Are There Spatial Spillovers in the Adoption of Clean Technology? The Case of Organic Dairy Farming

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ABSTRACT. *This paper examines spatial spillovers associated with the adoption of organic dairy farming. We hypothesize that neighboring farmers can help to reduce the uncertainty of organic conversion by lowering the fixed costs of learning about the organic system. A spatially explicit 10-year panel dataset of more than 1,900 dairy farms in southwestern Wisconsin is used as input into a reduced-form econometric model of the decision to convert to organic production. Using an identification strategy that exploits the panel aspect of the micro dataset, we find evidence that the presence of neighboring organic dairy farms affects the conversion decision.* (JEL Q15, Q24)

I. INTRODUCTION

Modeling and identifying explicit and implicit land-use coordination behavior has become a popular topic among public finance, urban, and resource economists. Examples include how amenities, neighboring land uses, and other local attributes affect housing choices (Irwin and Bockstael 2002; Wu and Plantinga 2003; Walsh 2007), how zoning laws and open-space conservation shape exurban and lakefront development (Newburn and Berck 2006; Lewis, Provencher, and Butsic 2009), and how conservation and land-use policies drive distinctive patterns of ecosystem service provision (Nelson et al. 2008; Lewis 2010). At the heart of these models is an effort to identify clustered behavior driven by sorting, spatial externalities, path dependence, and other types of economically meaningful processes. Empirical methods to examine spatial clustering typically rely on integrating geospatial data with spatially explicit econometric models that pay sufficient attention to identifying coordinated behavior from various spurious effects that might otherwise drive spatially similar outcomes.

Models of land use in agriculture have paid much less attention to the potential for coordinated decisions among farmers, though recent attention to organic farming choices relative to neighbors (Parker and Munroe 2007), coexistence of genetically modified and nongenetically modified crop farmers (Beckman and Wesseler 2007), and farmland preservation (Towe, Nickerson, and Bockstael 2008) suggests a more substantive push in this direction. Driving all of these examples is the potential for spillover externalities, such as pesticide contamination, pollen drift, the proximity to protected open-space, or land attributes, to affect neighboring farmers' decisions. Another possibility is that farmers coordinate around more positive external effects, such as learning, reciprocal exchanges, cooperative marketing, and volume premiums, to cluster similar types of land-use behavior. Identification of these types of behavior could be of significance in shaping how agricultural and resource economists model a wide range of spatially important outcomes, including agrobiodiversity conservation, watershed ecosystem service production, biomass provision for distributed cogeneration facilities, and regional product niche strategies (Lewis, Barham, and Zimmerer 2008).

This article examines the spatial spillovers associated with the adoption of an important agricultural "clean" technology: organic dairy farming. The application is set in southwest-

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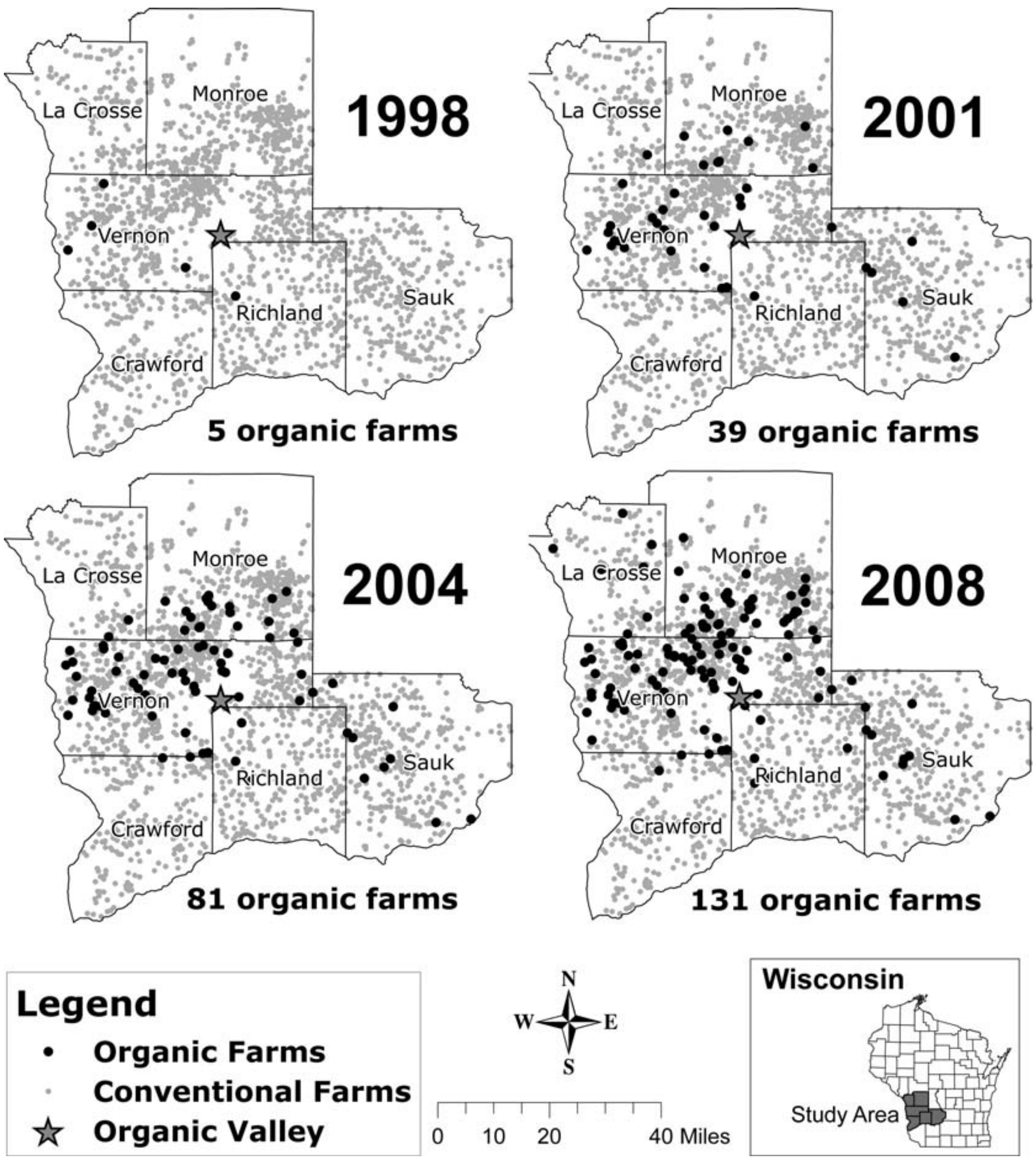

FIGURE 1
Spatial Expansion of Organic Dairy Farms in Southwestern Wisconsin

ern Wisconsin, a major production source for the recent dramatic growth in organic milk production across the United States, and the home base to Organic Valley, a cooperative that along with Horizon (Dean Foods) is responsible for marketing about two-thirds of the country's organic dairy products. Set against the spatial distribution of conventional dairy farms, the four panels of Figure 1 demonstrate the very rapid growth in organic dairy farm numbers in this region between 1998 and 2008, and especially since 2001. A closer look at Figure 1 shows several types of clustering. One is along an upper-middle transverse between Vernon and Monroe counties. Another is within a relatively proximate distance to the home base of Organic Valley (though they actually do very little processing within 50 miles of their corporate headquarters in LaFarge, so local transportation clustering around LaFarge is itself not a crucial factor).[1] A third type of clustering is more local, groups of organic farms in a neighborhood or watershed. A closer look at the organic dairy farms in the fourth panel of Figure 1 reveals that many of the farms are adjacent to, or very near to, one or several other organic neighbors, despite the fact that only about 6% of the farms in these six counties are organic. One simple descriptive statistic captures the extent of spatial clustering. As of 2008, an average organic dairy farm in this region had 23 other organic dairy farms within a 10-mile radius, compared to a nonorganic farm, which had only 14.

One explanation for this clustering is the location of Organic Valley and its initial recruitment strategy of seeking nearby farmers to convert to organic farming. Another would be the type of local biophysical conditions (e.g., sloped pastureland over flat row-crop land) that might limit the potential for a dairy farmer to follow the conventional dairy farm expansion option and enhance the performance of an alternative grazing-based farming system option (Brock and Barham 2009). A third would be the learning and reciprocity that might develop around a technological option as distinctive as organic dairy farming is from conventional.[2] For example, in addressing the challenges involved in learning organic production, George Siemon, CEO of Organic Valley, claims that "there is no better teacher than your fellow farmer" (Siemon 2006). All of these spatial explanations are explored below using a reduced-form panel data model of organic conversion decisions. Only the last explanation would be confirmation of the type of "spillover" effect that we seek to identify.

Conceptual, data, and econometric identification challenges constrain the capacity of researchers to identify land-use coordination decisions among farmers. At the conceptual level, agricultural economists almost always conceive of farmer decisions primarily as an individual agent utility or profit maximization decision under perfect information, sometimes under risk, but rarely under uncertainty. Typically, a learning process is not explicitly included. Even more rarely are those decisions considered in relationship to what neighboring farms might be doing and how neighbors might shape the knowledge, production, marketing, or other aspects of the farm management decision. While Conley and Udry (2010) and Foster and Rosenzweig (1995) do explicitly consider social learning, they do not explicitly consider the landscape or spatial patterns of that process. Rural sociologists writing on the adoption of alternative farm practices often stress the importance of local knowledge, farmer information-sharing networks (e.g., pasture walks), and other forms of coordination (Hassanein 1999; Bell 2004). Those contributions have yet to make much headway into formal models of farmers' land-use decisions, in part because learning itself receives little explicit attention in agricultural economics models beyond technology adoption models (Marra, Pannell, and Ghadim 2003). There, learning issues have been repeatedly identified as central (Griliches 1957; Lindner 1980; Feder and O'Mara 1982), but they have not been linked explicitly to neighbors or spatial considerations. In the next section, we contribute a broad conceptual discussion of the organic dairy farm conversion decision, focused on a real options model with sunk costs, uncertainty, and learning. Our broad hypothesis is that neighboring farmers can help to reduce the uncertainty by lowering the fixed costs of learning about the emerging and distinctive farming system. In the real options context, this reduction in fixed costs of learning could help to reduce the hurdle rate

[1] Organic Valley owns one moderate-sized butter processing plant in Chaseburg, Wisconsin. It contracts for the rest of its dairy processing with processors in Wisconsin and in other states around the country.

[2] Family farms, which to this day dominate global agricultural production, are an institutional form that internalizes knowledge transfer (especially across generations) and reciprocity arrangements. While they could well be an important source for information transfer and shared arrangements around a new technological option, such as organic farming, we also have in mind farmer-to-farmer information transfers, exchanges, and coordination mechanisms, which depend on spatial and social proximity beyond family ties.

associated with the sunk costs of converting from conventional to organic production.

Data availability has constrained economists' capacity to identify spatial phenomena, especially coordination of behavior across farms. Most available datasets do not provide enough information on neighboring farmers' management practices to allow a spatially explicit approach to individual farmer decisions. Gathering survey data from a population of farms in a large enough area to develop such an inventory would tend to be very expensive and is not standard in most regular government-sponsored surveys, such as the Agricultural Resource management Survey or National Resources Inventory (NRI), which agricultural economists exploit for many of their land-use studies.[3] Recent innovations in geospatial methods allow more comprehensive land-use inventories to be developed, especially if they can be geocoded and integrated with datasets capturing biophysical, infrastructural, and other spatial features. This article integrates a population list of Wisconsin dairy farms with information from third-party certifiers on the entry of organic dairy farms, geocodes these operations, and links them explicitly to information on the biophysical and tax values of the property, which help to identify the econometric model. The final dataset consists of a 10-year panel of the spatial location of organic dairy farms across southwestern Wisconsin. This novel spatial panel dataset of organic conversion decisions overcomes the data constraints that limit more explicit spatial analysis of farmer behavior in typical datasets.

The third constraint relates to identification of spatial spillovers. Similar to Manski's (1993) analysis of social interaction, Irwin and Bockstael (2002) argue that spatially correlated unobserved characteristics can confound the estimation of spillover externalities when modeling land-use change. In the case of adopting organic dairy techniques, the presence of spatially correlated unobservable characteristics could push farmers toward making similar decisions that are unrelated to their effect on one another. This argument is similar to Ellison and Glaeser's (1997) point that geographic concentration in an industry does not by itself imply the existence of a spillover effect, because certain regions may have natural advantages to location over other regions. Our econometric approach exploits the panel nature of our data to control for this prospect, building on the correlated random-effect estimation approaches originally developed by Mundlak (1978) and Chamberlain (1982), and now widely applied to nonlinear panel data estimation (see Wooldridge 2002). The correlated random-effects framework treats unobserved farm-level heterogeneity as a function of the average of time-varying covariates (such as the number of neighboring organic farmers). This approach mimics the identification strategy of fixed-effects estimation but can be applied to nonlinear models. Since the actual number of neighboring organic farmers varies over time, we are then able to separately identify the impact on organic conversion of the previous adoption decisions of neighbors. As applied to the land-use decision, our spatial application of the correlated random-effects model provides an alternative strategy to identify spatial spillovers from conventional spatial econometric models that are designed for cross-sectional data (e.g., Anselin 2002; Pinske and Slade 1998; Klier and McMillen 2008). Our approach could be widely applicable to the many other land-use analyses that attempt to model the effects of surrounding land uses on the decisions of landowners (e.g., Irwin and Bockstael 2002; 2004; Carrión-Flores and Irwin 2004; Newburn and Berck 2006; Towe, Nickerson, and Bockstael 2008). This strategy does not, however, provide a behavioral identification of why these spatial spillovers arise in the adoption of this technology, which will require further detailed on-farm survey data.

II. ORGANIC ADOPTION, REAL OPTION MODEL CONSIDERATIONS, LEARNING COSTS, AND NEIGHBORS

A general explanation for the fundamental role of learning from neighbors can be drawn

[3] The NRI presents repeated samples of land plots and tracks current land use and soil quality on each plot. However, since the exact location of NRI plots is not revealed due to confidentiality restrictions, this data is of limited value in examining spatial spillovers.

from the technology adoption literature. In a broad class of models (Griliches 1957; Lindner 1980; Feder and O'Mara 1982), as the fixed costs of learning about the technology decline, knowledge about its performance under various conditions becomes more widely available, and the potential for adoption of the technology spreads. The spatial reflection of this process would be that farmers with more neighbors adopting the organic technology would see their fixed costs of learning decline more rapidly than farmers without proximate neighbors adopting the organic technology. That more rapid decline would allow for adoption patterns to be clustered in a manner that would not be predicted by more-general time trends of the diffusion of the technology (Brock and Durlauf 2009).

Because adoption of new technologies, especially alternative "farming systems," often involve substantive sunk costs or irreversible investments (Purvis et al. 1995), we focus the rest of this section on developing a real options model version of the conversion decision. In the case of organic farmland conversions, most of those sunk costs are incurred in the three-year certification period during which farmers are required to replace certain conventional management practices with organic alternatives, such as organic soil nutrients, no chemical pesticides or herbicides, and organic feeds. As a result, farmers usually incur higher costs of production *before* they receive the anticipated price premium for their product. These foregone profits, or start-up costs of organic conversion, are irreversible in the sense that the farmer's certification costs are not fully recoverable if the farmer decides to exit from farming or organic management practices.[4]

Conversion to organic dairy farming generally involves major reorganization of several systems of farm management, including animal health, crop and pasture cultivation, forage and feed purchasing and storage, and manure storage and handling. Each of these system reorganizations can involve substantive changes in equipment, facilities, types of allowable inputs, and basic managerial strategy. These changes increase both the extent of sunk costs involved and the potential for uncertainty regarding the performance of and interactions among these new systems of farm management. For example, securing the optimal mix of forage and feed for pasture-grazed cows becomes more challenging in part because their feed consumption is not as observable as it would be in a fixed-stall confinement operation. That, in turn, makes identifying the source of lower milk yields (changing feed inputs versus health problems) more challenging. Identifying potential solutions for such problems and learning new ways to manage information in order to reduce uncertainty in these new systems takes time, experience, and integration of various types of information.

We treat this conversion (or start-up) decision as a real option model involving sunk costs, uncertainty, and fixed costs of learning. Our conception builds on an extensive literature in agricultural economics that was largely spawned by Dixit and Pindyck (1994), drawing from efforts to model technology adoption of perennial crops with yield and price uncertainty (Price and Wetzstein 1999; Shively 1999), modern irrigation technology with emerging water markets (Carey and Zilberman 2002), and conservation technology (Purvis et al. 1995). As in all of these examples, the presence of sunk costs and uncertainty introduce an option value that makes the investment decision depend on satisfying a "hurdle rate" that is greater than the typical positive net present value of the investment relative to other choices. Our addition is to suggest that the fixed costs of learning about organic farming methods and practice introduce what can be considered a second wedge in the hurdle rate that must be reached before

[4] Sunk cost recovery will likely depend on the farmer's decision to sell assets. If farmers exit organic farming without selling lands and cows, the sunk costs are lost. If they sell cows and/or land on a certified organic dairy farm, then they can potentially recover a significant portion of the costs associated with conversion. But, if they want to continue farming, there may be other major losses associated with moving their operations. In that case, they would need to compare the pecuniary and nonpecuniary losses of moving their farm and potentially their family in order to exit organic farming and recover sunk costs.

the farmer invests.[5] As a result, as neighbors adopt the technology, proximate farmers would face a lower net hurdle rate associated with fixed costs of learning and be more likely to adopt the organic technology sooner.

Formally, our decision rule for farmer n to convert to organic (O) dairy farming from conventional (C) in time t can be written as follows:

$$NV_{nt} = ENPV(O_{nt}) - ENPV(C_{nt}) - OPV_{nt} - L_t(N_{nt}) > 0, \qquad [1]$$

where NV_{nt} is the net value at time t of converting farm n from conventional to organic agriculture into the future, $ENPV$ is the farm's expected net present value given conventional or organic practice, OPV is the option value under uncertainty of killing the option to wait, and $L(N_{nt})$ is the fixed cost of learning, which declines with the number of N neighbors that in time t have adopted organic dairy farming within a certain radius of farm n.[6] Both OPV and $L(N_{nt})$ are likely to evolve over time. For example, one could imagine the fixed costs of learning declining over time as general knowledge of a technology spreads; this could be captured with another argument in L related to broader diffusion trends. Meanwhile, OPV could decline (or rise), as uncertainty over relevant product and input prices falls (increases). Depending on the path of the hurdle rate decline, it is not hard to imagine an accelerating adoption rate of the organic technology. But, what should distinguish the two hurdle rates empirically is whether the number of neighbors adopting matters to the decision of individual farmers. Controlling for spurious but spatially correlated unobservable variables becomes the fundamental empirical challenge.

We provide no further explicit structure on this decision rule here, because our econometric model in the subsequent section is a reduced-form panel-data model that does not explicitly treat the evolving dynamics of the farmer's decision problem by considering such phenomena as product and input price uncertainty, production uncertainty, or direct investments in learning. The reduced-form econometric model has the advantage of being less sensitive to specific modeling assumptions. In particular, while we motivate spatial spillovers with a real options framework, our reduced-form econometric model would provide consistent estimates of the spillover effect even if farmers instead made the organic decision based on a net present value rule.

III. ECONOMETRIC MODEL OF THE LANDOWNER'S ORGANIC CONVERSION DECISION

We cast the farmer's decision problem as a matter of deciding whether to convert his conventional dairy farm to organic production at time t. The decision problem is cast in terms of the reduced-form net value of converting to organic dairy. As defined in equation [1], conventional farm n is converted to organic production at time t if the net value of converting the farm to organic is positive. Formally, we denote the reduced-form net value of conversion by

$$NV_{nt} = V(\mathbf{x}_n, \mathbf{on}_{nt}, \mathbf{z}_t) + \mu_n + \nu_{nt}, \qquad [2]$$

where $\mathbf{x}_n$ is a vector of time-invariant farm characteristics, $\mathbf{on}_{nt}$ is a vector of variables indicating the number of organic neighbors surrounding farm n at time t, $\mathbf{z}_t$ is a vector of period t-specific dummy variables that capture period-specific shocks that influence the value of converting to organic for all farms, v_{nt} is an i.i.d. standard normal random variable, and μ_n denotes a farm-specific characteristic ob-

[5] Fixed costs of learning in technology adoption have been studied in numerous papers (e.g., Just and Zilberman 1983), but they have not been included in irreversible investment and uncertainty models, which generally assume that uncertainty is purely random rather than being potentially related to the emergence of a new option that requires learning. However, the potential effect of sequential learning about related investment projects in a real options framework has been a topic of recent interest and is explored by Smith and Thompson (2009). Our line of inquiry is distinct from their effort, because the information spillovers considered in their and related papers have to do with firm discoveries about correlated asset options, such as petroleum leases, and not in what they might learn about returns from proximate choices by neighboring farms.

[6] It is worth pointing out that if there are other positive effects associated with having neighbors adopting the technology, such as reciprocal labor and equipment sharing or other logistical cost savings, then the L term could become positive.

TABLE 1
Number of Organic Dairy Farms Certified by Year

Year of Certification	Number of Farms
1998	5
1999	11
2000	19
2001	7
2002	12
2003	19
2004	11
2005	8
2006	16
2007	17
2008	6

served by the farmer but not by the analyst. The observable portion of the land value function is specified as a linear function of the form

$$V(\mathbf{x}_n,\mathbf{on}_{nt},\mathbf{z_t}) = \mathbf{x}_n'\boldsymbol{\beta} + \mathbf{on}_{nt}'\boldsymbol{\delta} + \mathbf{z}_t'\boldsymbol{\alpha}. \qquad [3]$$

The data used in the analysis includes repeated observations of the farm-level decision to convert, y_{nt}, where $y_{nt} = 1$ if the net value of conversion defined in [2] is positive, farm characteristics $\mathbf{x}_n$, and $\mathbf{on}_{nt}$. Our use of the term *repeated* is not meant to imply that farms move back and forth between organic farming. Rather, we observe the implicit organic conversion decision for all conventional farms repeatedly over time (e.g., whether farms convert in 1995, convert in 1996, etc.). Letting $\Phi(\cdot)$ denote the standard normal cumulative distribution function, the probability of conversion, conditional on $\mathbf{x}_n$, $\mathbf{on}_{nt}$, $\mathbf{z}_t$, and μ_n is given by a probit model[7]:

$$\Pr(y_{\mathrm{nt}} = 1 \mid \mathbf{x}_n,\mathbf{on}_{nt},\mathbf{z}_t,\mu_n) = \Phi(\mathbf{x}_n'\boldsymbol{\beta} + \mathbf{on}_{nt}'\boldsymbol{\delta} + \mathbf{z}_t'\boldsymbol{\alpha} + \mu_n). \qquad [4]$$

The parameters in equation [4] can be estimated by maximum likelihood, where Gaussian quadrature or simulation techniques may be necessary depending on the treatment of μ_n.[8]

Data Sources

The data used for estimation are derived from a novel spatial panel dataset, where the conversion decision is tracked for a set of over 1,800 independent dairy farms in southwestern Wisconsin over a period of 10 years.[9] The location of each farm was digitized to a geographic information system, and the dataset was constructed in the following way. First, we gathered a list of dairy farms within our study area from the Wisconsin Department of Agriculture, Trade, and Consumer Protection records. Using owner names and/or addresses, we matched farms to digital parcels in space from county land record offices or digitally rectified Wisconsin plat maps. Since many farmers own multiple parcels, the dairy parcels were identified by finding those parcels with significant improvement values (typically over $50,000) for the "other" tax category, indicating structural improvements. The existence of farm facilities within the parcel was verified with aerial photos from the U.S. Department of Agriculture's National Agriculture Imagery Program and, for a subsample of questionable farms, through physical ground-truthing. Organic dairy farms were identified with records from organic certifiers throughout the Midwest, from which we also obtained organic certification dates.[10] The date of certification is directly provided by the certifying agencies, and contemporary organic certification standards require 3 years of organic production before certification of

[7] One could alternatively motivate the decision process as a survivor model, such as Irwin and Bockstael's (2002) hazard model of the urban land development decision, estimated with a Cox partial likelihood approach. However, as noted by Cameron and Trivedi (2005, 600), our approach using a binary probit model of the probability of conversion in each period, with separate intercepts for each period, can be interpreted as a simple hazard model.

[8] Manski's (1993) reflection problem does not arise in equation [4] because we include the actual number of organic farmers in the reference group, not the average number from the group.

[9] The implicit assumption in the analysis is that the organic decision is a "conversion" from a conventional dairy farm rather than a new "start-up" of an organic dairy farm. This assumption provides a conservative estimate of the value of social learning, since new entrant organic farmers would likely face even larger learning costs associated with farm entry. Empirically, new start-up farms are quite rare. New entrants almost always purchase a previous farm.

[10] Midwest Organic Services Association, Organic Crop Improvement Association, and Oregon Tilth are the primary certifiers in the region.

TABLE 2
Summary Statistics of Independent Variables

	Mean	Std. Dev.
Soil quality (LCC Scale)	2.18	0.46
Distance to OV (miles)	22.35	9.83
Structure ($1000s)	$106	$74.17
Number of neighboring organic farms within 5 miles		
1995	0.00	0.00
1996	0.00	0.00
1997	0.00	0.00
1998	0.09	0.32
1999	0.45	0.65
2000	0.96	1.17
2001	1.20	1.43
2002	1.67	2.03
2003	2.18	2.63
2004	2.52	2.82
2005	2.81	3.24
Number of neighboring organic farms between 5 and 10 miles		
1995	0.00	0.00
1996	0.00	0.00
1997	0.00	0.00
1998	0.27	0.57
1999	1.09	1.22
2000	2.36	2.38
2001	2.95	2.98
2002	4.11	4.05
2003	5.46	5.33
2004	6.17	5.75
2005	6.91	6.35

Note: LCC, Land Capability Classification.

land, and 1 year for certification of a dairy herd. However, in addition to certifying their herd, every organic farmer in our sample also has her land certified for producing crops such as corn and wheat, or for pasture. Therefore, we define the year the conversion decision was made as 3 years prior to the certification date. Table 1 shows the number of farms certified in each year from 1998 to 2008.

The spatial panel dataset is supplemented in several ways to calculate data on farm-specific variables that might influence the value of converting a farm to organic production. First, since all organic dairy farms in our region also produce crops, the soil quality of farms may influence organic conversion decisions. A farm's agricultural productivity potential is classified into four categories of increasing agricultural productivity as derived from the U.S. Department of Agriculture Natural Resources Conservation Service's nonirrigated Land Capability Classification dataset, and spatially matched to each farm. Soil characteristics are determined by averaging the land capability class measure for 100 acres surrounding each farm location (*Soil quality*).[11] Second, since a farm with large capital investments might face a larger sunk cost in converting to organic, we use local tax assessor data to obtain the value of the structural improvements on the farm (*Structure*). Third, given that the country's largest organic cooperative—Organic Valley—is located in the study area, we calculate the distance of each farm to Organic Valley (*Distance to OV*) to account for the effects of physical proximity to an important institution that has the potential to influence organic conversion. Finally, the number of neighboring certified organic farms is calculated for two radii around each farm: within a 5 mile radius (*Organic farms within 5 miles*), and between 5 and 10 miles (*Organic farms between 5 and 10 miles*). Table 2 presents descriptive statistics from all farms.

These statistics demonstrate a steady increase in the average number of neighboring organic farms surrounding each conventional dairy farm, a phenomenon that is reinforced by examining the spatial expansion of organic dairy in Figure 1. Nonetheless, the conversion of a conventional to organic farm is a relatively rare phenomenon, ranging from just 0.2% of conventional farms in 1998 to just over 1% of conventional farms in 2000 and 2003. Relative to conventional dairy farms, organic farms, on average, are closer to Organic Valley headquarters,[12] have a lower assessed value of their structural improvements,[13] have lower soil quality,[14] and have

[11] We used the 100 acres surrounding the location of the primary structure on each farm because it is not possible to spatially delineate the farm's boundaries. Many farmers own multiple parcels, and the available data only allows us to identify the parcel with the principal dairy infrastructure.

[12] The average distance of organic (conventional) farms to Organic Valley is 18 miles (22.4 miles).

[13] The average assessed value of structural improvements on organic (conventional) farms is $93,940 ($106,223).

[14] The average Land Capability Classification rating on organic (conventional) farms is 2.24 (2.17).

more organic neighbors.[15] Using a Z-test, the difference in means across organic and conventional farms for the above variables is significantly different from zero at the 1% level.

Identification Strategy

We are particularly interested in identifying the effects of the number of organic neighbors, $\mathbf{on}_{nt}$, on the probability of converting to organic dairy at time t. The set of variables $\mathbf{on}_{nt}$ are likely endogenous in the econometric model for two reasons. First, since the dataset used for estimation includes repeated conversion decisions over time, $\mathbf{on}_{nt}$ is, by construction, a function of the past conversion decisions from all farms that neighbor farm n. Formally, endogeneity bias arises in estimation because $\mathbf{on}_{nt}$ is an explicit function of $\mu_{n'}$ and $\upsilon_{n',t'}$, where n' indicates the set of parcels that are neighbors to parcel n, and $t' < t$. Second, $\mathbf{on}_{nt}$ may be endogenous if there are spatially correlated unobservable characteristics that influence the conversion decisions of neighboring farms. For example, multiple neighboring farms may all be on a major road network used by processors to buy organic milk. Regardless of its source, any estimation strategy that aims to obtain consistent estimates of the effects of $\mathbf{on}_{nt}$ on the organic conversion decision must account for the endogeneity of $\mathbf{on}_{nt}$.

Prior work on discrete-choice panel data models has exploited the repeated observations of individual choices to correct for the endogeneity of time-varying covariates. In particular, the most notable work in this area has developed a correlated random-effects estimation strategy (Mundlak 1978; Chamberlain 1982). In our case, treating μ_n as a random effect induces bias if it is correlated with $\mathbf{on}_{nt}$. As applied to this dataset, a correlated random-effects model builds correlation between μ_n and $\mathbf{on}_{nt}$ into the model by specifying the farm-specific unobservable as

$$\mu_n = \omega_n + \frac{1}{T_n}\sum_{t=0}^{T_n} \mathbf{on}'_{nt}\boldsymbol{\varphi} = \omega_n + \overline{\mathbf{on}}'_n\boldsymbol{\varphi}. \qquad [5]$$

The vector $\overline{\mathbf{on}}_n$ in equation [5] is commonly referred to as the Mundlak-Chamberlain device, and in our case, equation [5] decomposes the farm-specific effect into a mean zero normally distributed random variable, $\omega_n \sim N(0,\sigma)$, and the average of $\mathbf{on}_{nt}$ over all T_n periods that farm n is observed in the data ($\overline{\mathbf{on}}_n$).[16] More generally, the Mundlak-Chamberlain device includes the average of all time-varying covariates included in estimation, which in our case is only $\mathbf{on}_{nt}$. The estimation problem now includes $\boldsymbol{\varphi}$ as a parameter vector to be estimated.

The identification strategy from a correlated random-effects model is simple and provides the advantages of a fixed-effects model when the regression function is nonlinear and fixed-effects estimation is not appropriate (Wooldridge 2002).[17] Including $\overline{\mathbf{on}}_n$ as an explanatory variable controls for the unobservables that would be correlated with $\mathbf{on}_{nt}$. In particular, by including $\overline{\mathbf{on}}_n$, we can identify the spillover effect by isolating the effects of the number of organic neighbors at the *conversion* time from simply being in a neighborhood where organic farming grows more rapidly (which would be measured by a high value of $\overline{\mathbf{on}}_n$). This identification strategy is in a similar spirit to Brock and Durlauf's (2009) idea of identifying social interactions by looking for jumps in the fraction of a population who have adopted by a particular date. In addition, including $\overline{\mathbf{on}}_n$ also serves to build relevant spatial correlation into the model, as $\overline{\mathbf{on}}_n$ will be spatially correlated with $\overline{\mathbf{on}}_{n'}$ if n and n' are neighbors. Identification of the parameter vector on $\mathbf{on}_{nt}$—the spillover effect

[15] The average number of neighboring organic dairy farms within 5 miles for organic (conventional) farms is 1.66 (1.05), while the average between 5 and 10 miles is 4.3 (2.6). Note that the ratio of the area of a 5-mile circle around a farm to the area of the doughnut defined by a 5- to 10-mile radius around a farm is 79:236 = 0.33. The ratio of the number of accompanying organic neighbors, 1.66:4.3 = 0.38, is pretty close to 0.33. In other words, we *expect* more farms within a 5- to 10-mile radius when the farm density is held constant.

[16] Since the model is defined for the decision to convert a conventional farm to organic, the panel is unbalanced as farms drop from the dataset once they convert to organic.

[17] In linear panel data models, Mundlak (1978) showed that such a correlated random-effects strategy is identical to fixed-effects estimation.

of interest—arises because this variable changes over time.

There are many time-varying but spatially constant factors that could potentially affect the conversion to organic. First, the uncertain conventional and organic pay price has changed significantly over the period of our study and will comprise a large component of the option value of conversion (Schatzki 2003). However, these prices do not vary across farmers within the region. Second, there have been structural changes in organic certification requirements corresponding to the National Organic Practices Act in 2002, and the 80/20 rule[18] that relaxed conversion requirements, but expired in 2007. The effects of $\mathbf{on}_{nt}$ are isolated from time-varying shocks that affect the conversion decisions of all farms by including year-specific dummy variables ($\mathbf{z}_t$) that account for all time-varying spatially constant factors.[19]

Correlated random-effects estimation provides a simple way to consistently estimate the effects of neighboring land uses on the land conversion decision, and this approach could potentially be applicable to urban economic models of spillovers in urban sprawl (e.g., Irwin and Bockstael 2002; Newburn and Berck 2006; Towe, Nickerson, and Bockstael. 2008). This identification strategy works particularly well when repeated land-use decisions are observed within a landscape that is changing over time, such as we have in this application. A changing landscape allows us to adequately control for time-invariant unobservables and time-specific shocks to all parcels, where identification of the spillover effect arises from spatial and temporal variation in the time of conversion.

Relationship to Other Spatial Econometric Models

Spatial econometric models are typically specified with a spatially lagged dependent variable included on the right-hand side, or with an error structure that is spatially correlated (Anselin 2002). While such spatial econometric models have traditionally been limited to small datasets when applied to discrete dependent variables, a recent development is the linearized method of moments estimator introduced by Klier and McMillen (2008), hereafter referred to as KM. The approach developed by KM is a binary choice model ($Y = 0$ or 1) that extends Pinske and Slade's (1998) GMM estimator with spatially dependent errors by introducing a spatially lagged dependent variable, WY, where W is a spatial weight matrix. Importantly, the linearization by KM allows the model to be estimated with large datasets. KM's strategy for identification relies on an instrumental variables approach that replaces the spatially lagged dependent variable with a value predicted by a regression of the lagged dependent variable on the lagged independent variables.

As argued by KM, the underlying assumption in their approach is that the propensity that $Y = 1$ depends on the *propensity* for neighboring observations to have $Y = 1$, and not simply on whether neighboring observations have $Y = 1$. While this assumption works for KM's analysis of auto plant location decisions, it is much less satisfactory for our application. Our hypothesis is that the cost of learning the organic technology is influenced by whether neighboring farmers are organic ($Y = 1$), not on the propensity to have organic neighbors. As such, our application of the Chamberlain-Mundlak panel data approach provides a more satisfactory identification strategy for our research question. In addition, most traditional spatial econometric estimation techniques (e.g., Anselin 1988; McMillen 1992; Kelijian and Prucha 1998; Klier and McMillen 2008) are designed for cross-sectional data, whereas our application exploits the panel aspect of our data for identification.[20] Further, our model relates to other ap-

[18] The 80/20 rule allowed farmers to feed their herd 20% conventional feed during the first 9 months of their 1-year herd transition.

[19] It is not possible to separately estimate the effects of $\mathbf{z}_t$ and the effects of other time-varying, but spatially constant factors such as the organic pay price.

[20] An exception is Pinkse, Slade, and Shen (2006) and Pinkse and Slade (2007), who develop a fixed-effects estimator for a spatial probit model. However, the fixed effects enter the probit model through the observed choice equation, rather than the latent variable equation (as we have in equation [2]). The interpretation of the fixed effect in this work

proaches with spatially correlated errors because the Chamberlain-Mundlak device adds an incidental parameter that creates spatial correlation in the unobservables.

IV. ESTIMATION RESULTS

The econometric model estimates the binary decision of whether a conventional dairy farm converts to organic, where the decision is implicitly observed in each year over a 10-year period. Once a conventional farm converts to organic, it is dropped from the estimation sample, creating an unbalanced panel for our probit model. Equation [4] is estimated using maximum likelihood techniques with Gaussian quadrature. A likelihood ratio test fails to reject the null hypothesis that the standard error on the random effect (σ) is 0 (5% level). Therefore, we restrict σ to be zero, which allows us to estimate [4] without Gaussian quadrature as a pooled probit with the Mundlak-Chamberlain device ($\overline{\mathbf{on}_n}$) using maximum likelihood with bootstrapped standard errors clustered by farm.[21] The bootstrapped cluster-robust standard errors allow inference robust to any form of heteroskedasticity or temporal correlation across years for each farm (Cameron and Trivedi 2005). A primary challenge with estimation is the small annual probability of converting to organic dairy of 0.6%. Such a small probability of conversion brings up a concern of whether results are sensitive to functional form assumptions. As such, we run several robustness checks. First, we estimate the binary organic conversion decision implied by equation [2] as both a probit and a logit model. Since probit and logit models vary primarily in terms of the tails of their distributions (Greene 2000), estimating the conversion decision with both models provides a check on the sensitivity of results to functional form. Second, to examine the sensitivity of the results to the time period used for estimation, we estimate the binary conversion decision on multiple subsets of the original dataset, restricting the years of estimation to 1998–2005, 2000–2005, and 2002–2005.

The econometric parameter estimates for all parameters are presented in Appendix Tables A1 and A2. For the nonspillover variables, farms further from Organic Valley headquarters are less likely to convert to organic than farms closer (5% level), while organic and conventional farms are not statistically different from one another in terms of average soil quality or the assessed structural value of their farm improvements (5% level). The estimated effect of primary interest is the discrete-change effect of one additional neighboring organic dairy farm on the probability of conversion (Table 3).[22] Results in Table 3 provide evidence that conventional farms are more likely to convert to organic dairy if they have additional neighboring organic dairies within either 5 or 10 miles. The estimated discrete-change effects are generally significant from zero at either the 5% or 10% level,[23] and the effects are quite robust across functional form specification and across various subsets of the data.[24] Using the full dataset and probit estimates, results in Table 3 suggest that having an additional organic dairy within 5 miles of a farm increases the farm's annual probability of converting to organic by approximately 1.3 percentage points. While an effect of 1.3 percentage points may seem small, this result implies that an additional farm increases the average annual organic conversion probability from 0.006 to 0.019. When spread out over 10 years, an additional farm increases the organic conversion probability from 0.06 to 0.18. While the discrete-change effect of an additional farm within the 5- to 10-mile radius is larger than having an additional farm within 5 miles, we cannot reject a null hypothesis that the dis-

is that it affects the probability of a choice through a different avenue than the latent variable equation.

[21] The conclusions from examining the discrete-change effects in Table 3 are essentially unchanged when estimating the model with σ.

[22] The discrete-change effect is the difference in the probability of organic conversion due to one additional organic neighbor.

[23] Standard errors for the discrete-change effects are calculated with the delta method.

[24] As expected, the efficiency of the estimates diminishes with fewer observations.

TABLE 3
Discrete-Change Effects of an Additional Neighboring Organic Dairy Farm

	Probit		Logit	
	≤ 5 Miles	5–10 Miles	≤ 5 Miles	5–10 Miles
All data				
Discrete-change effect	0.013*	0.022*	0.015**	0.026*
Standard error	0.006	0.009	0.008	0.012
Z-Statistic	2.085	2.471	1.797	2.284
Years 1998–2005				
Discrete-change effect	0.009*	0.016*	0.011**	0.019*
Standard error	0.004	0.006	0.006	0.008
Z-Statistic	2.101	2.606	1.784	2.280
Years 2000–2005				
Discrete-change effect	0.009**	0.010*	0.012**	0.012*
Standard error	0.005	0.004	0.007	0.006
Z-Statistic	1.950	2.337	1.844	2.208
Years 2002–2005				
Discrete-change effect	0.014	0.022**	0.022	0.031**
Standard error	0.009	0.011	0.015	0.017
Z-Statistic	1.626	1.939	1.497	1.892

Note: Standard errors are calculated with the delta method.
* Significantly different from zero (5% level); ** significantly different from zero (10% level).

crete-change effect is identical for both radii (5% level).

V. LANDSCAPE SIMULATIONS

The econometric estimates provide information on the discrete-change effects of an additional neighboring organic farm on the one-year probability of organic conversion. However, landscape patterns comprise decisions from many independent farms, and a related question concerns the effects of an additional neighboring organic farm on the time-path of landscape change within a particular region, such as a watershed. The simulation methodology deployed here builds on the Monte Carlo approach from Lewis and Plantinga (2007) and Lewis (2010) that links discrete-choice land conversion models with spatial landscape data. We use the methodology to generate distributions of the number of new organic farms within a watershed of similar characteristics to our study region over a 10-year period. We highlight the role of the number of initial organic farms and the density of farms within the watershed on its time-path.

The simulations algorithm works as follows:

1. N farms are randomly distributed across a circular watershed with 5-mile radius, with G organic farms and $N-G$ conventional farms. This watershed size ensures that every farm is within 10 miles of every other, and therefore, each farm's organic conversion decision affects the probability that all neighboring farms convert.
2. To ensure that the farms are representative of our study region, farm characteristics are randomly assigned to each hypothetical farm on the landscape by assuming that each variable is drawn from a truncated normal distribution with mean and variance from Table 2.[25] Each farm's variables for the number of organic farms within 5 and 10 miles are calculated using the distributed landscape from Step 1.
3. Using the parameter estimates from Table A1, the "all data" probit model, every conventional farm is matched with an estimated organic conversion probability[26] (Krinsky and

[25] The normal distribution is appropriately truncated to ensure that we get no unreasonable values of each variable, such as, for example, a negative land quality measure.

[26] A simulated parameter vector is equal to $\boldsymbol{\beta}_s = \hat{\boldsymbol{\beta}} + C'\mathbf{x}_K$, where $\hat{\boldsymbol{\beta}}$ is the estimated parameter vector, C is the $K \times K$ Cholesky decomposition of the estimated variance-covariance matrix, and $\mathbf{x}_K$ is a K-dimensional vector of draws from a standard normal distribution.

Robb 1986). Following Lewis and Plantinga (2007) and Lewis (2010), the fitted probabilities are interpreted as a set of rules that govern the decision of each farm to convert to organic.[27]

4. A complete time path ($t = 1, \ldots, T$) of landscape change is estimated.
   a. A $U \sim [0,1]$ random number r is drawn for each conventional farm, and conversion to organic occurs if r is less than or equal to the estimated conversion probability for that farm; otherwise the farm is assumed to remain in conventional production.
   b. The conversion probability estimates are updated for $t = t + 1$ to account for any newly certified organic farms for time t (accounting for the 3-year certification lag), and Step 4a is repeated until $t = T$.
5. Step 1 is repeated until all simulations ($S = 500$) have been completed.

The simulations are performed with multiple densities of farms within the watershed. For a circular watershed with a 5-mile radius, including 35 farms exactly replicates the average density of dairy farms observed in our study region. To test the sensitivity of results to different farm densities, we also perform simulations with 17 and 70 farms within the circular watershed, both of which can be found for particular 5-mile-radius areas in our study region.

Sample landscape simulation results for three different farm density classes are presented in Figure 2. To illustrate the spatial nature of the landscape simulations, we pull out one simulated watershed, represented by the circular plots, from each of the three farm density classes and present a final simulated landscape at $t = 10$. Within a watershed the dots represent farms; encircled farms indicate those that have turned organic by the final simulation period. Watershed 1 (Wshd1) has one organic farm at $t = 0$ and, to highlight the ceretis paribus effect of having an additional neighboring organic farm, Watershed 2 (Wshd 2) differs from Watershed 1 only in that it began with two organic farms at $t = 0$. The full

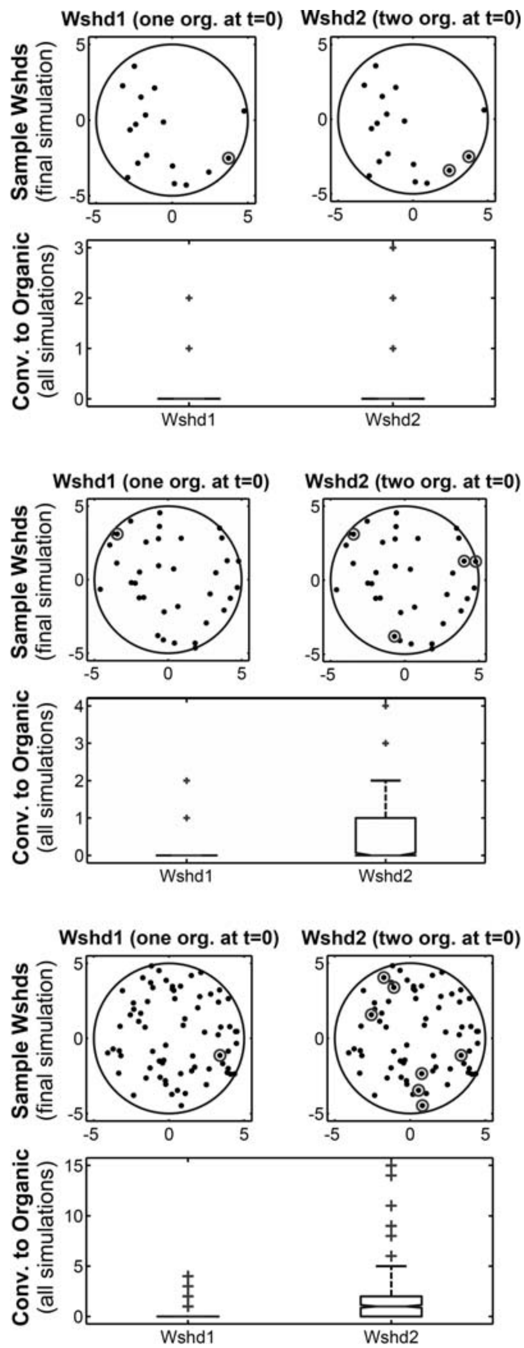

FIGURE 2
Sample Landscape Simulation Results and Box Plots: Watershed with *(top)* 17 Farms, *(middle)* 35 Farms, and *(bottom)* 70 Farms

[27] For example, if the conversion probability is 0.05 for a particular farm, the farm will convert 5% of the time if the choice situation is repeated many times.

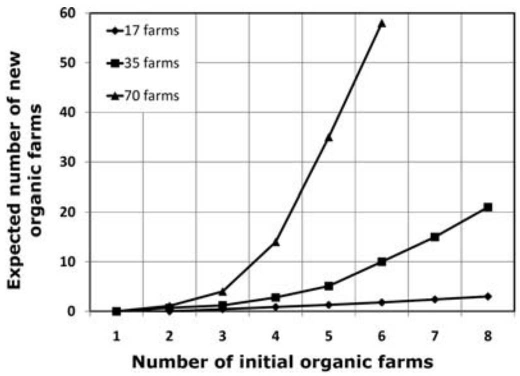

FIGURE 3
Landscape Simulation Results: Expected Number of New Organic Farms on Landscapes of Varying Farm Density

set of simulations consists of 500 distinct circular landscapes for each density class.

Figure 2 also shows box plot distributions of the number of additional farms that converted to organic from all 500 simulations (" + " signs indicate outliers). For instance, Watershed 1 in Figure 2a shows that only two simulations produced additional organic farms (in one simulation one farm converted and in one simulation two farms converted), but the other 498 simulations produced no additional organic conversions. In contrast Watershed 2 in Figure 2c shows that the median conversion rate was one additional organic farm per simulation (indicated by the notch in the box plot), but many simulations produced more. As can be seen, the effect of an additional organic farm to each watershed density in $t=0$ notably shifts the distribution of the number of new organic farms by $t=10$.

Figure 3 shows watershed simulation results focused on the expected number of new organic farms based on the number of initial organic farms in the watershed in $t=0$ for the three farm densities. Each point in Figure 3 indicates the average number of new organic farms across the 500 simulations. Results highlight the path-dependence property of the organic conversion process, in particular showing the nonlinear relationship between the number of initial organic farms and the expected number of new conversions over a 10-year period. Further, Figure 3 highlights the degree to which this relationship depends on the density of farms within a watershed. The implications are that the effects of an additional organic farm on the conversion of new organic farms are higher for watersheds that have a higher density of dairy farms. Intuitively, this finding is consistent with our discussion in Section II, in that knowledge spillovers from one organic dairy farm have more outlets to spillover to when occurring on landscapes with a higher density of farmers.

VI. CONCLUSION

Economists have long been interested in the logic and patterns of technology adoption and diffusion. Despite a long and heralded tradition of research on the determinants of technology adoption, spatial spillovers across economic agents that might shape adoption choices, and especially clustered use of the technology, have been given very little explicit attention at conceptual, empirical, or econometric levels. This article provides an integrated approach to the issue by examining the role of spatial spillovers in organic dairy farming in southwestern Wisconsin, a region that has led the way during the past decade of dynamic growth in the use of this "clean" technology. To the extent that governments or nongovernmental organizations are interested in promoting such clean technology for environmental purposes, developing an understanding of the presence of spatial spillovers in the adoption decision can provide policy-relevant insights.

At a conceptual level, the article makes the basic point that in a real options model of sunk costs and uncertainty, the potential role of economic agents learning from other neighboring adopters can reduce both uncertainty and the fixed costs of information acquisition associated with a new (farm) system. In addition, we argue that there are competing explanations for spatial spillovers, including positive or virtuous ones, such as learning or reciprocity, negative or vicious ones, such as contaminants or damage to valuable inputs, and spurious ones, such as proximity to a buyer or a correlated unobservable.[28] Perhaps

[28] Rapid expansion of organic agriculture would also

the more subtle point though is that the outcomes associated with spatial spillovers can vary within the same sector, such that one local neighborhood could experience a virtuous cycle of learning and reciprocity that advances rapid adoption of a high-return technology outcome, while another could not. Path dependence and nonlinear processes underscored in the work of Arthur (1994), Krugman (1995), and David (2007) thus have an explicit microspatial foundation in technology adoption contexts, such as the one we have introduced here based on sunk costs, uncertainty, and learning.

Our empirical contribution is to construct a unique spatial panel dataset of organic conversion decisions and use that dataset to identify the presence of spatial spillovers using panel data techniques to account for both observed and unobserved spatial effects that could otherwise confound the analysis of organic conversion decisions. A novel aspect of our econometric model is the spatially explicit specification of the correlated random-effects model. Its structure mirrors the real option model set forth in the paper by considering the conversion decision in each time period for a conventional dairy farmer. The results show that while other spatial and local variables matter, the presence of neighboring organic dairy farms is a statistically and economically significant explanatory measure in the conversion decision. The simulation exercise we construct from the empirical data and econometric estimates shows that spatial spillovers are sensitive to initial conditions, the number of early adopters in the region, and the density of dairy farms, with a strongly nonlinear dynamic at play that can drive a clustered technology diffusion process. In the case of southwestern Wisconsin, while many neighborhoods (or watersheds) had the underlying spatial conditions for organic dairy conversion, our results suggest that the presence of an early adopter or two may have swung the balance between a cluster of dairy farms converting to organic or remaining conventional. The potentially stochastic nature of this process is suggestive that path dependence could play an important role in shaping technology adoption behavior, at least in certain situations where the barriers to conversion are high. Lastly, while our results provide quantitative evidence of the presence of a spatial spillover in the adoption of organic dairy farming, further research is needed to provide a behavioral identification of why these spatial spillovers arise in the adoption of this technology.

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raise the demand for organic inputs. However, such an increase in demand may not necessarily lead to higher input prices for others if the market for organic inputs is initially thin.

APPENDIX

TABLE A1
Econometric Parameter Estimates (Probit)

	All Data		Years 1998–2005		Years 2000–2005		Years 2002–2005	
Constant	− 0.32	(0.50)	− 0.25	(0.48)	− 0.75	(0.47)	− 1.26*	(0.50)
Soil quality	− 0.04	(0.12)	− 0.07	(0.12)	− 0.01	(0.12)	− 0.14	(0.14)
Distance to OV	− 0.06*	(0.01)	− 0.06*	(0.01)	− 0.03*	(0.01)	− 0.014*	(0.01)
Organic farms within 5 miles	0.73*	(0.15)	0.47*	(0.11)	0.37*	(0.10)	0.52*	(0.18)
Organic farms between 5 and 10 miles	0.98*	(0.14)	0.66*	(0.09)	0.4*	(0.07)	0.68*	(0.16)
Structure	− 0.00012	(0.0009)	− 0.0002	(0.0009)	− 0.00078	(0.0010)	− 0.00118	(0.0009)
1996	0.4	(0.47)						
1997	0.74	(0.45)						
1998	0.29	(0.45)						
1999	0.33	(0.45)	0.18	(0.24)				
2000	0.4	(0.44)	0.28	(0.23)				
2001	0.35	(0.44)	0.08	(0.25)	− 0.28	(0.15)		
2002	− 0.15	(0.59)	− 0.38	(0.27)	− 0.62*	(0.17)		
2003	0.04	(0.46)	− 0.49	(0.28)	− 0.86*	(0.24)	− 0.22	(0.20)
2004	− 0.84	(0.50)	− 1.21*	(0.36)	− 1.33*	(0.33)	− 0.9*	(0.39)
2005	− 3.17*	(1.00)	− 3.14*	(0.73)	− 2.74*	(0.63)	− 2.81*	(1.00)
Avg. Organic farms within 5 miles	− 1.94*	(0.40)	− 1.14*	(0.17)	− 0.54*	(0.15)	− 0.54*	(0.19)
Avg. Organic farms between 5 and 10 miles	− 2.52*	(0.38)	− 1.14*	(0.17)	− 0.48*	(0.10)	− 0.7*	(0.17)
Number of observations	20,299		14,611		10,882		7,203	

Note: Standard errors (in parentheses) are bootstrapped with 500 replications and clustered by farm.
* Significantly different from zero (95% confidence level).

TABLE A2
Econometric Parameter Estimates (Logit)

	All Data		Years 1998–2005		Years 2000–2005		Years 2002–2005	
Constant	0.12	(1.20)	1.45	(1.30)	0.3	(1.22)	− 1.49	(1.28)
Soil quality	− 0.11	(0.25)	− 0.27	(0.27)	− 0.17	(0.30)	− 0.47	(0.34)
Distance to OV	− 0.15*	(0.02)	− 0.15*	(0.02)	− 0.095*	(0.02)	− 0.039	(0.03)
Organic farms within 5 miles	1.83*	(0.44)	1.25*	(0.32)	1.10*	(0.26)	1.68*	(0.50)
Organic farms between 5 and 10 miles	2.5*	(0.36)	1.76*	(0.20)	1.12*	(0.17)	2.00*	(0.37)
Structure	0.0002	(0.0020)	− 0.0003	(0.0021)	− 0.0025	(0.0028)	− 0.0031	(0.0024)
1996	0.99	(1.10)						
1997	1.9	(1.09)						
1998	0.94	(1.11)						
1999	0.85	(1.10)	0.32	(0.81)				
2000	0.81	(1.10)	0.48	(0.76)				
2001	1	(1.11)	0.03	(0.81)	− 0.66	(0.42)		
2002	− 0.32	(1.23)	− 1.18	(0.89)	− 1.52*	(0.43)		
2003	− 0.4	(1.31)	− 1.96	(1.08)	− 2.62*	(0.73)	− 0.73	(0.69)
2004	− 2.9*	(1.23)	− 4.09*	(1.14)	− 4.18*	(0.91)	− 3.13*	(1.18)
2005	− 9.6*	(2.57)	− 9.54*	(1.91)	− 8.42*	(1.50)	− 9.47*	(2.65)
Avg. Organic farms within 5 miles	− 4.6*	(1.10)	− 2.31*	(0.59)	− 1.57*	(0.38)	− 1.70*	(0.52)
Avg. Organic farms between 5 and 10 miles	− 6.46*	(0.99)	− 3.06*	(0.40)	− 1.35*	(0.24)	− 2.07*	(0.40)
Number of Observations	20,299		14,611		10,882		7,203	

Note: Standard errors (in parentheses) are bootstrapped with 500 replications and clustered by farm.
* Significantly different from zero (95% confidence level).

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