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# Interregional Input-Output Linkages as Driver of Regional Diversification: Evidence from United States Counties

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### What is Regional Diversification?

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## Background

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### Why *regional*?

Regions often depend on a few main industries as compared to nations, and hence are more vulnerable to the decline sectors that they are specialised in.

## Related and Unrelated Diversification

Industries are related if they demand similar capabilities, such as infrastructures, institutions, knowledge and skills (Boschma, 2017).

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*Principle of Relatedness* (Hidalgo et al., 2018):

- Regions tend to diversify into new economic activities that are related to the existing mix of industries (Neffke et al., 2011; Boschma, 2013; Essletzbichler, 2015; Cortinovis et al., 2017; Xiao et al., 2018; Balland et al., 2018).



**Related Diversification**

- Regions occasionally diversify into new economic activities that are relatively unrelated to existing ones (Pinheiro et al., 2018; Pinheiro et al. 2021).



## **Unrelated Diversification**

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## **Unrelated Diversification**

- Supports the avoidance of lock-in and provides new opportunities for development (Saviotti & Frenken, 2008).
- Jumps in the industrial evolution (Boschma and Capone, 2015), profound shifts in local capabilities (Neffke et al., 2018) and radical innovation (Castaldi et al., 2015) are associated with unrelated diversification.



## Drivers of Diversification

- Beside the role of relatedness to endogenous capabilities, diversification studies also analysed other, albeit primarily local factors:
  - ▶ level of development (Pinheiro et al, 2021, Petralia et al. 2017)
  - ▶ institutions (Cortinovis et al., 2017; Boschma & Capone, 2015)
  - ▶ innovation capacity (Xiao et al., 2018; Fagerberg et al., 2013; Montresor & Quatraro, 2017).

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- The diversification literature has been criticized of its 'container view' on regions, displaying a fixation on endogenous capabilities and a lack of engagement with the role of extra regional factors (Yeung, 2021).

## Regions are not closed systems, isolated from the wider global economy!

- Connectivity to and absorption of external capabilities is usually regarded as a fundamental element to sustain and refine the local economy (Pyke et al., 1990; Ernst and Kim, 2002; Bathelt et al., 2004)
- Studies on regional growth, innovation & industrial path-creation showed that regions benefit from links to external capabilities (Boschma & Iammarino, 2009; Tavassoli, 2014; Boschma, 2017; Isaksen et al., 2014; Trippel, 2018; Ascani et al., 2020; Coe et al., 2004).

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Recombinations between local and external capabilities could mediate the role of relatedness:

External knowledge is more likely to be technologically distant and unfamiliar which could aid the development of completely new specialisations → **unrelated diversification**

## Diversification and Interregional Linkages

- The specialisations of neighbouring countries or regions (Bahar et al., 2014, Boschma, 2017) and imports support product diversification (Andersson et al., 2013; Zhu et al., 2017).
- Inventor cooperation across regions enhances technological diversification (Santoalha, 2019; Whittle et al., 2020), especially if regions have complementary capabilities (Balland & Boschma, 2021).
- Imports and FDI (Zhu et al., 2017), as well as foreign owned firms (Elekes et al., 2019) induced unrelated diversification, while Whittle et al. (2020) showed the opposite with interregional collaboration.

External capabilities can reach regions via different linkages:

commuting and migrant flows, international trade, foreign direct investment, strategic alliances, or **input-output linkages**.

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- Interdependence of industries as an important channel for knowledge creation and diffusion (Leontief, 1936)
  - ▶ Incentivizes the sharing of ideas, product or managerial innovations, which creates collective benefits (Von Hippel, 2005; Isaksson et al., 2016).
- Input-output linkages provides the vehicle for knowledge diffusion that can lead to novel re-combinations out of which new specialisations emerge.

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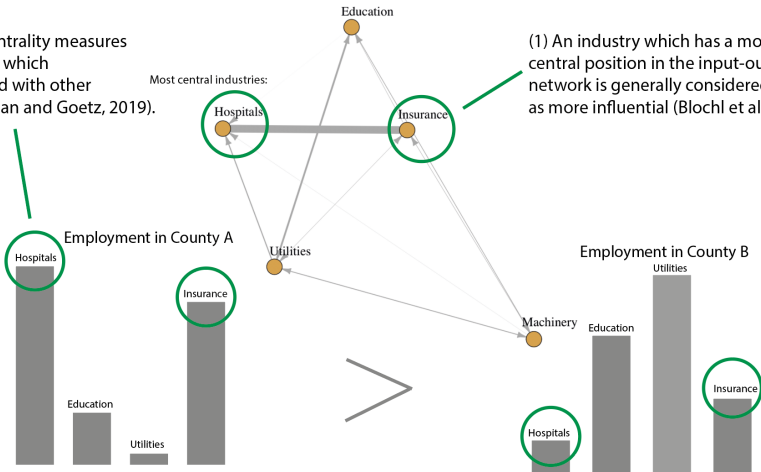
⇒ *The challenge is, how to proxy interregional input-output linkages in the US in the absence of county level data?*



# Input-Output Linkages and County Centrality

(2) County centrality measures the degree to which it is interlinked with other economies (Han and Goetz, 2019).

(1) An industry which has a more central position in the input-output network is generally considered as more influential (Blochl et al., 2011).



## Research Hypothesis

- Flows of intermediate goods and services among regions are a vehicle for the diffusion of external capabilities, upon which regional economies can thrive and diversify

H1: the probability that a county specializes in a new industry is positively related to the centrality of a county in terms of input-output relations

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- Flows of intermediate goods and services among regions are a vehicle for the diffusion of external capabilities, upon which regional economies can thrive and diversify

H1: the probability that a county specializes in a new industry is positively related to the centrality of a county in terms of input-output relations

- Interregional linkages may relax the role of relatedness, as external knowledge is likely to be unfamiliar, which provides opportunities for new and unrelated recombinations.

H2: relatedness has a weaker effect on the probability that a county specializes in a new industry if a county has a higher level of centrality

## Measuring Regional Diversification

- Employment data on 3221 counties and 675 six-digit traded industries, 1998 - 2017 (WholeData, Bartik et al. 2018).
- Diversification refers to the **entry of a new industrial specialization** to a regions' specialization portfolio.

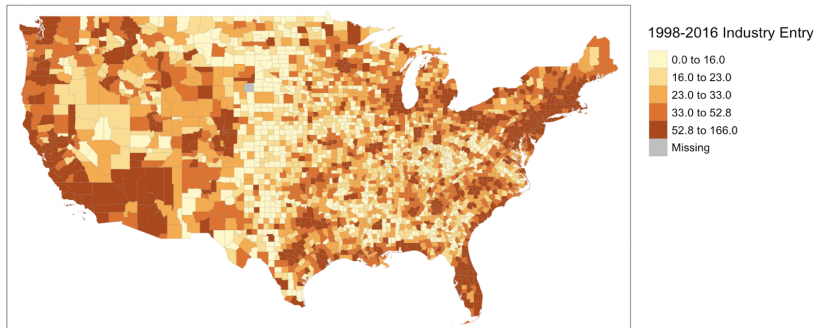
### The Location Quotient

... quantifies how concentrated a particular industry is in a region as compared to the nation. The higher the  $LQ_{i,c}$ , the more specialized a region is in that industry.

- We follow Tian (2013)'s bootstrapping method to retrieve a cut-off value for the standardized LQ at a the 5% significance level for each single industry.

- We observe the specialization status of an industry in a county over several **five year intervals** which leads to a **binary dependent variable**:

$$Y_{i,c,t+5} = \begin{cases} 1, & \text{if } SLQ_{i,c,t+5} > \text{cutoff}_{i,t+5} \text{ \& } SLQ_{i,c,t} < \text{cutoff}_{i,t} \\ 0, & \text{otherwise} \end{cases} \quad (1)$$

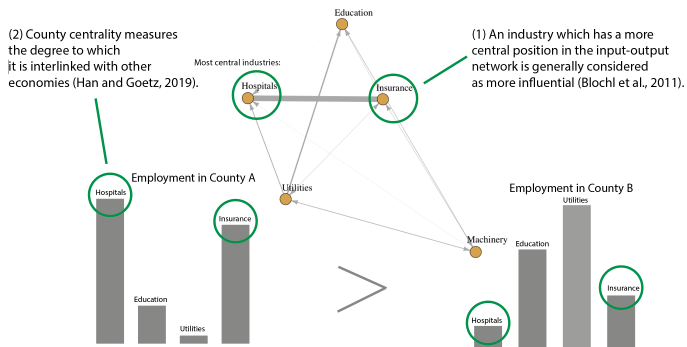


## Measuring Relatedness

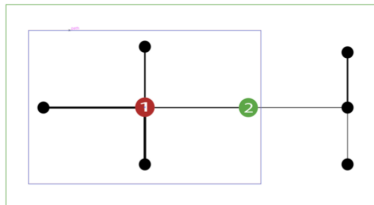
- 1 Proximity index developed by Hidalgo et al. (2007): co-occurrence of industry specialisations; using the LQ instead revealed comparative advantage of Balassa (1965).
- 2 Density indicator to link the industrial relatedness to the regional specialisation portfolios.

## Interregional Linkages: the County Centrality Measure

- Input-Output data of 66 three-digit industries on the national level (U.S. Bureau of Economic Analysis) and county employment data on the same industries.

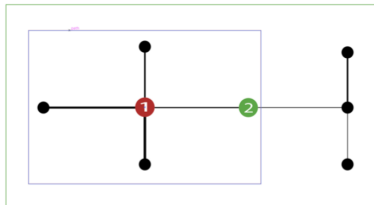


Different concepts of centrality: *Global* versus *Local* centrality (Gao et al. 2014).





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- **Closeness:** measures the distance from a node to every other node (Borgatti, 2005) → global measure.
- **Strength:** measures the relative size of a nodes' activity (Barrat et al., 2004) → local measure.
- **Entropy:** reflects a nodes' diversity of connections (Tutzauer, 2007) → global measure.

**Logit model with county, industry and year fixed effects:**

$$\underbrace{Y_{i,c,t+5}}_{0 \text{ or } 1} = f(\alpha + \beta_1 \text{relatedness}_{i,c,t} + \beta_2 \text{centrality}_{c,t} + \underbrace{\beta_3 \text{relatedness}_{i,c,t} * \text{centrality}_{c,t}}_{\text{interaction term}} + \underbrace{\gamma_{c,t} + \Phi_{i,t} + \psi_c + e_{i,c,t}}_{\text{fixed effects}})$$

H1: the probability that a county specializes in a new industry is positively related to the centrality of a county in terms of input-output relations.

Dependent Variable:	Count			
Model:	(1)	(2)	(3)	(4)
<i>Variables</i>				
Relatedness.Density	0.4908*** (0.0212)	0.4673*** (0.0219)	0.5050*** (0.0242)	0.4679*** (0.0221)
Closeness		0.1644*** (0.0256)		
Strength			0.0431*** (0.0153)	
Entropy				0.1523*** (0.0257)
<i>Fixed-Effects</i>				
State_t	Yes	Yes	Yes	Yes
NAICS_t	Yes	Yes	Yes	Yes
RUCC	Yes	Yes	Yes	Yes
<i>Fit statistics</i>				
Observations	7,744,202	7,744,202	7,744,202	7,744,202
Adj-pseudo $R^2$	0.06627	0.06673	0.06635	0.06658
BIC	1,166,932.79	1,166,431.86	1,166,875.88	1,166,597.83

*Clustered (State\_t) standard-errors in parenthesis. Signif Codes: \*\*\*: 0.01, \*\*: 0.05, \*: 0.1*

⇒ We can accept H1.

H2: relatedness has a weaker effect on the probability that a county specializes in a new industry if a county has a higher level of centrality

Dependent Variable:	Count		
Model:	(1)	(2)	(3)
<i>Variables</i>			
Relatedness.Density	0.5054*** (0.0318)	0.8390*** (0.0339)	0.5102*** (0.0311)
Closeness	0.3559*** (0.0243)		
Relatedness.Density:Closeness	-0.0995*** (0.0234)		
Strength		-0.0978*** (0.0147)	
Relatedness.Density:Strength		0.2968*** (0.0155)	
Entropy			0.3559*** (0.0221)
Relatedness.Density:Entropy			-0.1106*** (0.0183)
<i>Fixed-Effects</i>			
State_t	Yes	Yes	Yes
NAICS_t	Yes	Yes	Yes
RUCC	Yes	Yes	Yes
<i>Fit statistics</i>			
Observations	7,744,202	7,744,202	7,744,202
Adj-pseudo R <sup>2</sup>	0.0691	0.07522	0.06923
BIC	1,163,703.69	1,156,581.68	1,163,553.77

*Clustered (State.t) standard-errors in parenthesis. Signif Codes: \*\*\*: 0.01, \*\*: 0.05, \*: 0.1*

⇒ We can accept H2 only in the case of closeness and entropy centrality (global centrality measures).

## Robustness Checks

- 1.) Differences among urban and rural areas
- 2.) Inter-industry differences
- 3.) Addition of control variables
- 4.) Time sensitivity
- 5.) Linear regression

Robustness checks confirm findings:

- county centrality based on closeness and entropy has a significant positive influence on regional diversification and relaxes the role of relatedness.
- results for strength centrality are mixed and the coefficient has sometimes turned insignificant.

## Conclusion

*This study aims to to understand the relation among relatedness, regional input-output linkages and industrial diversification of U.S counties from 1998 to 2017.*

### **We find, that...**

- counties diversify into industries that are strongly related to existing industries in the county.
- interregional input-output linkages, proxied by country centrality, matter:

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### **We find, that...**

- counties diversify into industries that are strongly related to existing industries in the county.
- interregional input-output linkages, proxied by country centrality, matter:

Interregional linkages via local industries that are prominently positioned within the national production system appear to stimulate regional diversification in general and unrelated diversification in particular.

## Conclusion

### Directions for Future Research:

- We proxy interregional linkages, but the usage of regional input-output data (such as EUREGIO/WIOD) would allow a direct observation of linkages across regions.
- What about the relatedness between local knowledge and the knowledge coming from other regions (Balland and Boschma, 2021)?
- Explore the role of linkages & unrelated diversification for catch-up across regions with different capabilities (rural vs. urban; core vs. periphery, leaders vs. followers) (Pineiro et al. 2021)



**Thank you for your attention!**

# Appendix - NAICS Codes

	20 2-Digit Sectors	4-Digits	650 5-Digit Industries
Primary Sectors	NAICS 11 Agriculture, forestry, fishing and hunting**		
	NAICS 21 Mining, quarrying, and oil and gas extraction		
Secondary Sectors	NAICS 22 Utilities		
	NAICS 23 Construction		
	NAICS 31-33 Manufacturing		
	NAICS 42 Wholesale trade		
Tertiary Sectors	NAICS 44-45 Retail trade		
	NAICS 48-49 Transportation and warehousing		
	NAICS 51 Information		
	NAICS 52 Finance and insurance		
	NAICS 53 Real estate and rental and leasing		
	NAICS 54 Professional and technical services		
	NAICS 55 Management of companies and enterprises		
	NAICS 56 Administrative and waste services		
	NAICS 61 Educational services	NAICS 6111 Elementary and secondary schools	
	NAICS 62 Health care and social assistance	NAICS 6112 Junior colleges	
	NAICS 71 Arts, entertainment, and recreation	NAICS 6114 Business, computer and management training	NAICS 61141 Business and secretarial schools
	NAICS 72 Accommodation and food services		NAICS 61142 Computer training
	NAICS 81 Other services, except public administration	NAICS 6115 Technical and trade schools	NAICS 61143 Management training
NAICS 92 Public administration**	NAICS 6116 Other schools and instruction		
NAICS 99 Unclassified	NAICS 6117 Educational support services		

## Appendix - Dependent Variable

[Tian, 2013] bootstrapping method to retrieve cut-off values in 4 steps:

1.) We calculate standardized location quotient

$$LQ_{ic} = \frac{E_{ic}/E_c}{E_{in}/E_n}, \quad SLQ_{ic} = \frac{LQ_{ic} - \overline{LQ_i}}{std(LQ_i)} \quad (2)$$

2.) We divide the SLQ into samples for each industry.

3.) We carry out the procedure of resampling with 1000 times replacement for each industry to obtain 1000 bootstrap samples, each having exactly the same length as the original sample of each industry.

4.) We retrieve the 95th percentile of each bootstrap sample and calculating the mean value of all 1000 samples, which represents the cut-off for the SLQ at the 5% level for each single industry.

# Appendix - Relatedness I

2 steps to calculate technological relatedness:

1.) Following [Hidalgo et al., 2007] industrial proximity is derived from the minimum conditional probability that a county has a specialization of one industry ( $x_{i,t}$ ) given its co-specialization of another ( $x_{j,t}$ ). In formal terms:

$$\phi_{i,j,t} = \min\{p(x_{i,t}|x_{j,t}), p(x_{j,t}|x_{i,t})\} \quad (3)$$

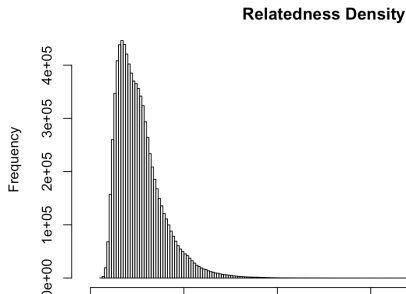
By doing so we obtain the 675 by 675 proximity matrix  $\phi$ .

## Appendix - Relatedness II

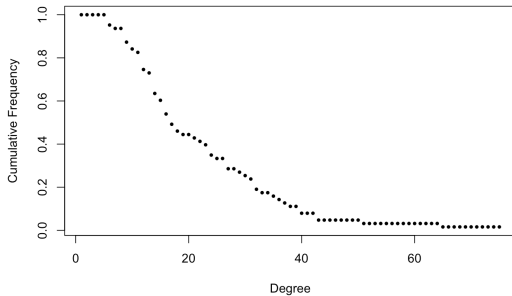
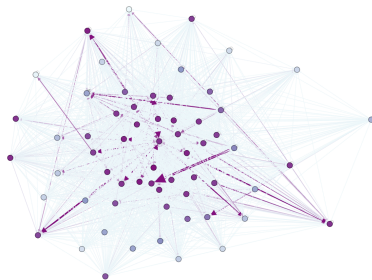
2.) [Hausmann et al., 2007]'s density indicator is used to link the industrial proximities to the regional specialization portfolios:

$$d_{i,c,t} = \frac{\sum_{j=1}^J (\phi_{i,j,t} x_{i,j,t})}{\sum_{j=1}^J (\phi_{i,j,t})} \quad (4)$$

where the subscript  $i$  refers to the focus industry;  $x_{i,c,t}$  takes a value of 1 when industry  $i$  is specialized in county  $c$ . The density indicator varies from 0 to 1, where a higher value means a higher level of relatedness of industry  $i$  with the industrial specialization portfolio of county  $c$  at year  $t$ .



# Appendix - Input - Output Network



# Appendix - Industry Centrality Measures

Centrality	Characteristics of a central industry	Equation
Closeness	Requires only few intermediaries for reaching other industries; can efficiently distribute information (Borgatti, 2005).	$Cl_i = \frac{J_j / (n-1)}{\sum_n l_{jk} / J}$
Strength	Trades intensively: high values of transactions to other nodes it is connected with. Transaction values may influence knowledge diffusion (Barrat et al., 2004).	$S_i = \sum_n^k w_{jk}$
Entropy	Has a diversified portfolio of supplies/purchasers and is therefore in a position to receive from or distribute knowledge to many different industries (Tutzauer, 2007; Eagle et al., 2010).	$E_i = \sum_n^k \frac{w_{jk}}{\sum_j^n \log(\frac{\sum_j^n w_{jk}}{w_{jk}})}$

$J_j$  is the number of reachable nodes to (or from) node  $j$ ,  $n$  is the number of nodes in a network, and  $l_{jk}$  is the maximum path length from node  $j$  to  $k$ .  $w_{jk}$  stands for the transaction value (edge weight) of node  $j$  to  $k$ .

## Appendix - County Centrality Measures

County centralities:

$$C_{c,t} = \frac{\sum_i E_{ic} C_i}{\sum_i E_{ic}} \quad (5)$$

Most central Industries:

- Legal, management and technical services (Closeness & Strength Centrality)
- Whole Sale (Entropy Centrality)

Least central Industries:

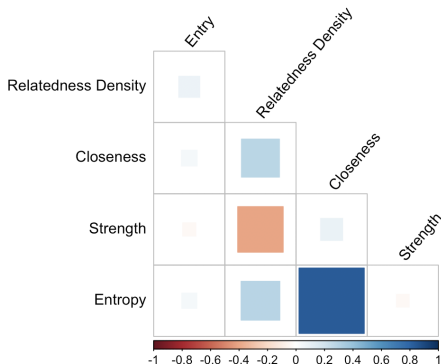
- Oil & Gas Extraction (Closeness & Strength Centrality)
- Social Assistance (Entropy Centrality)

Most connected Counties:

- Los Angeles (Closeness & Strength Centrality)
- Washington DC (Entropy Centrality)



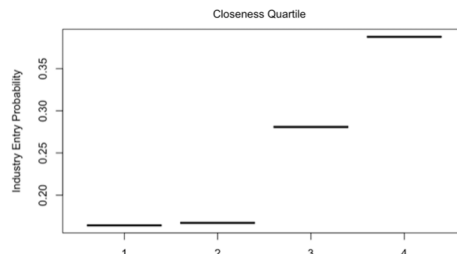
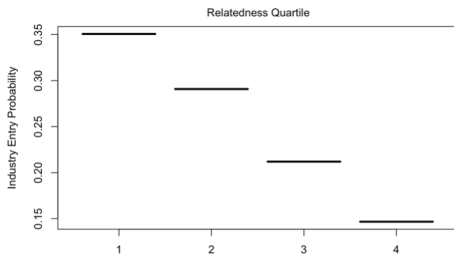
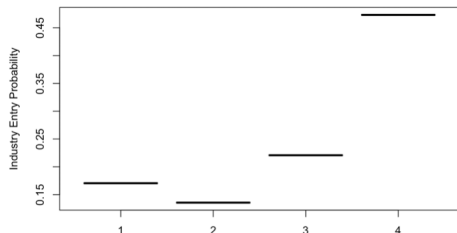
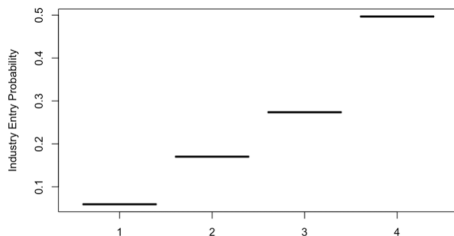
# Appendix - Descriptives I



Statistic	N	Mean	St. Dev.	Min	Max
Entry	8,337,340	0.01	0.11	0	1
Relatedness.Density	8,337,340	10.53	4.93	2.45	69.81
Closeness	8,337,340	-0.03	0.01	-0.07	0.001
Strength	8,337,340	386 626	644 047.	-2 108 172	2 646 111
Entropy	8,337,340	4.65	2.42	0.10	10.94

# Appendix - Descriptives II

Probabilities of acquiring new industrial specializations:



## Appendix - Estimation Strategy

Unbalanced dependent variable: 111 047 entry events vs. 8 226 293 non-events.

$$\text{Entry Probability: } \frac{0}{0.987} \mid \frac{1}{0.014}$$

→ Linear Probability Model vs. Logit Model (King et al., 2001; Greene, 2012; Allison, 2012)

# Appendix - Robustness Checks

# Appendix - Urban Rural Differences

	Relatedness	Closeness	Strenght	Entropy
Relatedness.Density	0.3162*** (0.0149)	0.4658*** (0.0214)	0.5609*** (0.0292)	0.4658*** (0.0218)
Centrality Variable		0.0999*** (0.03)	0.3192*** (0.0364)	0.0999** (0.0322)
Variable:factor(RUCC)2	0.2431*** (0.0168)	0.0811** (0.0251)	-0.3118*** (0.0281)	0.0957*** (0.0233)
Variable:factor(RUCC)3	0.5665*** (0.0245)	0.1316*** (0.0285)	-0.4047*** (0.0341)	0.1349*** (0.0281)
Variable:factor(RUCC)4	0.6618*** (0.0321)	0.1071*** (0.0266)	-0.3498*** (0.036)	0.1179*** (0.026)
Variable:factor(RUCC)5	0.6772*** (0.0572)	0.0752* (0.037)	-0.3602*** (0.0441)	0.0983** (0.0371)
Variable:factor(RUCC)6	1.1402*** (0.0247)	0.2533*** (0.0288)	-0.3679*** (0.0376)	0.2172*** (0.0274)
Variable:factor(RUCC)7	1.1298*** (0.0268)	0.2711*** (0.03)	-0.3713*** (0.0395)	0.2359*** (0.0312)
Variable:factor(RUCC)8	1.4527*** (0.0345)	0.4359*** (0.0346)	-0.3824*** (0.0421)	0.3955*** (0.0376)
Variable:factor(RUCC)9	1.4884*** (0.0319)	0.4942*** (0.0374)	-0.4223*** (0.0374)	0.4946*** (0.0343)
Fixed-Effects:				
State_t	Yes	Yes	Yes	Yes
NAICS_t	Yes	Yes	Yes	Yes
RUCC	Yes	Yes	Yes	Yes
Observations	7,744,202	7,744,202	7,744,202	7,744,202
S.E. type	Clustered (State..	Clustered (State..	Clustered (State_t)	Clustered (State..

# Inter-Industry Differences

Diversification of SC industries							
	1	2	3	4	5	6	7
Relatedness.Density	0.5038*** (0.0205)	0.4841*** (0.0213)	0.5236*** (0.0237)	0.4848*** (0.0215)	0.5231*** (0.0319)	0.859*** (0.0334)	0.5282*** (0.0309)
Closeness		0.1363*** (0.0244)			0.3285*** (0.0238)		
Strength			0.0594*** (0.0162)			-0.0929*** (0.0144)	
Entropy				0.1247*** (0.0248)			0.3295*** (0.0221)
Relatedness.Density:Closeness					-0.1012*** (0.0237)		
Relatedness.Density:Strength						0.3037*** (0.0158)	
Relatedness.Density:Entropy							-0.1126*** (0.0184)
Fixed-Effects:							
State_t	Yes	Yes	Yes	Yes	Yes	Yes	Yes
NAICS_t	Yes	Yes	Yes	Yes	Yes	Yes	Yes
RUCC	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	5,561,205	5,561,205	5,561,205	5,561,205	5,561,205	5,561,205	5,561,205
S.E. type	Clustered (State..)	Clustered (State..)	Clustered (State..)	Clustered (State..)	Clustered (State_t)	Clustered (State_t)	Clustered (State_t)
Squared-Corr.	0.011	0.011	0.011	0.011	0.011	0.013	0.011
Adj-pseudo R2	0.06518	0.06549	0.06532	0.06539	0.06787	0.07455	0.06806
BIC	832,089.39	831,859.82	832,001.05	831,945.73	829,915.05	824,392.79	829,763.85

# Inter-Industry Differences

Diversification of B2C Industries	1	2	3	4	5	6	7
Relatedness.Density	0.4555*** (0.0236)	0.4228*** (0.0242)	0.4554*** (0.0262)	0.4226*** (0.0243)	0.4592*** (0.032)	0.777*** (0.0362)	0.4625*** (0.0321)
Closeness		0.2362*** (0.0323)			0.4281*** (0.0317)		
Strength			-2e-04 (0.0161)			-0.1129*** (0.0185)	
Entropy				0.224*** (0.0323)			0.4258*** (0.0306)
Relatedness.Density:Closeness					-0.0965*** (0.0231)		
Relatedness.Density:Strength						0.2737*** (0.0163)	
Relatedness.Density:Entropy							-0.1066*** (0.0185)
Fixed-Effects:							
State_t	Yes	Yes	Yes	Yes	Yes	Yes	Yes
NAICS_t	Yes	Yes	Yes	Yes	Yes	Yes	Yes
RUCC	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,182,997	2,182,997	2,182,997	2,182,997	2,182,997	2,182,997	2,182,997
S.E. type	Clustered (State..	Clustered (State..	Clustered (State..	Clustered (State..	Clustered (State_t)	Clustered (State_t)	Clustered (State_t)
Squared-Corr.	0.013	0.014	0.013	0.013	0.014	0.015	0.014
Adj-pseudo R2	0.07092	0.07186	0.07092	0.0716	0.07422	0.07857	0.07417
BIC	336,742.61	336,455.62	336,771.80	336,543.37	335,691.35	334,231.00	335,706.63

# Inter-Industry Differences

Diversification of Manufacturing Industries	1	2	3	4	5	6	7
Relatedness.Density	0.4966*** (0.021)	0.4563*** (0.0222)	0.4889*** (0.0228)	0.4487*** (0.0216)	0.4977*** (0.0293)	0.8206*** (0.0366)	0.4941*** (0.028)
Closeness		0.3138*** (0.0427)			0.5559*** (0.0428)		
Strength			-0.0236 (0.017)			-0.156*** (0.0172)	
Entropy				0.3512*** (0.0377)			0.6147*** (0.0337)
Relatedness.Density:Closeness					-0.1042*** (0.0221)		
Relatedness.Density:Strength						0.2763*** (0.0177)	
Relatedness.Density:Entropy							-0.1196*** (0.0166)
Fixed-Effects:							
State_t	Yes	Yes	Yes	Yes	Yes	Yes	Yes
NAICS_t	Yes	Yes	Yes	Yes	Yes	Yes	Yes
RUCC	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4,003,233	4,003,233	4,003,233	4,003,233	4,003,233	4,003,233	4,003,233
S.E. type	Clustered (Stat..)	Clustered (State..)	Clustered (State..)	Clustered (State..)	Clustered (State_t)	Clustered (State..)	Clustered (State_t)
Squared-Corr.	0.01	0.01	0.01	0.01	0.01	0.011	0.011
Adj-pseudo R2	0.07306	0.07448	0.07308	0.07448	0.07713	0.08052	0.07763
BIC	493,401.29	492,738.12	493,420.98	492,742.37	491,480.87	489,834.04	491,239.20



# Inter-Industry Differences

Diversification of Service Industries	1	2	3	4	5	6	7
Relatedness.Density	0.4695*** (0.0217)	0.4547*** (0.0226)	0.4956*** (0.025)	0.4595*** (0.0232)	0.4918*** (0.0339)	0.8163*** (0.0314)	0.5004*** (0.0332)
Closeness		0.0953*** (0.0242)			0.269*** (0.0212)		
Strength			0.0771*** (0.0166)			-0.0662*** (0.015)	
Entropy				0.0615* (0.0269)			0.2409*** (0.0231)
Relatedness.Density:Closeness					-0.1014*** (0.0247)		
Relatedness.Density:Strength						0.2997*** (0.0143)	
Relatedness.Density:Entropy							-0.1086*** (0.0195)
Fixed-Effects:							
State_t	Yes	Yes	Yes	Yes	Yes	Yes	Yes
NAICS_t	Yes	Yes	Yes	Yes	Yes	Yes	Yes
RUCC	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3,740,969	3,740,969	3,740,969	3,740,969	3,740,969	3,740,969	3,740,969
S.E. type	Clustered (State..)	Clustered (State..)	Clustered (State..)	Clustered (State..)	Clustered (State_t)	Clustered (State..)	Clustered (State_t)
Squared-Corr.	0.012	0.012	0.011	0.012	0.012	0.014	0.012
Adj-pseudo R2	0.05646	0.05662	0.0567	0.05651	0.05901	0.06601	0.05897
BIC	673,006.37	672,922.70	672,867.68	672,998.49	671,353.00	666,654.68	671,374.20

# Control Variables

	1	2	3	4	5	6	7
Relatedness.Density	0.5446*** (0.0275)	0.5398*** (0.0277)	0.5994*** (0.0426)		0.8911*** (0.0379)		0.6024*** (0.0402)
Closeness		0.1904*** (0.0326)	0.4204*** (0.0406)				
Relatedness.Density:Closeness			-0.1038*** (0.026)				
Strength				0.0205 (0.0139)	-0.1261*** (0.0153)		
Relatedness.Density:Strength					0.288*** (0.0157)		
Entropy						0.1971*** (0.0307)	0.4505*** (0.0307)
Relatedness.Density:Entropy							-0.1161*** (0.02)
Los	-0.8733*** (0.1183)	-0.5956*** (0.1398)	-0.1403 (0.152)	-0.888*** (0.1184)	-0.3747** (0.1194)	-0.5837*** (0.1373)	-0.08 (0.1346)
Employment.Growth	0.8199*** (0.1565)	0.9374*** (0.1497)	1.0971*** (0.1495)	0.8298*** (0.1567)	0.6722*** (0.1647)	0.9247*** (0.1498)	1.0765*** (0.1484)
Commuting	-0.6348*** (0.1152)	-0.6715*** (0.1206)	-0.6719*** (0.1223)	-0.6248*** (0.1135)	-0.5745*** (0.0896)	-0.6886*** (0.1225)	-0.7015*** (0.1261)
Education	0.0113*** (9e-04)	0.0107*** (9e-04)	0.0098*** (0.001)	0.0113*** (9e-04)	0.0057*** (0.001)	0.0109*** (9e-04)	0.0103*** (9e-04)
Population.Density	-0.025* (0.0101)	-0.0516*** (0.0108)	-0.0821*** (0.0142)	-0.0214* (0.0097)	-0.0507*** (0.0091)	-0.0515*** (0.0103)	-0.0854*** (0.0127)
Gini.Index	-2.746*** (0.1827)	-2.6916*** (0.1777)	-2.4651*** (0.1671)	-2.7316*** (0.1806)	-1.5451*** (0.1947)	-2.6859*** (0.1804)	-2.406*** (0.1722)
Share.of.SC.Industries	-1.1749*** (0.0673)	-1.1557*** (0.0677)	-1.0993*** (0.0689)	-1.1658*** (0.0675)	-1.0635*** (0.0675)	-1.1754*** (0.0676)	-1.1357*** (0.0649)
Fixed-Effects:							
State_t			Yes	Yes	Yes	Yes	Yes
NAICS_t			Yes	Yes	Yes	Yes	Yes
RUCC			Yes	Yes	Yes	Yes	Yes

# Time Period

	1	2	3	4	5	6	7
Relatedness.Density	0.6138*** (0.03)	0.5593*** (0.0324)	0.7016*** (0.048)	0.5647*** (0.033)	1.3905*** (0.0338)	1.1286*** (0.0434)	1.3657*** (0.0279)
Closeness		0.1708*** (0.0291)			0.0205 (0.0275)		
Strength			0.146*** (0.0295)			-0.0369 (0.0266)	
Entropy				0.1432*** (0.0284)			0.0242 (0.025)
Relatedness.Density:Closeness					-0.6198*** (0.0216)		
Relatedness.Density:Strength						0.238*** (0.0115)	
Relatedness.Density:Entropy							-0.5619*** (0.0159)
Fixed-Effects:							
State	Yes	Yes	Yes	Yes	Yes	Yes	Yes
NAICS	Yes	Yes	Yes	Yes	Yes	Yes	Yes
RUCC	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,752,904	1,752,904	1,752,904	1,752,904	1,752,904	1,752,904	1,752,904
S.E. type	Clustered (Sta..)	Clustered (State)	Clustered (State)	Clustered (State)	Clustered (State)	Clustered (State)	Clustered (State)
Squared-Corr.	0.027	0.027	0.027	0.027	0.035	0.032	0.035
Adj-pseudo R2	0.0788	0.07939	0.07979	0.07926	0.09727	0.09107	0.09717
BIC	452,229.77	451,976.17	451,788.64	452,037.12	443,559.94	446,489.71	443,610.38

# Linear Probability Model

	1	2	3	4	5	6	7
Relatedness.Density	0.01411*** (0.00006)	0.01389*** (0.00007)	0.01455*** (0.00007)	0.01405*** (0.00007)	0.01399*** (0.00007)	0.01828*** (0.00008)	0.01426*** (0.00007)
Closeness		0.00091*** (0.00009)			0.00128*** (0.00009)		
Strength			0.00103*** (0.00006)			0.00135*** (0.00006)	
Entropy				0.00022** (0.00010)			0.00095*** (0.00011)
Relatedness.Density:Closeness					-0.00053*** (0.00004)		
Relatedness.Density:Strength						0.00367*** (0.00005)	
Relatedness.Density:Entropy							-0.00096*** (0.00004)
Observations	7744202	7744202	7744202	7744202	7744202	7744202	7744202
R2	0.01461	0.01462	0.01464	0.01461	0.01464	0.01539	0.01467
Adjusted R2	0.01426	0.01427	0.01430	0.01426	0.01430	0.01504	0.01433
Residual Std. Error	0.11382	0.11382	0.11382	0.11382	0.11382	0.11377	0.11381
Note:	*p<0.1;	**p<0.05;	***p<0.01				

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