Charles M. Tiebout lecture - Pacific Northwest Regional Economic Conference

How do regions innovate? Debunking the myths of knowledge spillovers

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Charles M. Tiebout – life and work (1)

- Fought against UNO headquarter move to Greenwich, Connecticut.
- Thesis at the University of Michigan under Wolfgang Stolper who was translating Lösch's *The Economics of Location* (1954).
- Paul Samuelson's article "The Pure Theory of Public Expenditure" (1954) influence was large…
  - for establishing the formal definition of public goods as those consumed collectively.
  - the underlying problem of public goods is the person's lack of incentive to reveal his/her preferences => no self-policing competitive pricing of private goods
  - "free-rider" problem makes it difficult to identify the amount of such goods to be produced and to determine the appropriate benefits tax

Charles M. Tiebout – life and work (2)

… but did not consider the location of public goods nor that mobility reveals the consumer-voter's demand for public goods and equalize the marginal rates of substitution between locations.

- When Lecturer at Northwestern University, Tiebout writes *A Pure Theory of Local Expenditures (*JPE, 1956) : "**voting with your feet**" idea: residents moving to communities that fit their preferences, which replaces the usual market test of willingness to buy a good and eliminates Samuelson's "free-rider" problem.
- Part of the American Economic Association, Regional Science Association and American Political Science Association in the 50's and 60's
- UCLA in 1958, U. of Washington in 1962 (Center for Urban and Regional Studies) until 1968

- Links between Tiebout and me

How do regions innovate? Debunking the myths of knowledge spillovers

- The literature of innovation has focused on creating innovation at the firm level (e.g. Jaffe, 1986; Blundell *et al*., 1995, Cincera, 1997)
  - Knowledge Production Function (Griliches, 1979) : $I_i = \alpha \cdot RD_i^{\beta} \cdot HK_i^{\gamma} \cdot \varepsilon_i$
  - Absence of knowledge spillovers

- Innovation and technological change are important sources of economic growth (Audretsch and Feldman, 1996; Romer 1986; Grossman and Helpman 1994)

- Regional approach to knowledge production function starts with Jaffe (1989)
  - Myth #1: Proximity is the most important (face-to-face interaction)
  - Myth #2: Knowledge spillovers are uniform in space
  - Myth #3: Knowledge spillovers are homogenous across sectors
  - Stylized facts about innovation in WA, OR, Benton county (WA), Deschutes county (OR)

Myth #1: Proximity is the most important

Modeling interregional knowledge spillovers based on geographical proximity

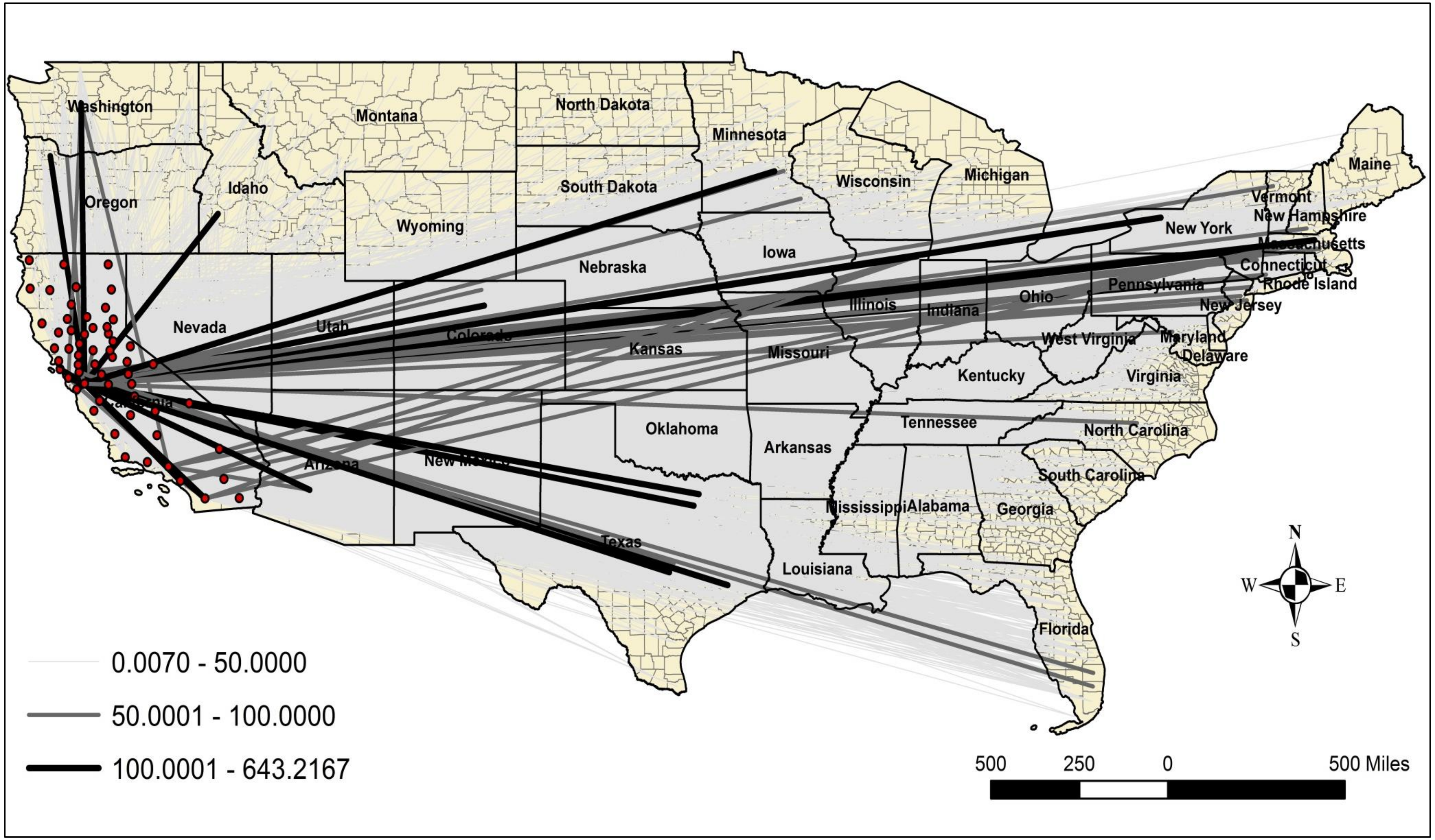
- University research and private R&D of neighboring regions within 75 miles (Anselin *et al.*, 1997)
- Innovation output of neighboring regions within 50 miles (Anselin *et al.,* 2000; Acs *et al*., 2002)
- Contiguity, k-nearest neigbors (Bode, 2004)
- Contiguity (Autant-Bernard and LeSage, 2011)

- Geographic+technological/transportation proximity (Parent and LeSage 2012)

However,

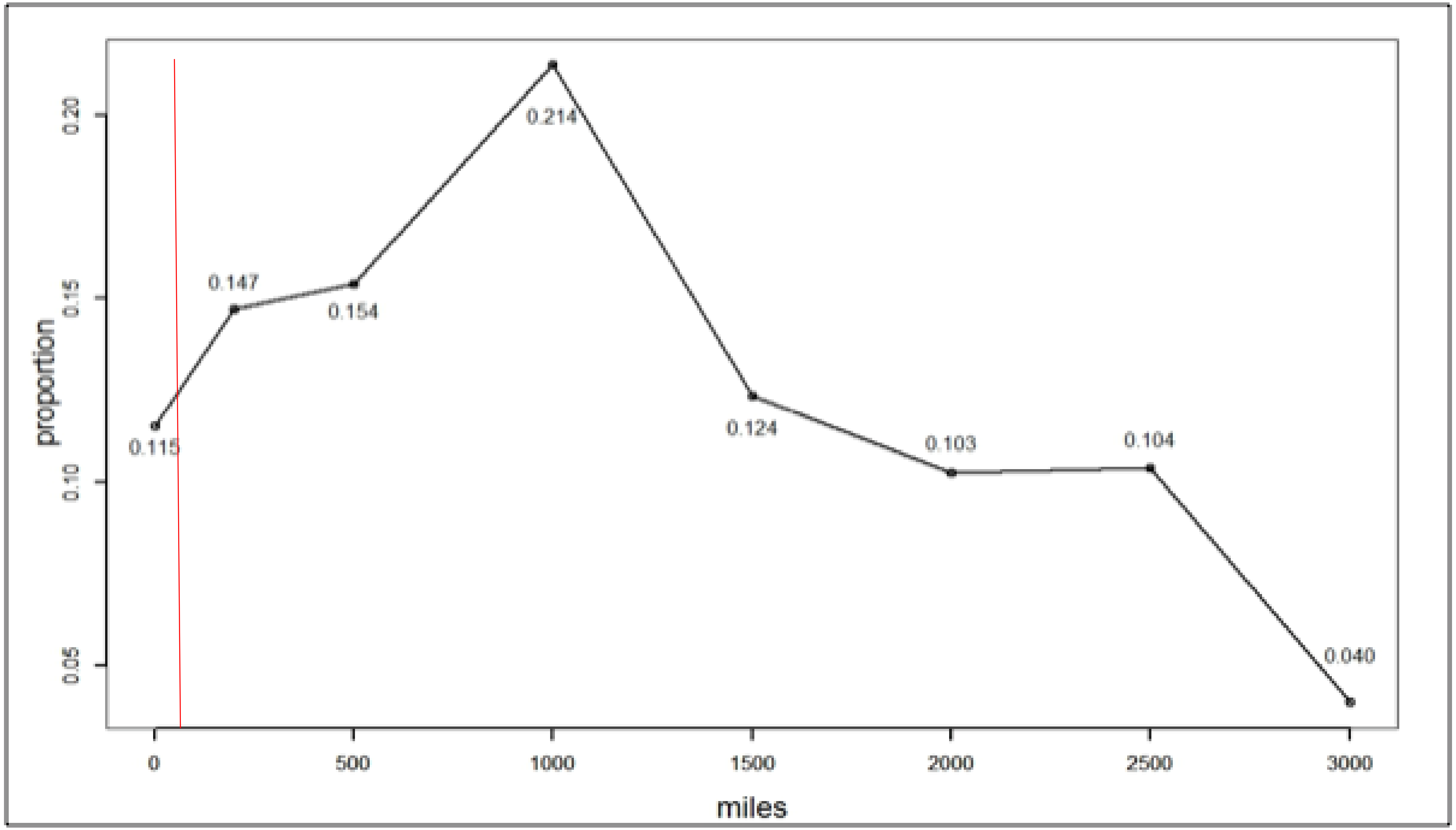
- Contribution of distant knowledge sources to innovation of biotech firms (Gertler and Levitte, 2005; Gittelman, 2007)
- Average distance between patent collaborators increased over 1975-1999 (Johnson *et al*. , 2006)

California’s Patent Citing Flows



Fractional counting method: $1/N_{D \times O}$ fraction of a patent is allocated to each inventor based on his/her home address (Jaffe *et al.,* 1993)

Proportion of patent citation by distance (Source: USPTO)



Few articles on distant knowledge spillovers…

Ponds *et al*. (2010) :

- Collaborations between industry and academia across Dutch regions.
- Patent co-publication matrix
- Localized and distant knowledge spillovers are <u>not individually identified</u>.

Peri (2005):

- USPTO patent citations over western Europe, US states, and Canadian provinces.
- Patent creation-patent citation matrix
- State level<u>, only private sector </u>knowledge spillovers are controlled for.

Model (N=3,109 US counties)

$$\boldsymbol{lnPatent_i} = \beta_0 + \beta_1 ln\boldsymbol{Private_i} + \beta_2 ln\boldsymbol{Univ_i} + \beta_3 ln\boldsymbol{Graduate_i} + \beta_4 ln\boldsymbol{Diversity_i} + \beta_5 ln\boldsymbol{Large_i} + \beta_6 ln\boldsymbol{Intra_i} + \beta_7 \ln \boldsymbol{Local.Private_i} + \beta_8 \ln \boldsymbol{Local.Univ_i} + \beta_9 ln\boldsymbol{Distant.Private_i} + \beta_{10} ln\boldsymbol{Distant.Univ_i} + \beta_{11} ln\boldsymbol{Size_i} + \sum_{i=1}^{48} \delta_i \boldsymbol{State}_i + \boldsymbol{\varepsilon_i} \quad \text{with } \boldsymbol{\varepsilon_i} \sim \boldsymbol{N}(\boldsymbol{0}, \boldsymbol{\sigma_\varepsilon^2})$$

Patent: 2003-2005 number of utility patent applications (USPTO)

- ***Private knowledge stock***: private R&D expenditures over 1995-2002 (Standard and Poor's COMPUSTAT)
- ***University knowledge stock***: R&D expenditures at univ. and colleges over 1995-2002 (NSF)
- ***Graduate***: share of local population 25 years and over with a Graduate or professional degree
- ***Diversity***: index of sectoral diversity of employment across 13 industries (Duranton and Puga, 2000)
- ***Large***: the share of firms with at least 500 employees
- ***Intra***: the level of intra-regional knowledge spillovers
    - ***Local.Private:*** interregional knowledge spillovers induced by private R&D & <75 miles
    - ***Local.Univ:*** interregional knowledge spillovers induced by university R&D & <75 miles
    - ***Distant.Private:*** interregional knowledge spillovers induced by private R&D & > 75 miles
    - ***Distant.Univ:*** interregional knowledge spillovers induced by university R&D & > 75 miles
- ***Size***: the number of employees ***State***: state-specific heterogeneity

Descriptive Statistics (non-MSA vs. MSA)

	Non-MSA county (2,256)				MSA county (853)			
Variable	Mean	Median	S.D.	# of zero	Mean	Median	S.D.	# of zero
Patent	3.4	0.9	9.2	433	150.9	22.4	494.3	5
Private ($1,000)	2,562.6	0.0	51,096.1	2,100	821,238.4	10.0	4,909,446.0	423
Univ ($1,000)	3,844.6	0.0	52,053.5	2,154	139,803.4	0.0	587,920.1	569
Intra	5.3	0.0	14.5	1,731	11.9	10.5	11.7	164
W75*Private	1,246.4	6.2	7,241.3	498	156,361.4	2,853.2	868,534.2	49
W75*Univ	1,215.2	17.4	5,719.9	482	22,885.6	1,118.2	98,246.2	49
M75*Private	13,124.7	816.4	37,021.9	915	541,172.4	92,510.5	1,671,672.0	27
M75*Univ	3,179.5	52.9	9,531.9	989	106,991.6	22,649.5	317,264.5	35

Estimation Results by ML

Variable	Estimate	(SHAC S.E.)		Variable	Estimate	(SHAC S.E.)	
Intercept	-3.486	(0.200)	***	MSA	-1.493	(0.320)	***
ln Private	0.043	(0.008)	***	MSA*ln Private	0.011	(0.009)	
ln Univ	0.027	(0.008)	***	MSA*ln Univ	-0.010	(0.009)	
ln Graduate	0.586	(0.053)	***	MSA*ln Graduate	0.334	(0.092)	***
ln Diversity	-0.177	(0.072)	**	MSA*ln Diversity	0.218	(0.107)	**
ln Large	-0.164	(0.028)	***	MSA*ln Large	-0.061	(0.093)	
ln Intra	0.084	(0.012)	***	MSA*ln Intra	0.017	(0.023)	
ln W*Private	**0.026**	**(0.006)**	***	**MSA*ln W*Private**	**0.035**	**(0.009)**	***
ln W*Univ	**0.010**	**(0.005)**	*	MSA*ln W*Univ	-0.015	(0.010)	
ln M*Private	0.005	(0.005)		**MSA*ln M*Private**	**0.077**	**(0.020)**	***
ln M*Univ	**0.029**	**(0.006)**	***	MSA*ln M*Univ	0.029	(0.020)	

*:p-val.<1%; **:p-val.<5%; ***:p-val.<10%

Spatial HAC standard errors (Parzen kernel with 91 miles bandwidth)

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Spatial HAC standard errors (Parzen kernel with 91 miles bandwidth)

Myth #2: Knowledge spillovers are uniform in space

Sources of spatial heterogeneity ("industrial atmosphere", "innovative milieu"):

- Differences in local institutions (David 1994; Zysman 1994)
- Differences in public capital infrastructures (Simmie 2011)
- Differences in the ability to utilize external knowledge (Mukherji and Silberman 2013; Döring and Schnellenbach 2006; Agrawal *et al.* 2010) based on historical linkages, institutions, economic structure

Accounting for spatial heterogeneity:

- Usually not: regional data used but $\partial y_i/\partial x_{ri} = \partial y_j/\partial x_{rj} = \partial y/\partial x_r = \beta_r$
- Split MSA vs. non-MSA in the previous study: $\partial y_{MSA}/\partial x_{r\ MSA} \neq \partial y_{non-MSA}/\partial x_{r\ non-MSA}$ but still assumes $\partial y_{i\ MSA}/\partial x_{r\ i\ MSA}$= $\partial y_{j\ MSA}/\partial x_{r\ j\ MSA} = \beta_{r\ \ MSA}$
- In order to suggest place-tailored innovation policies, what is needed is a unique $\partial y_i/\partial x_{ri} = \beta_{ri}$ for each location *i* (use the GWR approach, Paez et al. 2011).
- If GWR holds true but a global approach is used instead, it leads to a locally biased misspecification (McMillen and Redfearn 2010)
- Verify that all or only some knowledge inputs vary spatially (MGWR, Wei and Qi 2012)

Calibration of GWR (Fotheringham et al. 2002)

$y_i = \beta_0(u_i, v_i) + \sum_k \beta_k(u_i, v_i)x_{ik} + \varepsilon_i$

(u_i, v_i) are the geographical coordinates of county *i*

β_k is kth local coefficient of county *i*

$\hat{\beta}(u_i, v_i) = [X'W(u_i, v_i)X]^{-1}X'W(u_i, v_i)Y$

$W(u_i, v_i)$ is a diagonal matrix with elements $w_{i1}, w_{i2}, \cdots, w_{in}$ that capture the adjacency effects of counties 1, 2,…, n to county *i*

$w_{ij} = exp\left[-\frac{1}{2}\left(\frac{d_{ij}}{b}\right)^2\right]\ if\ d_{ij} < b\ and\ w_{ij} = 0\ otherwise$

where *b* is an adaptive bandwidth of a fixed number of nearest neighbors which minimizes AICc (best option among several)

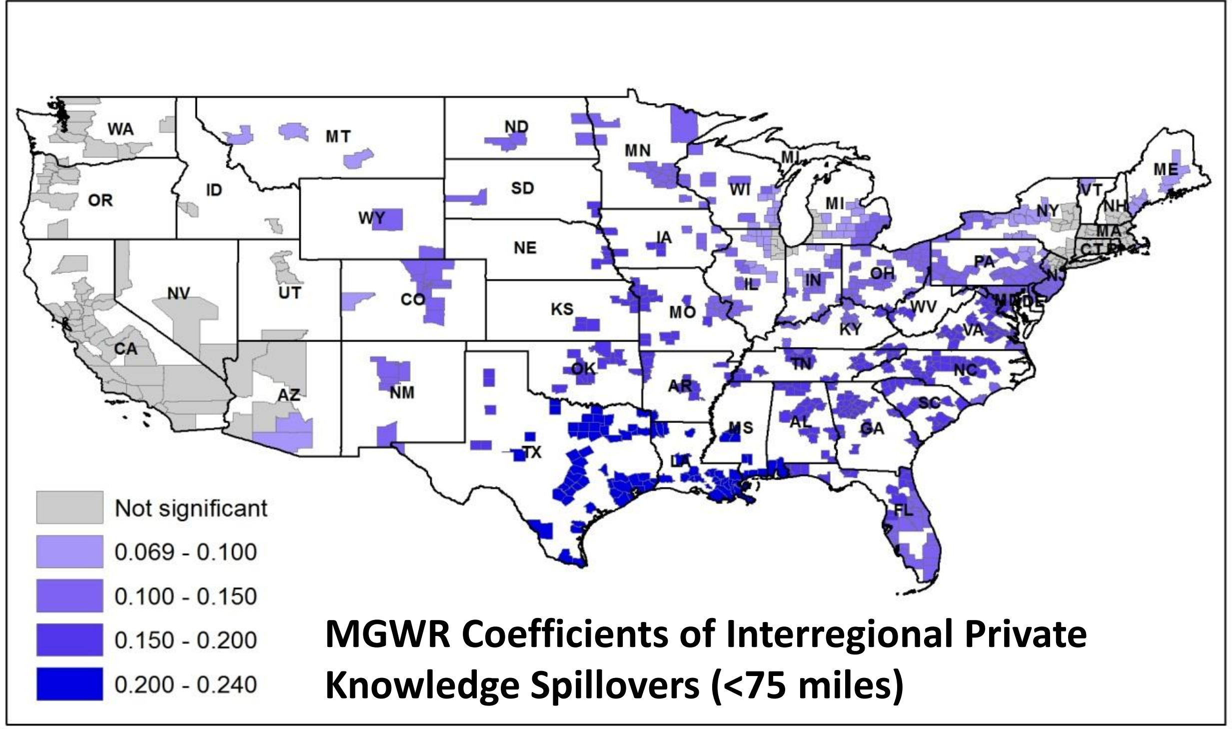
Model fit by kernel function (MSA)

		Fixed cut-off (50 miles)				33 NN	27 NN
Model	Model fit statistic	Gaussian	Exponential	Bisquare	Tricube	Gaussian	Exponential
GWR	Bandwidth	61	56	305	305	61	59
	Adjusted R^2	0.934	0.932	0.934	0.933	0.936	0.933
	RSS	146.9	141.8	149.4	152.2	142.8	140.54
	AICc	1120	1131	1123.6	1124.8	1094.95	1112.12
Mixed GWR	Bandwidth (in 1st & 2nd steps)	61	56	305	305	61	59
	Bandwidth (in 4th step)	54	36	234	258	54	38
	Adjusted R^2	0.933	0.93	0.933	0.933	0.934	0.933
	RSS	156.3	152.3	154.5	157	152.7	151.9
	AICc	1113.8	1142.9	1114.9	1120.2	1093.3	1105.7

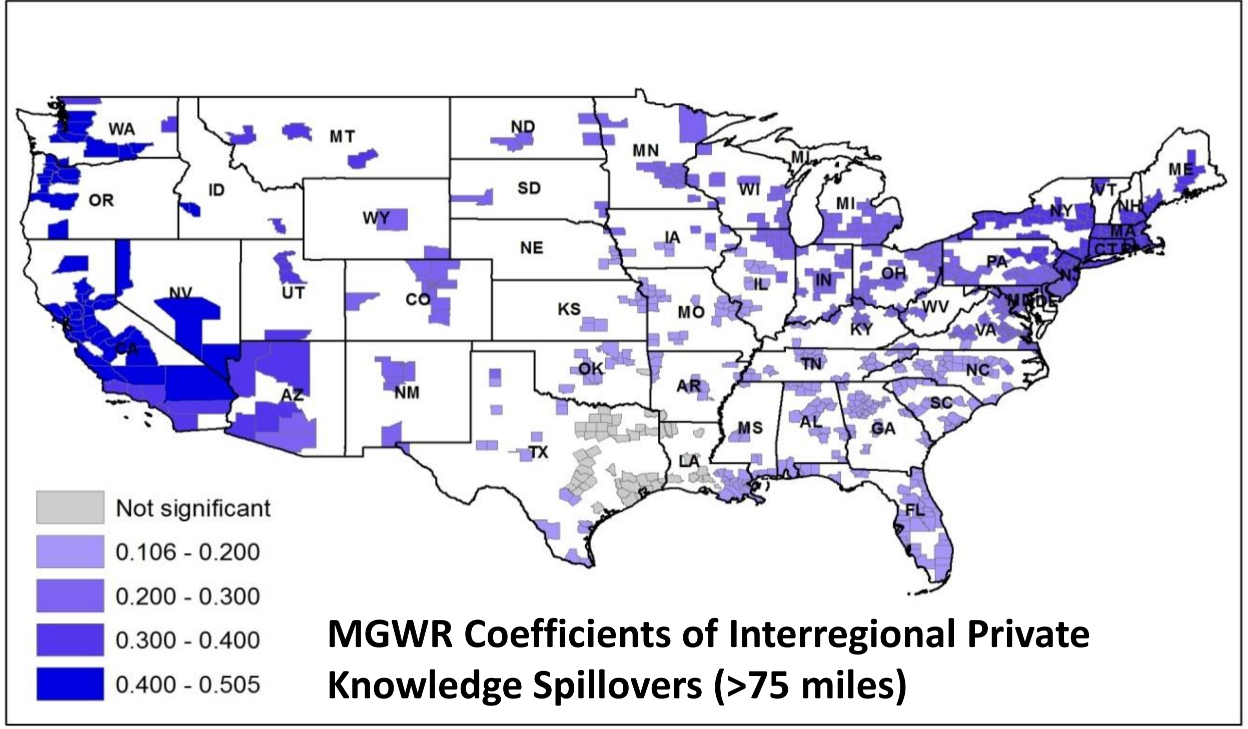
Calibration Results: MSA (33 nearest neighbors)

Dependent variable:	Model 7			Model 9				
ln Patent	OLS			Mixed GWR				
	2.5%	Estimate	97.5%	Min.	Q1	Median	Q3	Max.
Intercept	-1.486	-1.088 ***	-0.689	-2.439	-1.548	-1.216	-0.965	-0.244
ln Private (G)	0.034	0.053 ***	0.073			0.042 ***		
ln Univ	0.004	0.023 **	0.041	-0.028	0.001	0.017	0.032	0.086
ln Graduate (G)	0.452	0.567 ***	0.683			0.671 ***		
ln Diversity	-0.142	-0.015	0.113	-0.448	-0.270	-0.038	0.139	0.316
ln Large	-0.099	0.016	0.130	-0.283	-0.106	-0.046	0.079	0.346
ln Intra (G)	0.004	0.038 **	0.071			0.027 ***		
ln Local.PrivateNN	0.104	0.132 ***	0.161	0.045	0.106	0.144	0.166	0.248
ln Local.UnivNN (G)	-0.002	0.040 *	0.081			0.054 ***		
ln Distant.PrivateNN	0.185	0.233 ***	0.280	0.087	0.156	0.212	0.251	0.458
ln Distant.UnivNN (G)	0.071	0.128 ***	0.184			0.097 ***		
ln Size	0.318	0.378 ***	0.438	0.196	0.288	0.486	0.572	0.713
Observations		853		853				
Adjusted R^2		0.922		0.934				
RSS		199.1		152.7				
AICc		1206.2		1093.3				

Note: * p-value < 10%, ** p-value < 5%, *** p-value < 1% (Bonferroni-adjusted p-values)



MGWR Coefficients of Interregional Private Knowledge Spillovers (<75 miles)



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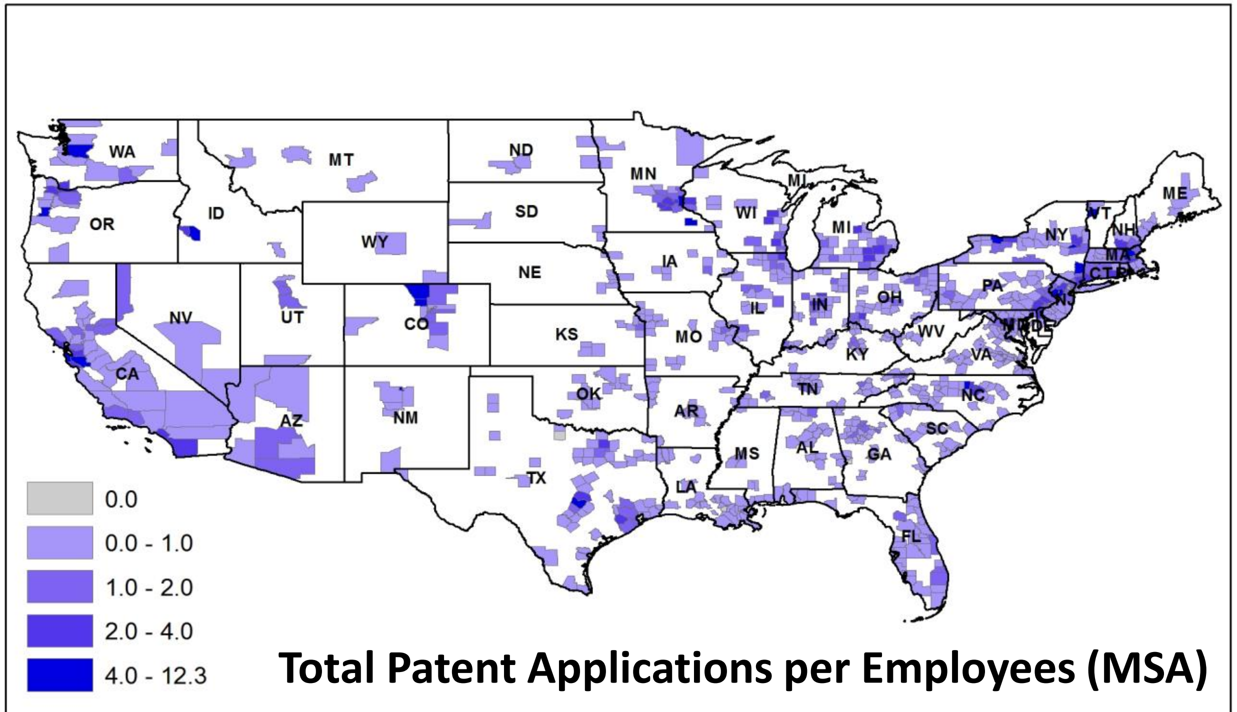

Total Patent Applications per Employees (MSA)

the average of sectoral diversity index (***Diversity***) across MSA counties		
CT	Connecticut	5.65
WA	**Washington**	**5.41**
NJ	New Jersey	5.03
CA	California	4.98
MA	Massachusetts	4.83
TX	**Texas**	**4.79**

Calibration Results: non-MSA (33 nearest neighbors)

Dependent variable:	Model 16			Model 18				
ln Patent	OLS			Mixed GWR				
	2.5%	Estimate	97.5%	Min.	Q1	Median	Q3	Max.
Intercept	-0.814	-0.650 ***	-0.485	-1.812	-1.204	-0.904	-0.499	0.054
ln Private	0.075	0.111 ***	0.147	-0.223	0.009	0.087	0.154	0.776
ln Univ (G)	0.055	0.089 ***	0.124			0.105 ***		
ln Graduate	0.362	0.443 ***	0.524	-0.704	0.199	0.333	0.476	0.935
ln Diversity (G)	-0.139	-0.024	0.091			0.055 ***		
ln Large	-0.221	-0.174 ***	-0.127	-0.619	-0.179	-0.059	0.012	0.335
ln Intra (G)	0.047	0.065 ***	0.084			0.054 ***		
ln Local.PrivateNN	0.070	0.116 ***	0.162	-0.614	0.037	0.130	0.29	1.663
ln Local.UnivNN (G)	0.119	0.192 ***	0.265			0.179 ***		
ln Distant.PrivateNN (G)	0.069	0.093 ***	0.116			0.071 ***		
ln Distant.UnivNN	0.088	0.122 ***	0.156	-0.046	0.059	0.109	0.163	0.652
ln Size	0.454	0.494 ***	0.534	0.125	0.399	0.510	0.640	0.984
Observations		2,256		2,256				
Adjusted R2		0.705		0.748				
RSS		536.8		397.5				
AICc		3189.6		2982.7				

Note: * p-value < 10%, ** p-value < 5%, *** p-value < 1%.

Myth #3: Knowledge spillovers are homogenous across sectors

- Sectorally aggregated data is commonly used in most empirical studies of knowledge production function literature (Anselin et al., 1997; Fischer and Varga 2003; Bode 2004; Parent and LeSage 2008). Exception: Autant-Bernard and LeSage (2011) with 11 industrial sectors but W based on proximity only and elasticity is averaged.

- Use 5 distinct sectors (Chemical; Drugs & Medical; Mechanical; Computer & Communication; Electrical & Electronic): 82% of the patent data
- Distinguish intra- vs. intersectoral spillovers and intra- vs. interregional spillovers.

- Example of interregional inter-sectoral long-distance flow: R&D spending in the electronics sector of Santa Clara county, CA, leads to a patent that is cited when a new patent in mechanical engineering in Champaign county, IL, is created

Model and Data

$$lnPatent_{iht} = \beta_0 + \beta_1 \ln Graduate_{iht-1} + \beta_2 lnEmp_{iht-1} + \beta_3 lnLarge_{it-1} + \beta_4 lnDiversity_{it-1} +$$

$$\beta_5 lnIntra_{iht} + \beta_6 lnPrivate_{iht} + \beta_7 lnPrivate.etc_{iht} + \beta_8 \ln Univ_{iht}$$

$$+\beta_9 \ln Local.Private75_{iht} + \beta_{10} \ln Local.Private.etc75_{iht} + \beta_{11} \ln Local.Univ75_{iht}$$

$$+\beta_{12} \ln Distant.Private75_{iht} + \beta_{13} \ln Distant.Private.etc75_{iht} + \beta_{14} \ln Distant.Univ75_{iht}$$

$$+\alpha_{ih} + \varepsilon_{iht}, \qquad \varepsilon_{iht} \sim N(0, \sigma_\varepsilon^2) \qquad i = 1, \cdots, 853;\ h = 1, \ldots, 5;\ t = 2001 - 2005, 2006 - 2009$$

- Cobb-Douglas functional form of Knowledge Production Function (Griliches 1979)
- County level data: 853 MSA US continental counties based on US Census 2000
- All variables defined by sector except “large” and “diversity”

$$lnPatent_{iht} = \begin{cases} lnPatent^*_{iht} & if\ \ Patent^*_{iht} > 0 \\ 0 & if\ \ Patent^*_{iht} \le 0 \end{cases}$$

Rely on a Tobit model to account for zero (latent) values of patent data

Summary Statistics

	Chemical	Drugs & Medical	Mechanical	Computer & Communication	Electrical & Electronic
Variable	Mean	Mean	Mean	Mean	Mean
Patent	12.70	12.50	18.10	33.70	42.40
Grad	91.40	177.90	306.00	131.20	235.70
Emp	742.00	914.20	3,253.40	595.50	1,548.50
Large	14.20	14.20	14.20	14.20	14.20
Diversity	3.40	3.40	3.40	3.40	3.40
Intra	13.30	7.10	10.80	4.80	8.40
Private	98,135.00	304,737.50	247,268.70	82,349.50	136,660.20
Private.etc	161,834.70	50,301.20	126,178.30	113,087.80	88,088.70
Univ	13,787.40	137,802.20	48,804.00	16,169.60	22,575.40
Local.Private	10,046.70	37,030.80	44,785.30	7,097.90	9,393.30
Local.Private.etc	74,313.00	35,632.20	57,333.00	73,029.60	59,228.70
Local.Univ	1,049.10	9,567.10	3,554.60	982.40	1,590.60
Distant.Private	50,212.10	216,210.20	130,098.00	58,544.40	89,425.30
Distant.Private.etc	499,218.70	444,909.10	383,092.70	540,082.10	523,612.40
Distant.Univ	9,586.50	108,833.10	35,115.60	14,325.30	18,830.40

Estimation Results

Dep.: ln Patent in h	Model 1	Model 2	Model 3	Model 4	Model 5
	h= Chemical	h= Drugs & Medical	h= Mechanical	h= Computer & Communication	h= Electrical & Electronic
Intercept	-4.069 **	-5.565 **	-2.797 **	-3.806 **	-2.099 **
ln Grad in h	0.048 **	0.044 **	0.039 **	0.04 **	0.04 **
ln Emp in h	0.051 **	0.076 **	0.317 **	0.026 **	0.073 **
ln Large	0.459 **	0.669 **	0.259 **	0.566 **	0.44 **
ln Diversity	-0.213 **	-0.061	-0.123 *	0.028	-0.043
ln Intra	0.11 **	0.118 **	0.067 **	0.055 *	0.089 **
ln Private in h	0.068 **	0.055 **	0.075 **	0.108 **	0.102 **
ln Private.etc	0.038 **	0.027 **	0.024 **	0.021 *	0.03 **
ln Univ in h	0.122 **	0.082 **	0.068 **	0.107 **	0.1 **
ln Local.Private in h	0.044 **	0.048 **	0.021 *	0.06 **	0.048 **
ln Local.Private.etc	0.031 **	0.018 *	0.009	0.012	0.007
ln Local.Univ in h	0.033 **	0.029 **	0.016	0.041 **	0.028 **
ln Distant.Private in h	0.019 *	0.032 **	0	0.066 **	0.057 **
ln Distant.Private.etc	0.02 **	0.003	0.018 **	0.002	0.008
ln Distant.Univ in h	0.043 **	0.035 **	0.031 **	0.07 **	0.017 **
R*	0.645	0.662	0.636	0.721	0.721
Log likelihood	-10741.8	-10384.7	-9603.2	-10365.4	-9214.2

Note: * P-value< 5%, ** P-value< 1%. Standard errors are calculated by the delta method.

Estimation Results

Dep.: ln Patent i h	Model 1	Model 2	Model 3	Model 4	Model 5
				h= Computer &	h= Electrical &
	h= Chemical	h= Drugs & Medical	h= Mechanical	Communication	Electronic
Intercept	-4.069 **	-5.565 **	-2.797 **	-3.806 **	-2.099 **
ln Grad i h	0.048 **	0.044 **	0.039 **	0.04 **	0.04 **
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Stylized facts (1)
Patent applications by sector: OR, WA, Deschutes (OR), Benton (WA)

OR				WA			
2000-2004: 10,704		2005-2010: 6,402		2000-2004: 17,437		2005-2010: 11,840	
Sector	Number	Sector	Number	Sector	Number	Sector	Number
SEMICONDUCTOR MANUFACTURING	525	APPAREL AND HABERDASERY	617	DATABASE AND FILE MANAGEMENT	590	RECORDING EQUIPMENT	780
PRINTING DEVICE	477	SEMICONDUCTOR MANUFACTURING	177	OPERATOR INTERFACE PROCESSING	394	DATABASE AND FILE MANAGEMENT	268
SOLID-STATE DIODES	246	SOLID-STATE DIODES	135	MULTICOMPUTER DATA TRANSFERRING	331	EQUIPMENT FOR FOOD OR DRINK PREPARATION	180
ELECTRICAL DEVICE: MEASURING	165	FRUITS, FLOWERS AND TREES	126	COMPUTER GRAPHICS PROCESSING	296	COMPUTER GRAPHICS PROCESSING	132
TRAVEL GOODS	154	GAMES, TOYS, AND SPORTS GOODS	119	SURGERY	243	OPERATOR INTERFACE PROCESSING	122

Stylized facts (2)
Patent applications by sector: Deschutes (OR), Benton (WA)

Deschutes (OR)				Benton (WA)			
2000-2004: 220		2005-2010: 148		2000-2004: 356		2005-2010: 140	
Sector	Number	Sector	Number	Sector	Number	Sector	Number
EXERCISE DEVICES	21	EXERCISE DEVICES	15	ELECTROMAGNETIC WAVE ENERGY	13	ELECTROMAGNETIC WAVE ENERGY	11
ELECTRICAL CURRENT PRODUCING APPARATUS	15	ELECTRICAL CURRENT PRODUCING APPARATUS	4	ELECTRICAL DEVICE: MEASURING	11	ELECTRICAL DEVICE: MEASURING	4
GAS SEPARATION: APPARATUS	7	TOOLS AND HARDWARE	4	ELECTRICAL DEVICE: COMMUNICATIONS	11	RADIO WAVE SYSTEMS AND DEVICES	3
DRUG AND MEDICINE	4	ELECTROMAGNETIC WAVE ENERGY	3	COATING PROCESSES	7	ELECTRICAL DEVICE: MEASURING	3
BUILDINGS STRUCTURE	4	OPTICAL APPARATUS	3	RADIO WAVE SYSTEMS AND DEVICES	6	INTERNAL COMBUSTION ENGINE	3

Stylized facts (3)
Innovation spillovers: from and to WA and OR

Top 5 States WA and OR cite (2000-2010)

WA		OR	
WA	16,018.80	OR	15,119.86
CA	10,317.51	CA	7,947.41
TX	1,893.06	NY	2,657.05
NY	1,713.70	TX	2,249.07
OR	1,568.97	WA	1,636.17

Top 5 States that cite WA or OR (2000-2010)

WA		OR	
CA	17,227.99	OR	15,119.86
WA	16,018.80	CA	14,458.07
NY	3,528.61	NY	3,455.17
TX	3,507.73	TX	2,660.22
MA	2,882.91	WA	1,568.98

(all patents created after 1999. Fractional counting method used)

Conclusions (1)

- Like people, innovative firms have the capacity to **"vote with their feet"** in search of the places that offer the best ratio of taxes for public goods (transportation, education, institutional quality) and promote an **innovative milieu** (capacity to absorb knowledge generated elsewhere).

- Generally, the MSA counties are able to benefit more from the research performed elsewhere than their non-MSA counterparts.

- While knowledge from private R&D spills over to innovative firms in MSA regions mostly, knowledge spillovers due to university R&D have a **spatially homogenous** return across MSA and non-MSA counties => support universities as an engine of both local and national innovation + efforts to **build local and long-distance networks** based on university-industry collaboration.

Conclusions (2)

- More attention needed on the spatial and sectoral heterogeneity in regional knowledge production.

- Goal is to identify **which type of spillovers** is the most beneficial to the local innovation process and **what sectors are locally present** before drawing strategies to facilitate knowledge spillovers.

- **Specialization** is more innovation-prone than diversity (MAR externalities > Jacobs externalities)

- Other channels of knowledge externalities (labor migration as in Almeida and Kogut 1999; Fang *et al*., 2016) and international knowledge spillovers.