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Entrepreneurial Space and Enterprise Richness In a Group of U.S. Counties Before, During, and After Economic Turmoil

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Abstract

The importance of economic diversity as a business measure prompted an investigation of the association between a period of economic turmoil (Great Recession) and the power law relationships of enterprise richness—a business diversity measure—and enterprise numbers—an expression of total entrepreneurship—in 22 U.S. counties. Before the onset of the turmoil from 2000–2007, the total enterprise numbers in the counties increased steadily. With the onset between 2008 and 2011, they declined sharply and thereafter from 2012–2016 continued decreasing slowly. However, enterprise richness–enterprise numbers relationships—expressed as power laws—were fairly stable before, during and after the turmoil. These power laws are apparently robust and not temporally sensitive. The power laws potentially provide predictive powers about different entrepreneurial types in U.S. counties: that is, new, existing, and total entrepreneurship.

Keywords: U.S. counties, entrepreneurial space, enterprise dynamics, enterprise richness, economic turmoil, Great Recession

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1.0 Introduction

In the twenty-first century, cities and global urbanization have emerged as the source of the greatest challenges the planet has faced since humans became social (Youn, Bettencourt, Lobo, Strumsky, Samaniego & West, 2016). The future of humanity and the long-term sustainability of the planet are inextricably linked to the fate of cities (West, 2017). Cities bring people together, facilitate human interaction, help to create ideas and wealth, and enhance innovative thinking and entrepreneurship (Florida, 2003; West, 2017). Industrial diversity, entrepreneurship, and education promote innovation and economic growth (Glaeser, 2011).

The observation of scale invariance over some range identifies general system types, be they ideal gases, ecosystems, or cities (Bettencourt et al., 2020). Urban scaling analysis reveals how general non-linear properties of cities work (Bettencourt et al., 2020). The use of scaling in the analysis of cities, therefore, quantifies many of the fundamental general city characteristics, especially their capacity to create interrelated economies of scale in infrastructure and increasing returns to scale in socioeconomic activities (Bettencourt et al., 2020).

Does urban scaling relate to characteristics other than human population sizes? Enterprise richness—the number of different enterprise types—of human settlements is a case in point because diversity enhances economic efficiency

(Quigley, 1998). Diversity expansion drives the success and resilience of cities (Youn et al., 2016). There have been surprisingly few quantitative investigations into possible systematic regularities and underlying dynamics that govern the diversity of cities across an entire urban system (Youn et al., 2016). Exceptions, apart from the investigation of Youn et al. (2016), are studies of South African towns (Toerien, 2017; Toerien & Seaman, 2014) and U.S counties (Toerien, 2018; Toerien, 2020a). Scaling—power law—analyses demonstrated that the number of enterprises scales super-linearly with the enterprise richness of these human settlements. Obviously, the converse that enterprise richness scales sub-linearly with enterprise numbers is also true. These relationships appear not be geographically or temporally sensitive (Toerien, 2017).

The relationship between enterprise richness and enterprise numbers can be interpreted in terms of two broad types of entrepreneurship. (a) 'new entrepreneurship' which is reflected by the enterprise richness levels of human settlements, that is, the number of different enterprise types present. Each different enterprise type recorded in a human settlement represents an occasion in the history of the town when an entrepreneur successfully founded an enterprise type that had not been present before. (b) 'existing entrepreneurship', which represents the number of times previously established enterprise types have been repeated in specific human settlements. It is quantified as the total number of enterprises—total entrepreneurship—minus new entrepreneurship of human settlements. New entrepreneurship scales sub-linearly and existing entrepreneurship scales super-linearly with 'entrepreneurial space' (Toerien, 2017; Toerien & Seaman, 2014). Entrepreneurial space represents the total number of enterprises that can be 'carried' in specific human settlements.

Does the demographic–socioeconomic orderliness observed in cities, that is, urban centers, extend to regions with a mix of urban centers and rural populations—for example, U.S. counties? An exploratory study of 68 U.S. counties recorded power laws between their enterprise richness and enterprise numbers (Toerien, 2018). As expected, enterprise numbers scaled super-linearly with enterprise richness, and enterprise richness scaled sub-linearly with enterprise numbers. These relationships are apparently robust because they were probably not geographically or temporally sensitive (Toerien, 2018). It is not known if, or to what extent, the dynamics of the enterprise richness–enterprise numbers relationships of U.S. counties might be associated with the events of an economic shock. To investigate this issue, a temporal analysis of the enterprise richness–enterprise numbers relationship of U.S. counties is needed because time, along with population size, is another essential variable in scaling analyses of human settlements (Bettencourt et al., 2020).

The economic turmoil that is now known as the Great Recession started in mid-2007. A global financial crisis quickly metamorphosed from the end of the housing bubble in the United States to the worst recession the world has witnessed in over six decades (Stiglitz, 2010; Verick & Islam, 2010). The U.S. unemployment rate spiked from 5% to 10% over the course of the Great Recession (Yagan, 2019). After eighteen months, the longest since the Great Depression of the 1930s, growth returned to the United States (Grusky, Western & Wimer, 2011). Economic dynamics and publicly available enterprise datasets about U.S. counties that cover the period 2000–2016, provide an opportunity to examine the dynamics of the enterprise numbers–enterprise richness relationships of U.S. counties before, during and after the Great Recession.

Two basic questions are examined here: (a) Is there evidence over the 2000–2016 period of the presence of statistically significant power laws between the enterprise richness—the number of different enterprise types—and enterprise numbers of a selection of U.S. counties? and (b) If such evidence is obtained, are there material changes in the properties of the power laws associated with the period of the economic turmoil and the recovery that followed?

The logic of the contribution is as follows. The nature of power laws and of self-regulating open systems are further considered before the methodology and the results are presented. A discussion and conclusions complete the contribution.

1.1 Power Laws

Scaling analyses have been a powerful tool across a broad spectrum of science and technology research. Scaling is a general analytical framework to characterize how population-averaged properties of a collective vary with its size (Bettencourt et al., 2020). Urban scaling analysis reveals how the general non-linear properties of cities work, manifested as economies of scale, when certain quantities grow more slowly than city size—sub-linearly—or as increasing returns to scale, when quantities grow faster than city size—super-linearly (Bettencourt et al., 2020). The functional properties of cities, such as the levels of conflict, economic productivity and material infrastructure, therefore, vary in a scale invariant way from the largest cities to the smallest towns within an urban system (Bettencourt, Lobo & Youn, 2013). Even the smallest settlements have elements that functionally find correspondences in larger modern cities. Cities are first and foremost self-organizing social networks embedded in space and enabled by urban infrastructure and services (Bettencourt, 2014).

Power laws as scale invariant functions are the preferred descriptors of cities across scales (Bettencourt et al., 2013). Their analytical punch stems from the fact that the response is often a simple, regular, and systematic function over a wide range of sizes, indicating that there are underlying generic constraints at work on the system as it progresses (Lobo et al., 2013).

Mathematically a power law is:

$$Y = \mathrm{c}X^{\beta}$$

where X and Y are two characteristics, β is an exponential coefficient and c is a constant (West, 2017). There is no hidden Hobbesian significance in the word ‘power’—it is just a mathematical term. If the value of some quantity Y depends on the value of another quantity X according to a power law relationship, it means each time X is doubled, Y increases by a constant factor (Ball, 2004). For open-ended, complex systems such as cities, time and population size—and possibly other scales—play a critical role because these systems are not in equilibrium (Bettencourt et al., 2020).

Cross-sectional urban scaling is the most common procedure for urban scaling analysis, as it identifies parameters that are averages over the system and of their deviations at a fixed time. In cross-sectional analyses time is held constant and the properties of all cities in an urban system are compared as a function of their populations (Bettencourt et al., 2020). This procedure can be repeated at consecutive times to derive the temporal dependence of the same parameters. Temporal scaling is an orthogonal approach to cross-sectional analyses where time is considered as a constant. Such an analysis reveals the trajectory in time of specific properties, for example, exponential coefficients, of applicable power laws (Bettencourt et al., 2020).

The use of power laws to describe the dynamics of cities is not without criticism. The central thinking behind some of the Santa Fe Research Institute research is that it might be possible to construct a sort of unified theory of complexity (Martin & Sunley, 2010). However, the latter authors do not think a formal—mathematical—modelling methodology is necessary or of itself sufficient for understanding the complex behaviour of the economic landscape. The views of Martin & Sunley (2010) have to be contrasted with the findings of the Santa Fe and other researchers. Many diverse properties of cities, from patent production and personal income to electrical cable length, are power law functions that indicate scaling impacts associated with population size (West, 2017; Bettencourt et al., 2020). Scaling exponents, β, fall into distinct universality classes. Quantities reflecting wealth creation and innovation have $\beta \approx 1.2 > 1$. These super-linear coefficients indicate increasing returns on scale in larger populations. In other words, larger cities have proportionally more wealth creation and innovation. However, the sub-linear coefficients of power laws associated with infrastructure development in cities are generally $\beta \approx 0.8 < 1$, indicating economies of scale in larger cities.

The extraordinary regularities first recorded by the Santa Fe group opened a window to study the underlying mechanisms, dynamics and structure common to all cities (Bettencourt et al., 2020; Bettencourt & West, 2010; West, 2017). Over the last few decades and in disciplines as diverse as economics, geography and complex systems, a perspective developed that proposed that many properties of cities are quantitatively predictable due to agglomeration or scaling effects (Bettencourt et. al. 2013; Gomez-Lievano, Youn, & Bettencourt, 2012: Gomez-Lievano, Patterson-Lomba & Hausmann, 2016). The endeavor to discover general mathematical regularities of urban life is relatively new but increasingly possible given the growing availability of more and better data and the multi-disciplinary scientific interest in the subject (Bettencourt et al., 2013). The importance of these regularities might mean that the difference between 'policy as usual' and policy led by a new quantitative understanding of cities could well be the choice between creating a 'planet of slums' or finally achieving a sustainable, creative, prosperous, urbanized world expressing the best of human spirit (Bettencourt & West., 2010).

It follows that it is necessary to determine if human settlements that have rural populations in addition to urban populations also exhibit extensive demographic–socioeconomic–entrepreneurial orderliness. Earlier studies of U.S. counties indicated the presence of entrepreneurial orderliness (Toerien, 2018; Toerien, 2020a). This investigation now adds an examination of the dynamics of entrepreneurial scaling of another group of U.S. counties before, during and after a period of economic turmoil.

2.0 Methodology

This analysis is based on U.S. counties for the following reasons: (a) the availability of extensive entrepreneurial information about U.S. counties that includes enterprise diversity information, (b) the fact that enterprise numbers–enterprise richness power laws have previously been recorded for U.S. counties (Toerien, 2018; Toerien, 2020a), and (c) U.S. counties represent a human settlement type that in most cases includes urban and rural populations, whilst cities include only urban populations. It is necessary to ascertain if mixes of urban and rural populations also exhibit demographic–socioeconomic–entrepreneurial orderliness and if this varies temporally. The research design involves repeated observations of the same variables over many years and is a combination of cross-sectional and time-series analysis. This research design is quite common in economics, epidemiology, and psychology (Bettencourt et al., 2020).

2.1 The Selected Counties

Power law analyses require extensive scales of different system properties (Bettencourt et al., 2020). To reduce the chances of inadequate definition of enterprise richness as experienced by Youn et al. (2016), county enterprise richness values were limited to a range of 30 to 320 (see Tables 1 and 2). Visual evidence indicated that a group of 22 counties (see Table 1) with a wide spread of enterprise richness values—within the above range—could be selected from County Business Pattern (CBP) datasets (see section 2.2). This conclusion was checked by two additional sets of power law analyses:

- To ensure that the use of only 22 counties could yield representative information about U.S. counties, three additional groups of 22 counties with enterprise richness values between 30 and 320 were selected from the 2010 County Business Pattern (CBP) dataset (see Table 2). Their enterprise richness–enterprise numbers power laws were compared with the ones recorded over the study period.
- Each of the additional groups of counties were then expanded to include eight additional counties—30 in total in each group—by selecting additional counties with different enterprise richness values. The power laws of the three expanded groups were compared with the other power laws. The comparisons indicated that analyses of the initial 22 selected counties (see Table 1) should indicate the extent to which some entrepreneurial properties of U.S. counties could be associated with the economic shocks of a period of economic turmoil.

Table 1. *The 22 Selected Counties and Their 2016 Enterprise Richness and Enterprise Numbers as an Example From the 2000–2016 Period*

County	**State**	**Enterprises**	**Enterprise richness**	**County**	**State**	**Enterprises**	**Enterprise richness**
Frontier	Nebraska	72	43	Converse	Wyoming	447	188
Cleburne	Alabama	160	83	Inyo	California	507	204
Garfield	Utah	171	80	Gray	Texas	563	205
Oscoda	Michigan	175	96	Orleans	New York	649	232
Perquimans	North Carolina	199	109	Lincoln	New Mexico	675	219
Caldwell	Kentucky	286	144	Wythe	Virginia	679	236
Murray	Minnesota	306	127	Autauga	Alabama	847	250
Tipton	Indiana	306	144	Calumet	Wisconsin	883	260
Marlboro	South Carolina	319	135	Elk	Pennsylvania	889	259
Colusa	California	369	147	Valencia	New Jersey	911	256
Lee	Georgia	394	177	Barton	Kansas	951	264

Table 2. *Three Additional Groups of 22 Enterprises, Each Selected From the 2010 County Business Pattern Dataset (United States Census Bureau, 2018)*

Additional Group 1				**Additional Group 2**				**Additional Group 3**			
State	County	Enterprises	ER	State	County	Enterprises	ER	State	County	Enterprises	ER
17	69	75	48	47	127	75	54	46	85	75	43
29	203	145	75	54	101	146	70	38	45	145	68
1	65	192	104	28	161	192	92	27	29	192	101
2	50	207	92	26	131	208	97	22	65	207	112
13	43	222	115	21	123	222	102	21	127	222	113
38	67	283	118	28	131	282	136	47	159	283	130
18	119	300	155	39	125	300	147	48	35	300	143
1	111	341	155	26	141	341	139	29	221	341	164
1	19	355	168	19	161	355	133	31	39	355	141
8	105	362	153	16	79	362	161	48	289	362	143
19	37	388	150	28	153	388	154	30	9	388	182
17	33	430	171	51	163	432	182	51	163	432	182
13	87	601	219	29	83	602	221	56	23	603	203
26	69	634	220	53	49	634	214	55	123	634	216
39	97	698	232	40	111	698	224	1	9	699	233

Table 2 continued

Additional Group 1				**Additional Group 2**				**Additional Group 3**			
State	County	Enterprises	ER	State	County	Enterprises	ER	State	County	Enterprises	ER
18	51	724	241	47	177	724	255	18	1	725	248
27	47	816	278	40	9	816	230	51	117	816	258
54	37	860	244	48	249	861	229	1	39	862	257
17	137	898	272	53	65	898	270	21	179	899	285
55	45	941	289	13	219	942	288	19	111	946	273
20	55	1002	297	25	7	1003	254	48	21	1007	320
31	53	1026	297	21	113	1028	317	49	3	1030	289

FIPS State and County Numbers are According to United States Census Bureau (n.d.). ER is Enterprise richness.

2.2 Entrepreneurial Information and Diversity

The study period was chosen to include a number of years before, during, and after the economic turmoil of the Great Recession. The County Business Pattern (CBP) datasets for 2000–2016 (United States Census Bureau, 2018) were used to extract the total number of enterprises and the enterprise richness of each of the selected counties for each year of the study period. A total of 374 county data points were extracted.

Measuring diversity typically involves identifying different types and counting their frequency for a given unit of analysis (Whittaker, 1972). The North American Industry Classification Scheme (NAICS) classifies enterprise types in a six-digit scheme (United States Government, 2017). The NAICS was used by Youn et al. (2016) to quantify the enterprise types of cities. However, they found there is a limit where the finite NAICS classification scheme could not fully capture the true extent of the economic diversity of larger cities. A similar problem was observed in an analysis of U.S. counties (Toerien, 2020a).

The six-digit NAICS system was also used in this investigation. The number of different six-digit classifications recorded for a county in any year, provides an estimate of its enterprise richness in that year. Because the potential inadequacy of NAICS to truly record the enterprise richness of large counties (Toerien, 2020a), the counties selected for use in this study were limited to maximum enterprise richness levels of 320, which corresponded to approximately 1,000 enterprises (see Tables 1 and 2).

2.3 Scaling Analyses

The main technical issue for scaling analysis is that there are—at least—two extensive scales with different characters (Bettencourt et al., 2020). Extensive refers to the property of a variable to account for the size of the system—not necessarily linearly. In this study, enterprise richness values as well as enterprise numbers varied by several orders of magnitude (see above). Cross-sectional urban scaling is the most common procedure for urban scaling analysis, as it identifies parameters that are averages over the system of and their deviations at a fixed time. This procedure can be repeated at consecutive times to derive the temporal dependence of the parameters (Bettencourt et al., 2020). This was done here.

2.4 Testing the Dynamics of County Enterprise Diversity and Entrepreneurship During an Economic Turmoil and its Aftermath

Previous research (Toerien, 2020a; Toerien & Seaman, 2014) indicated that enterprise numbers scale super-linearly with enterprise richness and enterprise richness scale sub-linearly with enterprise numbers. These responses differ substantially: the one is a super linear relationship and the other a sub-linear relationship. Therefore, both relationships were calculated for the group of selected counties and for every consecutive year from 2000–2016. The assumption was made that impacts of the economic turmoil could register as changes in the properties of these power laws. Log-log regression analyses of enterprise richness and enterprise numbers—and their reciprocal—of the 22 counties provided the power law characteristics for each year. Microsoft Excel software was used for the analyses.

Two methods were used to assess the impacts of the economic turmoil and its aftermath: (a) calculation of the exponential coefficients of the power laws, and (b) calculation of ‘doubling impacts’. Doubling impacts were calculated as follows:

using the power laws of the different years, Y_1 and Y_2 were calculated for X_1 and X_2, where X_2 is double X_1. For each year, the percentage increase of Y_2 relative to Y_1 is then compared with a 100% increase of X—which represents a doubling of X.

2.5 Entrepreneurial Spaces and Entrepreneurship in the Selected Counties

The total number of enterprises in a county represents its total entrepreneurial space. The enterprise richness of a county represents its new entrepreneurship level. The difference between the total number of enterprises and its enterprise richness represents its existing entrepreneurship level.

3.0 Results

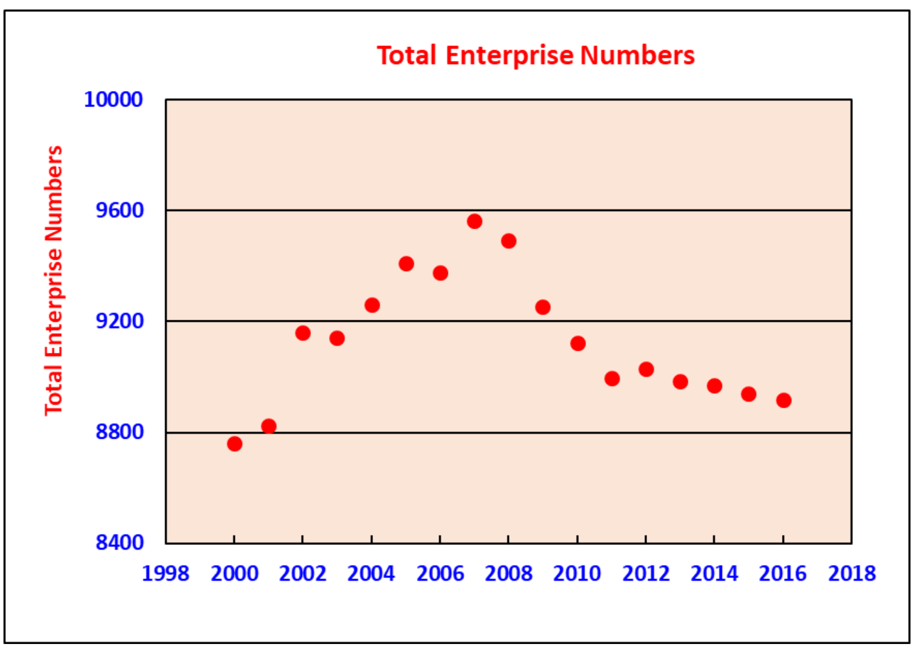
3.1 Selection of Counties

In 2016, the enterprise richness and enterprise numbers of the 22 counties ranged between 43 to 264 and 72 to 951 respectively (see Table 1). This indicated a wide data spread meeting the extensiveness requirement for power law analysis outlined by Bettencourt et al. (2020). The enterprise richness and enterprise numbers of the three additional groups of counties and the three expanded group states ranged between 43 and 320 and between 75 and 1030 respectively in the 2010 CBP dataset (see Table 2).

3.2 Total Enterprise Numbers

Changes in the total enterprise numbers of the 22 counties (see Figure 1) were associated with the economic turmoil of the Great Recession. There was a steady increase of enterprise numbers—from 2000–2007—until the onset of the Great Recession. The total enterprise numbers in the counties peaked at about 9600 in 2007. During the Great Recession—2007 and 2011—the numbers declined by about 9.3% to 8,924. In the recovery period thereafter—2011–2016—a slow decline continued and growth in enterprise numbers did not re-occur.

Figure 1. The total enterprise numbers of the selected counties over the 2000–2016 period.



3.2.1 The relationship between enterprise richness and enterprise numbers. The enterprise richness–enterprise numbers power laws for the period 2000–2016 of the selected group of 22 counties are presented in Table 3. Very similar results were obtained for the three additional groups of 22 counties and the three expanded groups of 30 counties each (see Table 3). The use of only 22 counties with a wide spread of enterprise richness and enterprise numbers for the temporal analysis was, therefore, justified.

For each year of the 2000–2016 period, the enterprise numbers and enterprise richness of the 22 counties were significantly ($P < 0.01$) correlated by way of power laws. Virtually all variation was explained as indicated by R^2-values close to 100% (see Table 3). The exponential coefficients (β) ranged from 1.40 to 1.49 with an average of 1.44 and standard deviation of 0.03. Over the whole of the study period, enterprise numbers increased by 164% to 181% when the enterprise richness increased by 100% (see doubling impacts in Table 3). Even during a major economic recession, enterprise numbers in the counties scaled strongly super-linearly relative to enterprise richness.

Table 3. *Enterprise Richness-Enterprise Numbers Power Laws of the Selected Counties and the Additional Groups (G1, G2 and G3) and Expanded Groups (AG1, AG2 and AG3)*

Year	Correlation	R^2 %	β	Pre-factor	n	Doubling impact %
2000	0.99	98.0	1.42	0.286	22	168.5
2001	0.99	98.0	1.44	0.260	22	171.6
2002	0.99	97.3	1.46	0.232	22	175.9
2003	0.99	97.6	1.48	0.208	22	179.7
2004	0.99	97.5	1.46	0.236	22	175.1
2005	0.99	97.5	1.48	0.208	22	179.6
2006	0.99	97.3	1.49	0.201	22	181.0
2007	0.99	97.2	1.47	0.227	22	176.9
2008	0.98	96.7	1.41	0.308	22	166.0
2009	0.99	97.1	1.40	0.322	22	164.5
2010	0.99	97.2	1.40	0.329	22	163.6
2011	0.99	97.4	1.40	0.321	22	164.2
2012	0.99	97.4	1.45	0.259	22	172.3
2013	0.99	97.6	1.43	0.277	22	170.0

Table 3 continued

2014	0.99	97.3	1.44	0.264	22	171.9
2015	0.99	97.7	1.43	0.281	22	169.5
2016	0.99	97.3	1.43	0.279	22	170.1
G1	0.99	98.0	1.43	0.278	22	169.6
G2	0.99	97.1	1.46	0.247	22	175.5
G3	0.99	97.4	1.39	0.347	22	161.7
AG1	0.99	97.8	1.47	0.231	30	176.4
AG2	0.99	97.7	1.46	0.247	30	175.4
AG3	0.99	97.9	1.39	0.340	30	162.7

β = exponential coefficient, doubling impact = percentage increase of enterprise numbers for every doubling (100 % increase) of enterprise richness, R^2 % = percentage variation explained.

Enterprise richness was also associated with the enterprise numbers of the 22 counties as shown by statistically significant ($P < 0.01$) correlations of the power laws for every year of the 2000–2016 period (see Table 4). Virtually all variation was explained as indicated by R^2-values close to 100 %. Exponential coefficients (β) ranged from 0.65 to 0.70 with an average of 0.68 and standard deviation of 0.01. Over the whole of the study period enterprise richness increased by only 57% to 62% relative to a 100% increase of enterprise numbers in the counties (see doubling impacts in Table 4). Enterprise richness, therefore, scales strongly sub-linearly with enterprise numbers in the counties.

Table 4. *Enterprise Numbers-Enterprise Richness Power Laws of the Selected Counties*

Year	Correlation	R^2 %	β	Pre-factor	n	Doubling impact %
2000	0.99	98.0	0.69	2.62	22	61.1
2001	0.99	98.0	0.68	2.77	22	60.2
2002	0.99	97.3	0.66	3.03	22	58.5
2003	0.99	97.6	0.66	3.18	22	57.7
2004	0.99	97.5	0.67	2.98	22	58.9
2005	0.99	97.5	0.66	3.18	22	57.7

Table 4 continued

2006	0.99	97.3	0.65	3.28	22	57.2
2007	0.99	97.2	0.66	3.08	22	58.2
2008	0.98	96.7	0.68	2.66	22	60.8
2009	0.99	97.1	0.69	2.54	22	61.5
2010	0.99	97.2	0.70	2.49	22	61.9
2011	0.99	97.4	0.70	2.51	22	61.9
2012	0.99	97.4	0.67	2.84	22	59.5
2013	0.99	97.6	0.68	2.71	22	60.3
2014	0.99	97.3	0.67	2.81	22	59.6
2015	0.99	97.7	0.68	2.67	22	60.6
2016	0.99	97.3	0.68	2.73	22	60.1

β = exponential coefficient, doubling impact = percentage increase of enterprise richness for every doubling (100 % increase) of enterprise numbers, R^2 % = percentage variation explained.

The analyses on which Tables 3 and 4 are based, suggest that over the whole of the 2000–2016 period there were statistically significant relationships between enterprise richness and enterprise numbers. That was indeed the case and the power laws are:

Enterprise numbers = 0.2645(enterprise richness)$^{1.4399}$
(equation 1)

Enterprise richness = 2.8127(enterprise numbers)$^{0.6761}$
(equation 2)

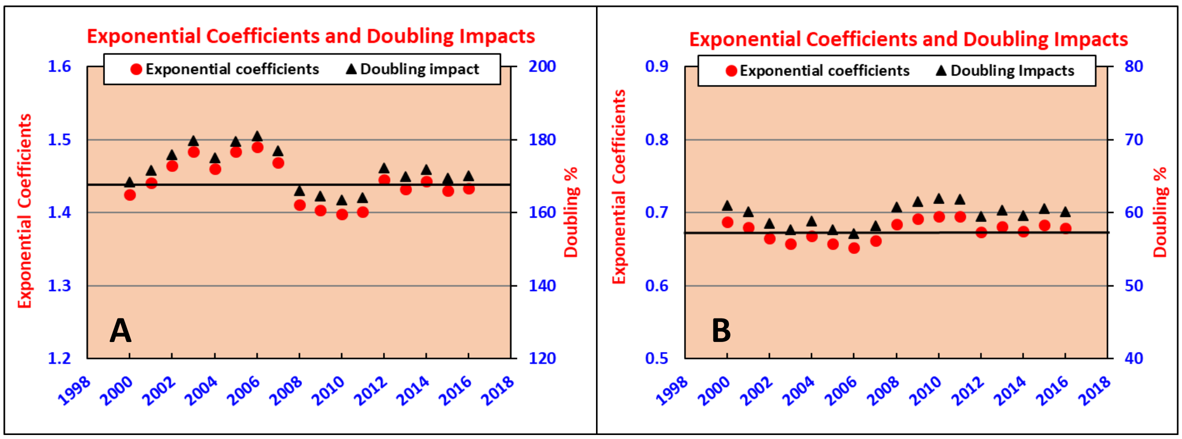
with r = 0.99 and n = 374 in both cases. Over the 2000–2016 period the relationships between enterprise numbers and enterprise richness clearly did not change much despite the economic turmoil of the Great Recession. These power laws, therefore, provide useful norms against which annual data could be tested (see later).

3.3 The Association of the Economic Turmoil and the Subsequent Recovery With the Enterprise Richness–Enterprise Numbers Relationships

The enterprise numbers in the selected counties were impacted during the Great Recession (see Figure 1). This is not unexpected given the spike in the U.S. unemployment rate over the course of the Great Recession (Yagan, 2019). Were the exponential coefficients of the 2000–2016 power laws between enterprise richness and enterprise numbers and the economic turmoil associated in any way? This was tested in a number of ways.

Firstly, the association of the economic turmoil with the exponential coefficients of the enterprise richness–enterprise numbers power laws is presented in Figure 2A. The solid black line indicates the level of the exponential coefficient of the overall power law for this relationship (equation 1). The exponential coefficients directly determine the doubling impacts over 2000–2016 of enterprise richness and these are also shown in Figure 2A. Secondly, the exponential coefficients of the enterprise numbers–enterprise richness power laws before, during and after the economic turmoil are presented in Figure 2B. The solid black line in Figure 2B indicates the level of the exponential coefficient of the overall power law of this relationship (equation 2).

Figure 2. Temporal Exponential Coefficients of Enterprise Richness–Enterprise Numbers Power Laws and their Doubling Impacts (A) and Enterprise Numbers–Enterprise Richness Power Laws and their Doubling Impacts (B).

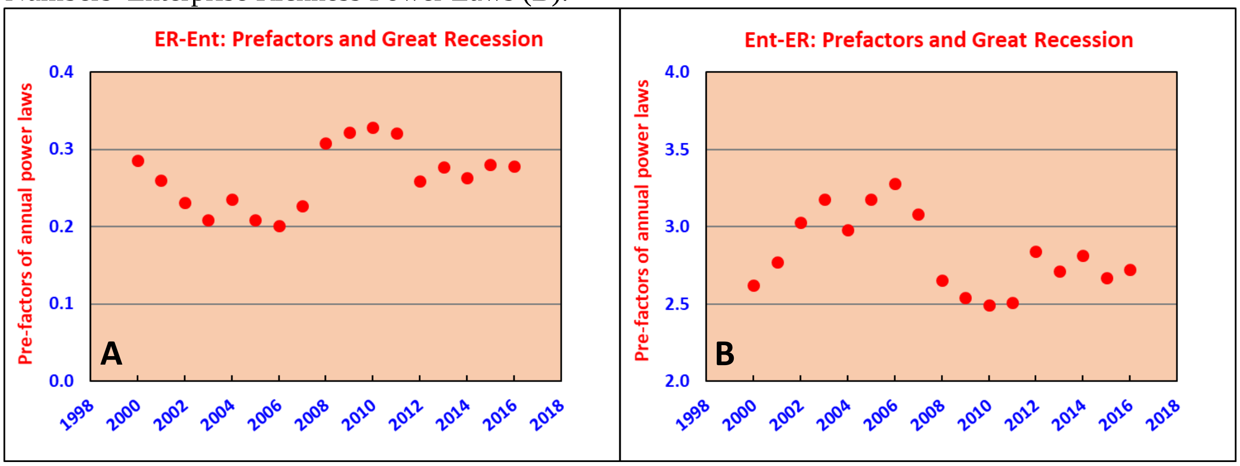


The black lines depict: A. The overall exponential exponent (1.44 from equation 1). B. The overall exponential exponent (0.68 from equation 4). Doubling % is: A. The percentage by which enterprise numbers increase relative to a 100 % increase of enterprise richness. B. The percentage by which enterprise richness increases relative to a 100 % increase of enterprise numbers.

In the period 2000–2006 when the total enterprises in the counties increased (see Figure 1), the magnitude of the exponential coefficients of the enterprise richness–enterprise numbers power laws increased somewhat (see Figure 2A). During the economic turmoil between 2007 and 2011 there was a distinct decline in enterprise numbers (see Figure 1) and a small decline was observed in the exponential coefficients of the enterprise richness–enterprise numbers relationships (see Figure 2A). The exponential coefficients were on their lowest from 2008–2011 and thereafter increased a bit and then remained more or less the same (see Figure 2A). They did not again reach the higher levels present before the onset of the economic turmoil. During the whole of the study period there was a continuous strong super-linearity in the enterprise richness–enterprise numbers relationships. During the economic turmoil and its aftermath, the scaling of enterprise numbers relative to the enterprise richness levels of the selected counties changed only subtly.

Thirdly, the exponential coefficients of the enterprise numbers–enterprise richness power laws before, during and after the economic turmoil are presented in Figure 2B. In the period 2000–2006 when the total enterprises in the counties increased (see Figure 1), the exponential coefficients of the enterprise numbers–enterprise richness power laws decreased somewhat (see Figure 2B). During the economic turmoil (2007–2011) the exponential coefficients increased to just above the long-term level and thereafter remained similar to the long-term value. The exponential coefficients directly determine the doubling impacts and these are also shown in Figure 2B. Over the whole of the study period, enterprise richness scales sub-linearly (55%–60%) with a doubling of enterprise numbers (i.e., 100% increase). During the economic turmoil and its aftermath, the scaling of enterprise richness relative to the enterprise numbers of the selected counties also changed only subtly.

Figure 3. Temporal Constants (Prefactors) of Enterprise Richness–Enterprise Numbers Power Laws (A) and the Constants (Prefactors) of the Enterprise Numbers–Enterprise Richness Power Laws (B).



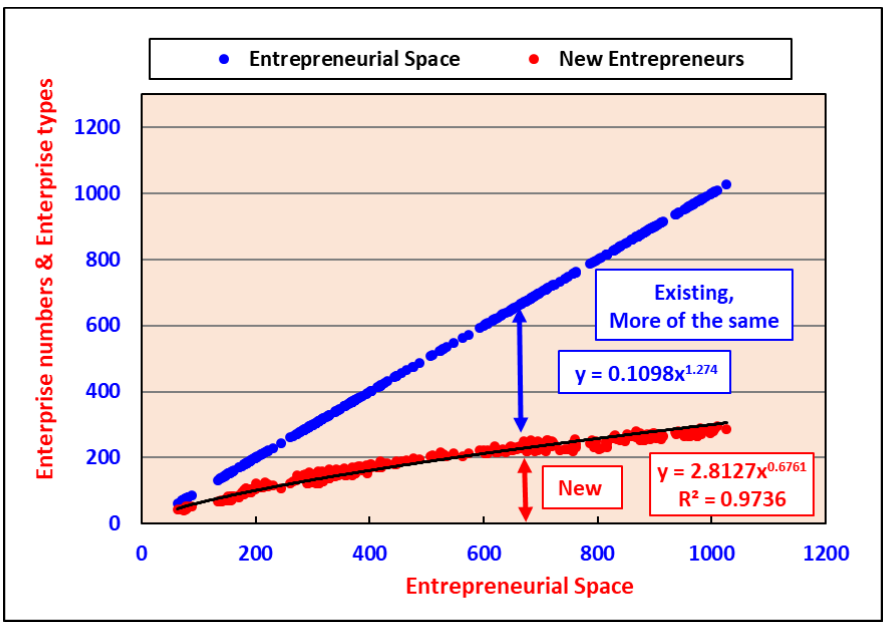
ER = enterprise richness, Ent = total enterprise numbers.

Fourthly, the behavior of the constants (prefactors) of the enterprise richness–enterprise numbers power laws are presented in Figure 3. The constants of the two types of power laws behaved in opposite fashion. In the period 2000–2007 when the total enterprise numbers in the counties increased (see Figure 1), the constants of the enterprise richness–enterprise numbers power laws decreased markedly (~ 30%) (see Figure 3A). By the onset of the economic turmoil the constants of these power laws increased markedly (> 50%) and remained at high levels until 2011. Thereafter they decreased somewhat but not to the levels before the onset of the recession. The constants of the enterprise numbers–enterprise richness power laws behaved in a precisely opposite fashion. The constants (see Figure 3) changed relatively much more before and during the economic turmoil than the exponential coefficients (see Figure 2) of both power law types. Constants include size-independent effects such as those caused by technology or institutional arrangements (Bettencourt et al., 2020). It is not yet clear if the changes in constants observed in Figure 3 are due to increases/decreases in enterprise numbers (see Figure 1) or due to other factors. This needs further investigation.

3.4 Entrepreneurial Space in the Selected Counties During a Period of Economic Turmoil

The total number of enterprises in a county reflects its total entrepreneurship, that is, its total entrepreneurial space. The number of enterprise types (i.e., enterprise richness) reflects the number of opportunities utilized by entrepreneurs that successfully founded enterprises of types that had not been present before (i.e., the new entrepreneurs). The difference between total entrepreneurship, that is, total number of enterprises, and enterprise richness, that is, new entrepreneurship, of a county reflects its existing entrepreneurship, that is, entrepreneurship that essentially represent more of the same. The new and existing entrepreneurship levels of the 2000–2016 period for all of the selected counties are presented in Figure 4. Whereas new entrepreneurship scales sub-linearly (exponential coefficient of 0.662) with entrepreneurial space, existing entrepreneurship scales super-linearly (exponential coefficient of 1.287) with entrepreneurial space. In other words, whilst opportunities for existing entrepreneurs increase more rapidly as entrepreneurial space increases in counties, those of new entrepreneurs do not increase at the same rate as increases of entrepreneurial space. During the economic turmoil there was a loss employment (Yagan, 2019) in the U.S. and of enterprises from the selected counties (see Figure 1). Judged by Figure 4, enterprise richness levels must have adjusted proportionately downwards with the losses of enterprises. During the 17-year period there is little or no evidence that the economic turmoil and its aftermath are associated with significant changes in the relationships between total, new and existing entrepreneurship in the counties (see Figure 4). These relationships appear to be extremely robust entrepreneurial qualities of U.S. counties and offer potential predictive capabilities.

Figure 4. Combined Power Laws between Entrepreneurial Space and New Entrepreneurship of the Selected Counties.



Entrepreneurial Space (blue dots) = Total Enterprise Numbers. Red dots represent New Entrepreneurship. Existing Entrepreneurship = Entrepreneurial Space minus New Entrepreneurship. For the Entrepreneurial Space-Existing Entrepreneurship Power Law see equation in blue. For the Entrepreneurial Space-New Entrepreneurship Power Law see equation in red.

4.0 Discussion

The availability of a long-term publicly-available business pattern datasets of U.S. counties (United States Census Bureau, 2018) successfully enabled answers to the two questions posed initially: if there is evidence over the 2000–2016 period of statistically significant power laws between the enterprise richness in the selected counties, and, if such evidence is obtained, if there are material changes in the properties of the power laws associated during the Great Recession and its aftermath. Such power laws were present (see Tables 3 and 4). Before the onset of the economic turmoil, the total enterprise numbers in the counties increased steadily. With the onset of the turmoil, they declined sharply and thereafter continued decreasing slowly (see Figure 1). However, changes in the enterprise richness–enterprise numbers relationships were muted (see Tables 3 and 4, Figures 2–4).

Power law analyses have revealed that many properties of cities scale with population size and the scaling exponents fall in distinct universality classes (Bettencourt et al., 2007). There is a universal structure common to all cities, which manifests in self-similarity in internal economic structures as well as aggregated metrics (e.g., of GDP, patents, crime) (Youn et al., 2016). This study revealed entrepreneurially-based power laws in selected U.S. counties over an extended period covering a period of economic turmoil. The findings add to the knowledge pool about human settlements as complex systems. U.S counties, many with urban and rural population mixes, seem to have a common entrepreneurial self-similarity structure.

There was limited evidence of major temporal or economic influences on the entrepreneurial relationships (see Tables 3 and 4, Figures 2–4). This is despite substantial differences across regions, states, and counties in the U.S. (Nunn et al., 2018). Evidence of such geographic disparities continues to pile up (Altman & Rubin., 2018) and the sheer size of the differences between American communities is staggering. Moretti (2013) refers to it as the Great Divergence. The enterprise richness–enterprise numbers relationships observed here are clearly very robust (see Figure 4). This raises a question about why the observed enterprise numbers–enterprise richness relationship is so robust?

The robustness might be linked to the fact that this relationship deals with business diversity. Quigley (1998) suggested that economic diversity enhances economic efficiency, which is linked with entrepreneurship and innovation, especially in places with large populations such as cities (Florida, 2003; West, 2017). Enterprise richness, which quantifies the number of times new enterprise types were successfully founded in a human settlement, reflects business creativity and quantifies the level of new entrepreneurship in the settlement. In turn, the new entrepreneurship level and the total enterprise numbers enable quantification of existing entrepreneurship level.

Creative destruction is the driving force behind economic development (Schumpeter, 1942). Creativity has come to be valued because new technologies, new industries, new wealth, and all other good economic things flow from it (Florida, 2002). Innovation has the power to reshape the economic fates of entire communities, as well as their cultures, urban form, local amenities, and political attitudes (Moretti, 2013). It creates enormous social benefits. Producing new things is quite different from producing more of the same (Hausmann & Klinger, 2006). All America's innovation hubs have a skilled labor force and a remarkably productive traded sector (Moretti, 2013). Nations tend to converge to the level of income that can be supported by the know-how that is embedded in their economies; that is, their so-called productive knowledge (Hausmann et al., 2017). More prosperous nations have more productive knowledge than poor nations, and vice versa. These differences are expressed in the diversity and sophistication of the things that each of these nations makes. The relationships between new and existing entrepreneurship with total entrepreneurship apparently reflect basic and constant entrepreneurial characteristics of U.S. counties despite the many disparities and differences mentioned by Moretti (2013), Altman & Rubin (2018) and Nunn et al. (2018).

Are the practical implications of the robust entrepreneurial relationships important? Kahneman (2011), Mayer-Schönberger & Cukier (2014), and Pearl & Mackenzie (2018) suggested that simple algorithms can be used effectively for predictions. Therefore, the enterprise richness versus enterprise numbers power laws (equations 1 and 2) as well as the power laws presented in Figure 4 that are all simple algorithms, appear to have promise as predictors of enterprise richness—business diversity—levels and entrepreneurial spaces—enterprise numbers—of U.S. counties.

The entrepreneurial space–business diversity relationships could perhaps also be used in predictions about job creation in U.S. counties. There are two sources of jobs in modern societies: those in the traded economic sector and those in the non-traded economic sector (Moretti, 2013). Most jobs are in the non-traded sector, that is, in local services. They include people that work as waiters, plumbers, nurses, teachers, and so forth. They offer products and services that are produced and consumed locally. The non-traded sector apparently corresponds with existing entrepreneurship (i.e., more of the same entrepreneurship). (Moretti, 2013) stated that the paradox is that while the vast majority of jobs are in the non-traded sector, the traded sector is the driver of prosperity in the U.S. human settlements. Enterprises in the traded sector produce goods or services that are mostly sold outside a region, thereby generating external income. This sector includes the innovative industries, traditional manufacturing, some services, the agricultural and extractive industries (Moretti, 2013) as well as tourism-based enterprises (Toerien, 2020b). The traded sector appears to correspond more closely with new entrepreneurship. However, the links between the different types of entrepreneurship and employment in U.S. counties need further elucidation.

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