan State University's home. As one can see by looking at Exhibit 11, Lansing's density lagged predicted density from 2009 to 2019. Similar to Kalamazoo, the percentage of funded startups significantly accelerates from 2017 to 2022, with the trend line beating the density factor. The correlation factor 9.84 between density and the percent of funded startups is very high.

Could this performance be because of the university and other R&D and accelerator training programs in the preceding years and a general surge in Michigan's economy? In these years, including during COVID from 2020 to 2022, observed density finally catches what our model predicts it should be.



Lansing

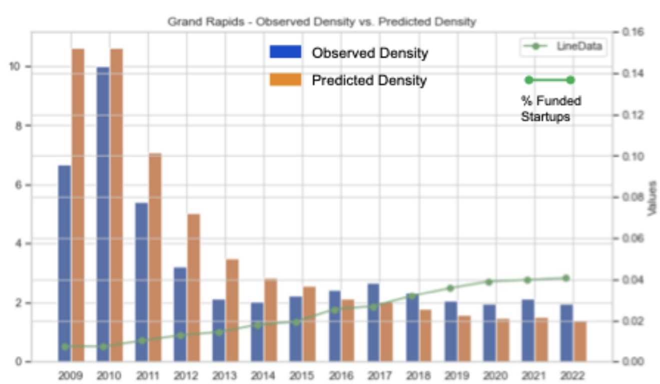
Year	SmartZone	density	total_orgs
2009	Lansing	9.09	11
2010	Lansing	14.55	11
2011	Lansing	10.99	14
2012	Lansing	10.99	14
2013	Lansing	9.56	17
2014	Lansing	6.72	23
2015	Lansing	6.33	25
2016	Lansing	4.46	34
2017	Lansing	4.46	34
2018	Lansing	4.13	36
2019	Lansing	3.43	43
2020	Lansing	4.21	43
2021	Lansing	4.02	44
2022	Lansing	4.02	44

- Underperforming 2009 to 2019: predicted > observed
  - 2009 large density error
- Shifts in 2020: density error becomes positive observed > predicted
  - Could be due to maintaining size
  - 2019 observed density decreased, then increased again. What happened in 2020?

Exhibit 11: Lansing

Grand Rapids

From 2009 to 2015, this SmartZone underperformed the density model, but in 2016 began to beat the predicted performance. What was happening in 2016 and what sustained that activity and the strong performance? As Exhibit 12 shows, the percentage of funded startups shows consistent growth over time. But there's not a lot of startup growth compared to the top performing SmartZones in terms of density. As indicated with a 9.34 correlation factor, Grand Rapids' .773 density correlates relatively closely with the percent of funded startups.



Grand Rapids

	Year	SmartZone	density	total_orgs
56	2009	Grand Rapids	6.67	16
57	2010	Grand Rapids	10.00	16
58	2011	Grand Rapids	5.43	24
59	2012	Grand Rapids	3.21	34
60	2013	Grand Rapids	2.13	49
61	2014	Grand Rapids	2.03	60
62	2015	Grand Rapids	2.22	67
63	2016	Grand Rapids	2.44	81
64	2017	Grand Rapids	2.69	85
65	2018	Grand Rapids	2.35	96
66	2019	Grand Rapids	2.06	108
67	2020	Grand Rapids	1.96	117
68	2021	Grand Rapids	2.12	113
69	2022	Grand Rapids	1.97	121

- 2009 to 2015: predicted density > observed density, underperforming, relatively large density error
  - What shifted in 2016? Grants/funding? Programs? Culture?

Exhibit 12: Grand Rapids

Comparison of SmartZones

Exhibits 13 and 14 compare density performance by SmartZone between 2009 and 2022. As shown in Exhibit 13, six of SmartZones have a density that is about only a third of Ann Arbor's. As shown in Exhibit 15, the production of funded startups in Ann Arbor compared to these other SmartZones over the 13-study period is consistent with these differences in density except for Marquette, which as noted above has an unusual situation.

Density Performance over 13 Years

	SmartZone	density_error_2009	percent_2009	density_error_2022	percent_2022	percent_change
0	Detroit	-0.560867	0.011628	0.308559	0.082019	0.070391
1	Southfield	-0.522552	0.010316	-0.130900	0.042975	0.032659
2	Troy	-0.522552	0.008621	-0.121406	0.038407	0.029787
3	Marquette	5.204471	0.038462	0.290456	0.068966	0.030504
4	Grand Rapids	-3.954662	0.007535	0.543684	0.040657	0.033122
5	Ann Arbor/Ypsilanti	0.239337	0.050388	0.341288	0.145669	0.095282
6	Kalamazoo	-3.279544	0.026667	1.573322	0.072222	0.045556
7	Lansing	-6.320844	0.018450	0.127170	0.055718	0.037268
8	Rochester	-0.522552	0.010316	-0.130900	0.042975	0.032659

Exhibit 13: Comparison of SmartZone Density Performance

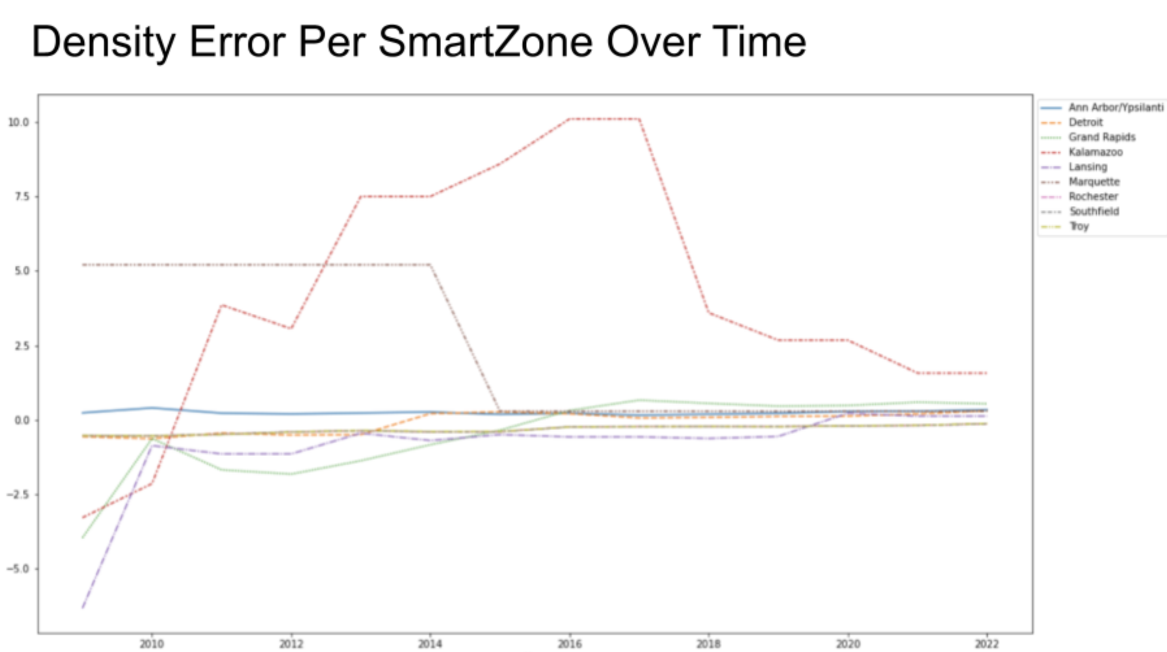


Exhibit 14: Density Variance per SmartZone over time

SmartZone Comparison: Ann Arbor Compared to Others (2009-2022)

SmartZone	Density	Density Percent Compared to Ann Arbor Smartzone	Change in Percent of Funded Startups Per SmartZone
Detroit	0.07039	74%	8.20%
Southfield	0.03266	34%	4.10%
Troy	0.02979	31%	3.80%
Marquette	0.0305	32%	7%
Grand Rapids	0.03312	35%	4%
Ann Arbor	0.09528	100%	14.40%
Kalamazoo	0.04556	48%	7.20%
Lansing	0.03727	39%	5.60%
Rochester	0.03266	34%	4.10%

Exhibit 15: SmartZone Comparison: Ann Arbor Compared to Others (2009-2022)

Exhibit 16 compares the percentage of funded startups across the SmartZones between 2009 and 2022.

But just by carefully observing Exhibit 16, a few observations can be made. First, six of the nine SmartZones produced 3 to 4% of funded startups over the study period. Kalamazoo reaches about 4.5% growth. Detroit gets to a 7% growth. Ann Arbor, which appears to be a standout region, achieves 9.5% growth in the percent of funded startups between 2009 and 2022 (14.40% minus 4.9%).

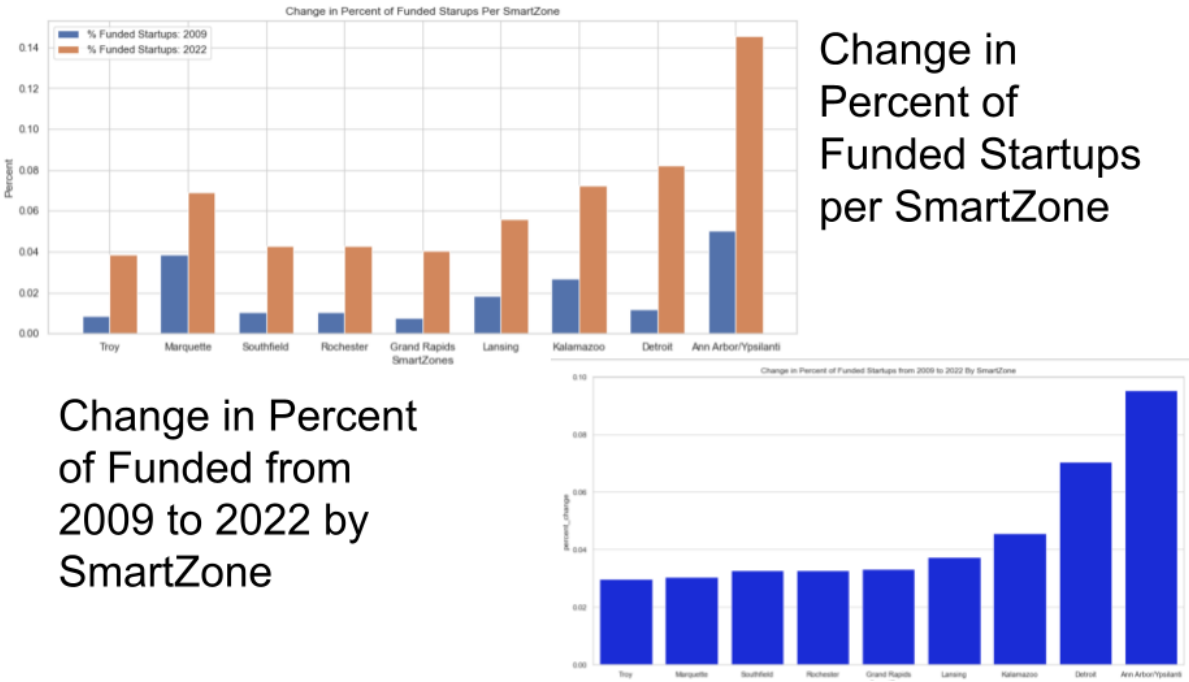


Exhibit 16: Comparison of Percent of Funded Startups across SmartZones

Density and Funding Correlation

As shown in Exhibit 17, correlation coefficients across smart zones ranged from 0.773 to 0.998, suggesting a generally strong positive association across different regions. For example, Ann Arbor displayed a correlation of 0.957, highlighting a high consistency in the observed density's impact on funded startups across zones.

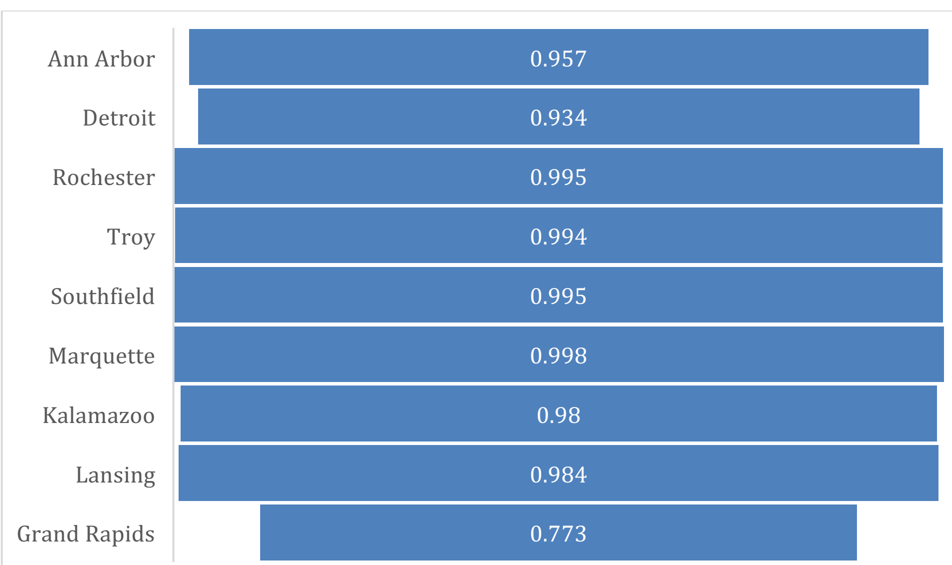


Exhibit 17: Network Density: Funding Correlation

Investigating the economic, governmental, and cultural situations that make up these differences could shed more light on the back story here. Exhibit 18, which shows funded startups by population, provides additional context.

It would be particularly interesting to look more into Lansing in 2020, Grand Rapids in 2016, Detroit in 2014 and Kalamazoo between 2011 to 2017 to understand what was happening. Were there any common factors that led to these shifts?

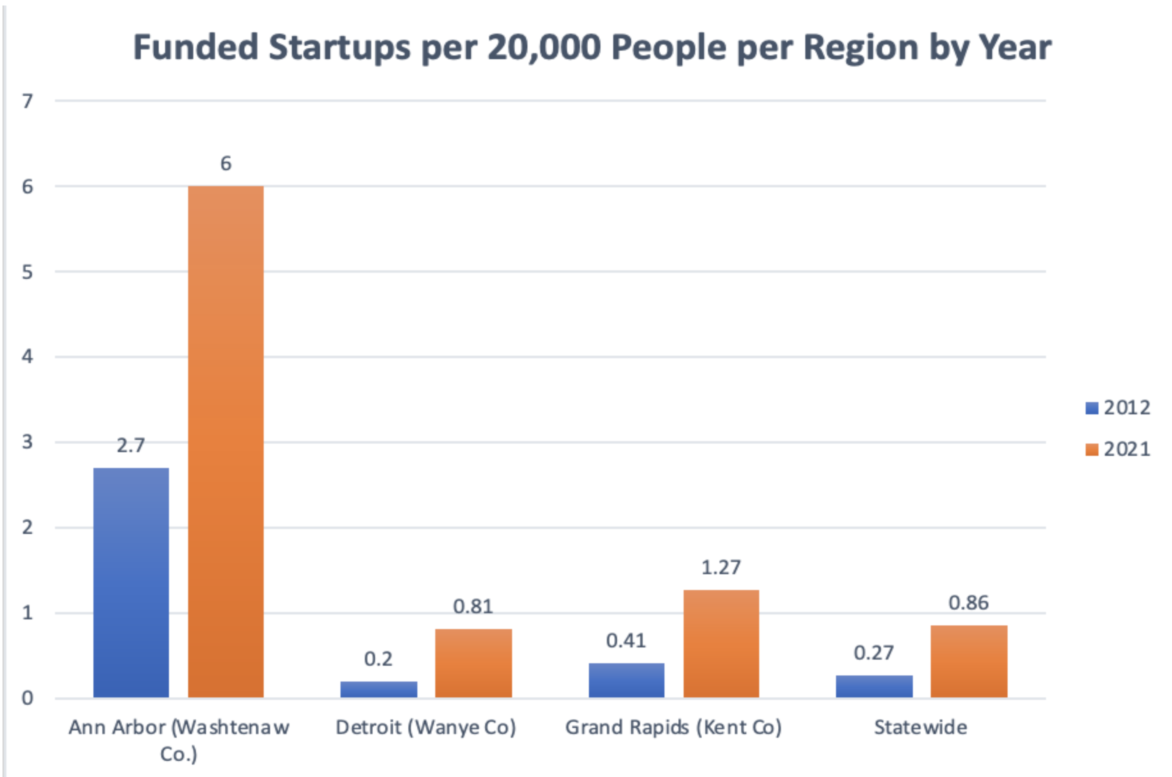


Exhibit 18: Funded Startups by Population

Conclusions

Our study shows to what extent a region is underperforming or over performing in terms of density considering network size. Further, our analysis shows a correlation between .77 and .99 between regional network density and funded startups. This finding shows that higher density correlates with a positive economic outcome. This correlation is supported by research conducted by others (Pittz, T, et al, 2019). Therefore, policy-makers can use our density performance: startup funding framework to better inform discussion on ecosystem dynamics and quality in order to improve policy and resource allocation decisions.

Because new funded startups produce significant jobs, there is a strong tie in between density and job creation in entrepreneurial ecosystems.

This research is important for federal, state, and local governmental policy-makers who make investments in regional R&D and startup programs. Corporate R&D executives, investors, and developers and managers of technology and science parks will also benefit from insight from this research about the ecosystems they invest and operate in, or may locate in   Further, university and private tech transfer and startup accelerator programs will benefit from a better understanding of how to build connectivity in their ecosystems.

Our model helps address a problem that public and private investors face – to get a simple but powerful and insightful metric of the region's startup ecosystem quality and trends and to enable easy comparison to other regions and programs.

This research contributes to policy-making by providing transparent, easy to apply tools for busy policy-makers that can easily be explained and lead to a basis for discussion to better understand what happens on the ground, including regional comparisons, in order to make better investment decisions.

Future Directions

Future research will integrate aggregate network centrality into our model to look at the question of "are some dense ecosystems different from others" by looking at the importance and influence of the people and organizations that interact in the ecosystem. This will enable more analysis of heterogeneities – such as the network influence of different actors, such as universities.   Looking at the influence of social media data on the centrality of various actors is also of interest. Further, we will refine the model to predict regional ecosystem behavior in specific industry sectors, and by type of area - urban, suburban, and rural areas.

Researching how to improve communication with decision makers about network connectivity may make a difference in how a decision maker understands network dynamics is of interest to us. An effective technique may be to pair real life cases with SNA metrics and visualizations. People we have interviewed who consult for US state and federal agencies told us that cases and examples help them better understand network dynamics. For example, these cases could include how a new program to build important connections for innovators/entrepreneurs may have resulted in more desired outcomes (e.g., strategic R&D partnerships). Our interviews have found that after a decision maker understands the case, then it may be easier for her/him to understand and perhaps feel more comfortable with density and centrality as important measures of connection and network value.

Also, we are interested in examining early-stage ecosystems to better understand how the density and centrality associated with different levels of pre-funding links, such as training, mentoring, and events, impacts grants/pre-seed funding. Further, we want to explore the role of network modularity and interactivity (i.e., exchanges between local and non-local groups) on ecosystems, particularly between rural and urban areas.

References

Ancona, A., Cinelli, M., Ferraro, G., Lovanella, A.(2023). Network-based principles of entrepreneurial ecosystems: a case study of a start-up network. Small Business Economics, 61:1497–1514

Audretsch, D., Colombelli, A., et al. (2020). Innovative start-ups and policy initiatives, Research Policy, Volume 49, Issue 10, 2020, 104027

Borgatti. S., Mehra, A., Brass. D., Labianca. G. (2009). Network analysis in the social sciences. Science 323(5916):892-5

Brüderl, J., Preisendörfer, P. (1996). Network Support and the Success of Newly Founded Businesses. Small Business Economics

Calvino, F., C. Criscuolo and C. Menon (2016-04-01), “No Country for Young Firms?: Start-up Dynamics and National Policies”, OECD Science, Technology and Industry Policy Papers, No. 29, OECD Publishing

Cavallo, A., Ghezzi, A., Balocco, R. (2019). Entrepreneurial ecosystem research: Present debates and future directions. International Entrepreneurship and Management Journal, 15(4), 1291–1321

Chua, R., Morris, M. (2012). Collaborating Across Cultures: Cultural Metacognition & Affect-Based Trust in Creative Collaboration. Organizational Behavior and Human Decision Processes

Chesmore, M., et al. (2003). Social Networks and Planned Organizational Change: The Impact of Strong Network Ties on Effective Change Implementation and Use. The Journal of Applied Behavioral Science

Colman, J. (1990). Foundations of Social Theory. Belknap Press

Cross, P., Parker, A. (2004). The Hidden Power of Social Networks. Harvard Business Publishing

Delgado, M., Porter, M. E., & Stern, S. (2010). Clusters and entrepreneurship. Journal of Economic Geography, 10(4), 495–518

Deller, S. C., Conroy, T. (2017). Business survival rates across the urban–rural divide. Community Development

Dempwolf, C. S., Lyles, L. W. (2012). The Uses of Social Network Analysis in Planning: A Review of the Literature. Journal of Planning Literature, 27(1), 3-21

Elfring, T., Hulsink, W. (2003).Networks in Entrepreneurship: The Case of High-technology Firms. Small Business Economics

Feldman, Maryann, P. (2020). Entrepreneurial Ecosystems, American Enterprise Institute

Furman, J., Porter, M., et al. (2022). The determinants of national innovative capacity, Research Policy, Volume 31, Issue 6, 2002, Pages 899-933,

Gornall, Will and Strebulaev, Ilya A. (2021). The Economic Impact of Venture Capital: Evidence from Public Companies (June 2021).

Haythornthwaite, C. (1996). Social network analysis: An approach and technique for the study of information exchange. Library & Information Science Research

Guzman, Jorge, Stern, Scott (2020) The State of American entrepreneurship: New Estimates of the Quality and Quantity of Entrepreneurship for 32 US States, 1988-2014

Johnson, E. J. Hemmatian, I., et al. (2022). A Framework and Databases for Measuring Entrepreneurial Ecosystems. Research Policy

Light, R., Moody, J. (2020). The Oxford Handbook of Social Networks, Oxford University Press, pg. 27

Liu, Ernest (2023), et al. Innovation Networks and R&D Allocation, National Bureau of Economic Research

Lundvall, B. Å. (2007). National innovation systems - Analytical concept and development tool. Industry and Innovation, 14(1), 95–119.

Kauffman Foundation (2018), ESHIP Goals, https://www.kauffman.org/eship-summit-2018/goals/

Kemeny, T., Feldman, M., Ethridge, F., Zoller, T. (2015). The economic value of local social networks. Journal of Economic Geography.

Kilduff, M., & Brass, D. J. (2010). Organizational social network research: Core ideas and key debates. The Academy of Management Annals

Lee, J., & Xu, J. (2020). Why do businesses grow faster in urban areas than in rural areas? Regional Science and Urban Economics

Lerner, J. (2000). The government as venture capitalist: The long-run impact of the SBIR program. Journal of Private Equity 3, 55–78.

Majumdar, S., Venkataraman, S. (1998). Network Effects and Technology Adoption in Us Telecommunications. Strategic Management Journal

Mason, Collin, Brown, Ross (2014), Entrepreneurial Ecosystems And Growth Oriented Entrepreneurship, OECD

Moretti, E. (2021). The Effect of High-Tech Clusters on the Productivity of Top Inventors. American Economic Review, 111(10), 3328–3375.

Pittz, T; White, R; Zoller, T (2019). Entrepreneurial Ecosystems and Social Network Centrality: The Power of Regional Dealmakers. Small Business Economics

Renski, H. (2008). New Firm Entry, Survival, and Growth in the United States: A Comparison of Urban, Suburban, and Rural Areas. Journal of the American Planning Association

Stangler, D., Bell-Masterson, J. (2015). Measuring an Entrepreneurial Ecosystem. Kauffman Foundation

Subhayan, B. et al. (2023). Chapter 5 - Online social-network sensing models, Academic Press

Tenkasi, R., Mohrman, S., et al. (2003). The Role of Networks in Fundamental Organizational Change. The Journal of Applied Behavioral Science

Tenkasi, R., Chesmore, M. (2003). Social Networks and Planned Organizational Change: The Impact of Strong Network Ties on Effective Change Implementation and Use. The Journal of Applied Behavioral Science

Yu, L., Orazem, P. F., & Jolly, R. W. (2011). Why Do Rural Firms Live Longer? American Journal of Agricultural Economics