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Firms' Innovation in Waste Management and Land Fertilizers within the Triad

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Abstract

In this paper we investigate agricultural innovation in three economic areas: the USA, Japan and Europe, taking into account simultaneously both the spatial and technological dimensions.

In particular, we introduce a theoretical framework and an empirical analysis based upon a dataset composed of worldwide R&D-intensive firms to discuss the role of spillover components in the waste management efficiency at firm level. The technological relatedness between the firms is computed through an original Mahalanobis Environmental industry weight matrix, based on the construction of technological vectors for each firm. Methodologically, from one hand, we explore the extent to which knowledge spillovers are important through spatial analysis procedure and from the other hand, we measure the effects of technology spillovers on firms' productivity through econometric methods to handle heterogeneity and endogenous explanatory variables. The findings show a positive impact of Jacobian R&D spillovers on firms' productivity and environmental performance and this result can be relevant repercussions in terms of policy implications.

Keywords: agriculture innovation, technology spillovers, spatial analysis

JEL codes: O32; O33; Q5.

1. Introduction

Agricultural sector assumes a strategic role for innovation, productivity, profitability and competitiveness (Läpple et al. 2016; OECD, 2013). However, we may identify considerable differences in agricultural innovation across countries, as discussed in Spielman and Birner (2008); OECD (2013); Läpple et al. (2016). This result might be explained through different policies, institutional settings and infrastructural environments of knowledge transfer systems between countries. Literature evidences more factors affecting agricultural innovation. Läpple et al. (2015) find that innovative performance is influenced by demographic structures, while according to Rand et al. (2009), geographic distance can have an impact on innovation process. It is recognized in the literature the role of spatial concentration in the knowledge flows among economic units (Case, 1992; Läpple and Kelley, 2015; Läpple et al., 2016). However, there are mixed theories in relation to proximity and innovation. Indeed, Jaffe et al. (1993) and Audretsch and Feldman (1996) find that firms located near knowledge centers display a higher innovation level than more distant firms, while Breschi (2000) stresses that the geographical concentration of innovative processes can differ strikingly across technology sectors. There are few studies that investigate innovation in the agricultural sector taking into account simultaneously both the spatial and technological dimensions. This article aims to overcome this deficit by discussing the role of knowledge spillovers in spatial context and on the basis of environmental technology proximity.

The paper is structured as follows: the next section provides the spatial analysis of waste and land innovation of firms located within the Triad. A theoretical framework about knowledge externalities is introduced, followed by Data and empirical Methods section. Thus, discussion of results is presented. Finally, the paper ends with some concluding remarks.

2. Agriculture Innovation and Spatial Analysis within the Triad

In table 1, we show land use percentages for countries considered in our analysis. As discussed in the previous section, different efficiency levels can be observed.

In order to assess agricultural innovation and explore its spatial distribution, we use particular spatial econometric tools (Pisati, 2008; Crow, 2015; Kondo, 2015 and 2016).

As in Marin and Lotti (2016), environmental innovations are identified through appropriate indicators on patent data, according to their technological class (Note 1). In Table 2, we report those patents with IPC code belonging to the groups selected by the OECD or the World Intellectual Property Organization (WIPO).

Table 1. Land use by economic area

	Agricultural land	Arable land	Permanent crops	Permanent posture
the USA	44.50%	16.80%	0.30%	27.40%
Japan	12.50%	11.70%	0.80%	0%
Europe:				
Germany	48%	34.10%	0.60%	13.30%
France	52.70%	33.40%	1.80%	17.50%
Italy	47.10%	22.80%	8.60%	15.70%
UK	71%	25.10%	0.20%	45.70%
the Netherlands	55.10%	29.80%	1.10%	24.20%
Finland	7.50%	7.40%	0%	0.10%
Sweden	7.50%	6.40%	0%	1.10%

Source: The CIA World Factbook Land Use, 2017.

Table 2. Environmental patent classes

Macro category	**IPC**
Waste management and Land fertilizers	E01H, B65F
	A23K, A43B, B03B, B22F, B29B, B30B, B62D, B65H, B65D, C03B, C03C, C04B, C08J, C09K, C10M, C22B, D01G, D21B, D21C, D21H, H01B, H01J, H01M
	B09B, C10G, A61L
	F03G, B60K, B60L, B09B, B65F
	A61L, A62D, B03B, B09C, D21B
	F23G
	A43B, B22F, C04B, C05F, C08J, C09K, C11B, C14C, C21B, C25C, D21F, B29B, B62D, C08J, C10G, C10L, C22B, D01G, D21C, H01J, H01M

First, we test for the existence of spatial autocorrelation in waste and land innovation, which characterizes the degree to which a region and its neighboring regions are mutually correlated. Moran's I test has the following form (Moran, 1950; Anselin, 1995): $I = \frac{z'Wz}{z'z}$, where z is an N – vector of standardized waste and land fertilizers patents, W is an N x N row-standardized spatial weight matrix (Note 2) and N is the number of observations. This study also presents Moran scatterplots, which depict how the geographical units depend on each other (Anselin, 1995).

As we may observe in Tables 3 – 5, the positive value of Moran-I indicates positive spatial autocorrelation across the regions of each economic area: that is, regions neighboring a region with high waste and land fertilizers patents also show high agricultural innovation rates.

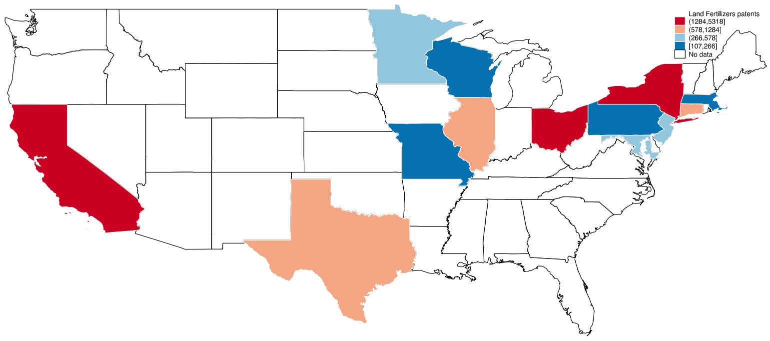
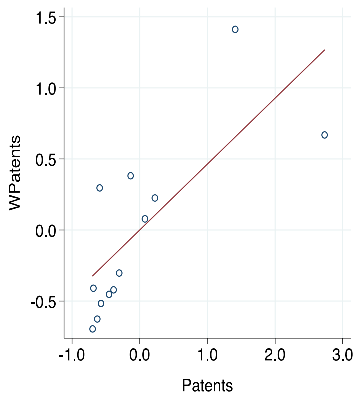


Figure 1. Waste and land fertilizers patents in the USA

Figures 1 – 3 explore hot/cold spot analysis by economic areas.

In Figure 1, where the USA country is clustered into 51 states, we may observe that New York and California exhibit the hot spots, while Massachusetts, Missouri and Wisconsin display the cold spots.

Table 3. Moran scatterplot for the USA



Note: Moran-I test: 0.463, p-value: 0.00

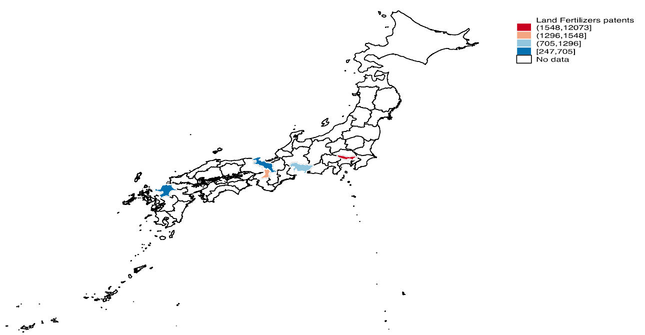
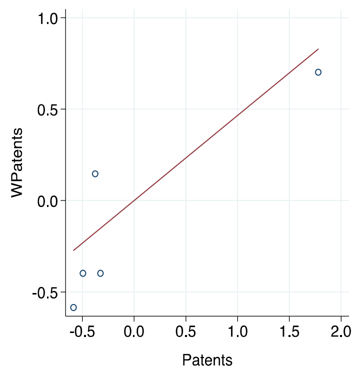


Figure 2. Waste and land fertilizers patents in Japan

In Figure 2, where Japan country is clustered into 47 prefectures, we observe that Tokyo exhibits hot spots, while Fukuoka displays cold spots.

Table 4. Moran scatterplot for Japan



Note: Moran-I test: 0.466, p-value: 0.048.

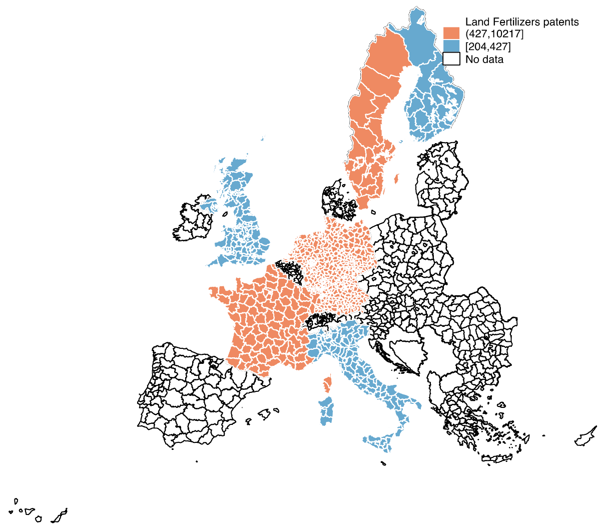
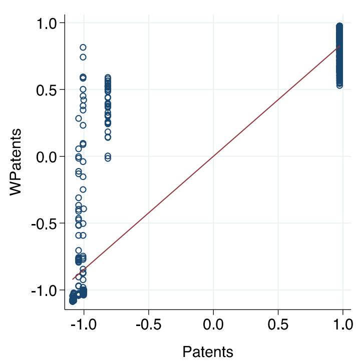


Figure 3. Waste and Land Fertilizers patents in Europe

In Figure 3, where Europe is clustered into 42 countries, we observe that Germany exhibits hot spots, while Finland displays cold spots.

Table 5. Moran Scatterplot for Europe



Note: Moran-I test: 0.847, p-value: 0.000.

3. Theoretical Framework

In this section, as in Aldieri, Kotsemir and Vinci (2017) we present a simple theoretical model, useful for our econometric analysis. We will refer to a multi-sector economy where production may pursue two different procedures: The standard, and a second one where production combines varieties of types of green energy concerning waste management and land fertilizers with physical, human and knowledge capital. The number of varieties in each sector is determined endogenously, and investment in these technology classes is assumed to depend on rational agents' decisions (Bretschger et al., 2017). In each sector the final output Y, depends on production of two different techniques: green (Y_g) and not (Y_N) may be taken as:

$$Y = Y\left(Y_g, Y_N\right) \tag{1}$$

$$Y_g = Y_g\left(C_g, K_g, H_g\right) \tag{2}$$

$$Y_N = Y_N\left(C_N, K_N, H_N\right) \tag{3}$$

$$K_N = K_N\left(K_g\right) \tag{4}$$

$$K_h = K_h\left(B_h; B_h^R\right) \tag{5}$$

$$B_g = B_g(\chi) \tag{6}$$

$$B_g^R = B_g^R(\chi^R) \tag{7}$$

$$\chi = \sum_{i=1}^{n} a_i x_i \tag{8}$$

With: $0 < a_i < 1$

$$\chi^R = \sum_{j=1}^{n_R} a_j x_j^R \tag{9}$$

With: $0 < a_j < 1$.

Parameters C_g and C_N, H_g and H_N stand respectively for physical and human capital, green and not, the innovation impact on the technology are embodied by the impact of knowledge capital levels denoted K_g and K_N, and patents denoted B_g, depends on χ, a variable capturing the effects of different *waste management and land fertilizers* technological fields x_i. At last B_g^R, χ^R measure respectively for patents, and the variable catching the above green special effects from abroad. We may easily derive that:

$$Y = Y\left(Y_N\left\{C_N, H_N, K_N\left[K_g\left(B_g\left(\sum_{i=1}^{n} a_i x_i\right), B_g^R\left(\sum_{j=1}^{n_R} a_j x_j^R\right)\right)\right]\right\}, Y_g\left\{C_g, H_g, K_g\left(B_g\left(\sum_{i=1}^{n} a_i x_i\right), B_g^R\left(\sum_{j=1}^{n_R} a_j x_j^R\right)\right)\right\}\right) \tag{10}$$

The short run impacts of innovation respectively on Y_g and Y may written as:

$$dY_g = \frac{\partial Y_g}{\partial C_g} dC_g + \frac{\partial Y_g}{\partial H_g} dH_g + \frac{\partial Y_g}{\partial K_g}\left\{\frac{\partial K_g}{\partial B_g}\frac{\partial B_g}{\partial \chi}\left[\sum_{i=1}^{n} a_i dx_i\right] + \frac{\partial K_g}{\partial B_g^R}\frac{\partial B_g^R}{\partial \chi^R}\left[\sum_{j=1}^{n_R} a_j dx_j^R\right]\right\} \tag{11}$$

$$dY = \frac{\partial Y}{\partial Y_g}\left\{\frac{\partial Y_g}{\partial C_g} dC_g + \frac{\partial Y_g}{\partial H_g} dH_g + \frac{\partial Y_g}{\partial K_g}\left\{\frac{\partial K_g}{\partial B_g}\frac{\partial B_g}{\partial \chi}\left[\sum_{i=1}^{n} a_i dx_i\right] + \frac{\partial K_g}{\partial B_g^R}\frac{\partial B_g^R}{\partial \chi^R}\left[\sum_{j=1}^{n_R} a_j dx_j^R\right]\right\}\right\} + \frac{\partial y}{\partial Y_N}\left\{\frac{\partial Y_N}{\partial C_N} dC_N + \frac{\partial Y_N}{\partial H_N} dH_N + \frac{\partial Y_N}{\partial K_N}\frac{\partial K_N}{\partial K_g}\left\{\frac{\partial K_W}{\partial B_W}\frac{\partial B_W}{\partial \chi}\left[\sum_{i=1}^{n} a_i dx_i\right] + \frac{\partial K_g}{\partial B_g^R}\frac{\partial B_g^R}{\partial \chi^R}\left[\sum_{j=1}^{n_R} a_j dx_j^R\right]\right\}\right\} \tag{12}$$

Inspection of eqs. (11) and (12) yields the following research hypothesis:

[H]*:* *The effect of spillovers due to diversified green technology fields concerning waste management and land fertilizers (Jacobian externalities) on firms' productivity is positive*

4. Data and Methodology

We derive data from OECD, REGPAT database, February 2016 (Note 3). This dataset covers firms' patent applications to the European Patent Office (EPO) including patents published up to December 2015. We match the name of the same 240 firms to applicant's name from European Commission (2013), as in Aldieri (2013). We follow two steps: patents are assigned to firms on the basis of their generic name; this procedure is repeated for each firm of our sample (Aldieri, 2013). The third source of data is the World Input Output Database (WIOD), which is made up of four different accounts (World Tables, National Tables, Socio Economic Accounts and Environmental Accounts). For purposes of this paper, we use the Environmental Accounts providing CO2 emissions variable by country and by year.

To identify the impact of environmental spillovers on firms' productivity, we consider the following specification model:

$$lnY_{it} = \alpha_i + \lambda_t + \beta_1 lnL_{it} + \beta_2 lnC_{it} + \beta_3 lnK_{it} + \gamma_1 lnMARS_{it} + \gamma_2 lnJS_{it} + \varepsilon_{it} \tag{13}$$

Where ln = natural logarithm;

Y_{it} = Productivity measured by net sales for firm *i* and year t;

C_{it} = physical capital stock for firm *i* and year *t*;

L_{it} = number of employees for firm *i* and year *t*;

K_{it} = R&D capital stock of firm *i* and year *t*;

α_i = firm's fixed effects;

λ_t = set of time dummies;

$MARS_{it}$ = vector of Marshall, Arrow, Romer spillovers (or externalities from firms of the same technology sector) for firm *i* and year *t*;

JS_{it} = vector of Jacobian spillovers (or externalities from firms of the different technology sector) for firm *i* and year *t*;

β, γ = vectors of parameters;

ε_{it} = disturbance term.

Moreover, in order to evaluate the environmental performance of knowledge spillovers, we estimate also another model with ratio between productivity and CO2 (SCO2) as dependent variable (Repetto, 1990) and regressors like in (13). In Table 6, we show the summary statistics of our sample. In particular, we consider both the environmental spillovers based on the Mahalanobis procedure (Aldieri, Kotsemir and Vinci, 2017) and the R&D capital stock based on the perpetual inventory method (Griliches, 1979) with a 5% initial growth rate and a 15% depreciation rate.

Table 6. Summary statistics

Variable	Mean[a]	Std. Dev.
lnY	8.50	1.450
lnSCO2	21.68	4.021
lnC	7.49	1.584
lnL	9.97	1.360
lnK	7.15	1.426
lnMARS	0.96	1.641
lnJS	1.117	1.913

Note: a) 1837 observations;

5. Results and Discussion

To address both firms' unobserved heterogeneity and the weak exogeneity of the explanatory variables, we estimate equation (13) using a one-stage generalized method of moments (GMM)) (Note 4) estimator, which combines the standard set of equations in the first difference with suitably lagged levels as instruments (GMM in first differences), with an additional set of equations in levels with suitably lagged first differences as instruments. The validity of these additional instruments, which consist of first difference-lagged values of the regressors, can be tested through over-identification tests. The one-stage GMM (GMM SYS) estimator can lead to considerable improvements in terms of efficiency compared to the GMM in first differences (GMM FD).

In Table 7 and Table 8, we present the empirical estimates for the GMM-SYS estimator. In particular, we show the effects of specialized activities spillovers (MARS) and diversified technology fields spillovers (JS) on firms' productivity in Table 7 and environmental performance effects of spillovers in Table 8. We lag environmental spillover components by a year to reflect delayed response and also mitigate contemporaneous feedback effects.

Table 7. Productivity of Environmental Spillovers effects: GMM estimates

Dependent variable: Δ ln LS_t		
	Estimate	S.E.[a]
ΔlnY(t-1)	0.86***	(0.054)
ΔlnL	0.14***	(0.037)
ΔlnC	0.01	(0.031)
ΔlnK	0.04	(0.027)
ΔlnMARS(t-1)	-0.11**	(0.050)
ΔlnJS(t-1)	0.97**	(0.043)
AR(1)[c] test	z=-5.00	p>z=0.000
AR(2) test	z= 0.29	p>z=0.772
Hansen[b]: χ^2 (129)=145.73		[0.149]

Notes: a: heteroskedastic-consistent standard errors; b: Hansen test of over-identifying restrictions, p-value in squared brackets; c: AR(1) and AR(2) are tests for first- and second-order serial correlation; ***, **, coefficient significant at the 1%, 5% level respectively. Country, time and industry dummies included. Endogenous variables are physical capital, labor, R&D capital stock and spillovers. Instruments are lagged values (2-9) of all explanatory variables.

Table 8. Environmental Performance of Spillovers effects: GMM estimates

Dependent variable: Δ ln LS_t		
	Estimate	S.E.[a]
ΔlnY(t-1)	0.84***	(0.044)
ΔlnL	0.66***	(0.114)
ΔlnC	-0.01	(0.090)
ΔlnK	-0.10	(0.104)
ΔlnMARS(t-1)	-0.37***	(0.152)
ΔlnJS(t-1)	0.31***	(0.131)
AR(1)[c] test	z=-5.89	p>z=0.000
AR(2) test	z= 0.30	p>z=0.768
Hansen[b]: χ^2 (169)=183.33		[0.213]

Notes: a: heteroskedastic-consistent standard errors; b: Hansen test of over-identifying restrictions, p-value in squared brackets; c: AR(1) and AR(2) are tests for first- and second-order serial correlation; ***, **, coefficient significant at the 1%, 5% level respectively. Country, time and industry dummies included. Endogenous variables are physical capital, labor, R&D capital stock and spillovers. Instruments are lagged values (2-9) of all explanatory variables.

As the model is over-identified in the sense that there are more instruments than parameters to be estimated, the validity of the instruments can be tested by means of the Hansen test for over-identified restrictions. Considering the set of instruments used and the need to satisfy the orthogonality conditions, it helps to verify the null hypothesis of the joint validity of the instruments. The Hansen test is X^2 distributed under the null with (p - k) degrees of freedom (where p is the number of instruments and k is the number of variables in the regression).

The model specification includes country, time, and industry dummies, which capture the impact of factors that change over time but not over the cross-sectional dimension of the sample. The results of the AR (1) and AR (2) tests are consistent with the assumption of no serial correlation in the residuals in levels and the Hansen tests do not reject the null hypothesis of valid instruments, indicating that the instruments are not correlated with the error term.

The interesting results are relative to causal effects of environmental spillovers on productivity and environmental performance. In particular, specialized environmental technology fields spillovers (MARS) have a negative impact, while the diversified activities portfolio (Jacobian spillovers) has a positive one, by confirming the theoretical predictions. This finding is extremely important for policy implications. In addition to economic incentives to favor the complementarity between dirty and environmental activities to balance competitiveness and sustainability, also the integration between the waste management and land fertilizers technology fields is crucial for a full sustainable achievement of firms.

6. Conclusions

Since there are few studies that investigate innovation in the agricultural sector taking into account simultaneously both the spatial and technological dimensions, the aim of this article is to overcome this deficit by discussing the role of knowledge spillovers in spatial context and on the basis of environmental technology proximity.

From one hand, we demonstrate that there is significant positive spatial autocorrelation across the regions of each economic area: that is, regions neighboring a region with high waste and land fertilizers patents also show high agricultural innovation rates.

In particular, hot/cold spot analysis evidences heterogeneous results in knowledge spillovers by economic areas.

From another hand, once we verify that spatial concentration matters for spillovers, we test for the effects of spillovers in technological sectors perspective. In particular, specialized environmental technology fields spillovers (MARS) have a negative impact, while the diversified activities portfolio (Jacobian spillovers) has a positive one, by confirming the theoretical predictions.

However, further analysis is needed. In particular, research could usefully focus on factors that determine heterogeneity in knowledge spillovers effects in spatial context and on the basis of technology sectors. Moreover, further empirical research should investigate the robustness of results also for other environmental fields, such as water or energy resources (Aldieri & Vinci, 2017).

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Notes

Note 1. http://www.oecd.org/env/consumption-innovation/indicator.htm

Note 2. We assume that spatial spillovers exists only within a distance of 300 km (Bottazzi and Peri, 2003).

Note 3. See Maraut et al. (2008) for the methodology used for the construction of REGPAT. Please contact Helene. DERNIS@oecd.org to download REGPAT database.

Note 4. See Arellano and Bover (1995) and Blundell and Bond (1998).

Appendix

Table A. Distribution of regions by economic area

	States		Prefectures		Countries
The USA	Alabama	**Japan**	Aichi	**Europe**	Andorra
	Alaska		Akita		Albania
	Arizona		Aomori		Austria
	Arkansas		Chiba		Bosnia
	California		Ehime		Belgium
	Colorado		Fukui		Bulgaria
	Connecticut		Fukuoka		Belarus
	Delaware		Fukushima		Switzerland
	District of Colombia		Gifu		Cyprus
	Florida		Gunma		Czech Republic
	Georgia		Hiroshima		Germany
	Hawaii		Hokkaido		Denmark
	Idaho		Hycgo		Estonia
	Illinois		Ibaraki		Spain
	Indiana		Ishikawa		Finland
	Iowa		Iwate		France
	Kansas		Kagawa		Gibraltar
	Kentucky		Kagoshima		Greece
	Louisiana		Kanagawa		Croatia
	Maine		Kochi		Hungary
	Maryland		Kumamoto		Ireland
	Massachusetts		Kyoto		Italy
	Michigan		Mie		Liechtenstein
	Minnesota		Miyagi		Lithuania
	Mississippi		Miyazaki		Luxembourg
	Missouri		Nagano		Latvia
	Montana		Naoasaki		Marocco
	Nebraska		Nara		Moldova
	Nevada		Niigata		Malta
	New Hampshire		Oita		Netherlands
	New Jersey		Okayama		Norway
	New Mexico		Okinawa		Poland
	New York		Osaka		Portugal
	North Carolina		Saga		Romania
	North Dakota		Saitama		Russian Federation
	Ohio		Shiga		Sweden
	Oklahoma		Shimane		Slovenia

	Oregon	Shizuoka	Slovakia
	Pennsylvania	Tochigi	San Marino
	Rhode Island	Tokushima	Turkey
	South Carolina	Tokyo	Ukaraine
	South Dakota	Tottori	United Kingdom
	Tennessee	Toyama	
	Texas	Wakayama	
	Utah	Yamagata	
	Vermont	Yamaguchi	
	Virginia	Yamanashi	
	Washington		
	West Virginia		
	Wisconsin		
	Wyoming		