The Diffusion of the H-2A Temporary Agricultural Workers Program: A Spatial Econometric Approach

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Abstract

Specialty crop producers in the United States remain highly dependent on labor, yet willing and qualified workers in the domestic labor market are increasingly difficult to find. For this reason, the H-2A temporary agricultural workers program, which allows US agricultural producers to bring in foreign workers on a seasonal basis, has seen exponential growth over the last decade. This analysis considers the different factors driving H-2A program participation across the US. We model the H-2A program as a technology modifying growers' production outcomes. As such, we find that program participation follows a diffusion process similar to other types of technology. Specifically, we use spatial econometric methods (dynamic spatial Durbin model) to model the intensity of H-2A program participation across all counties in the continental United States. We control for contagion effects: defined as the phenomenon where an individuals' neighbors' participation positively influences his or her own participation in the program. Results indicate the intensity of program participation at the county level is positively affected by the intensity of program participation in neighboring areas. These findings imply that program stakeholders can further increase participation in underserved areas by strategically targeting locations with outreach programs.

1. Introduction

Labor shortages are a persistent issue in the U.S. agriculture sector (Martin P. , 2007). Specialty crop growers are especially vulnerable to shifts in the labor supply curve, because of their reliance on manually intensive production techniques. The federal government administers the H-2A temporary agricultural workers visa program, to remediate the negative effects of labor shortages. The H-2A program provides firms with access to foreign workers on a seasonal basis.

H-2A program usage levels have increased significantly in recent years. A growing number of producers are opting to meet their labor needs partially or exclusively with H-2A workers. This rapid growth in the aggregate number of H-2A visas requested by U.S. growers has garnered the attention of policy analysts and academic researchers. However, there is still much to explore about the factors motivating individual firms to participate in the. Program usage rates vary widely by geography, with growers in certain states (e.g. North Carolina and Florida) consistently employing higher numbers of H-2A workers than growers in more manual labor reliant regions such as California.

This research contributes to the literature on the H-2A program by using spatial econometrics to model the intensity of program participation across the US. A dynamic spatial Durbin model is applied to a balanced panel of all counties in the coterminous United States. We estimate the number of visa positions certified within counties, while controlling for spatial relationships, and demographic and economic characteristics. We detect the presence of contagion effects and estimate their magnitude by decomposing the direct and indirect effects. We determine that several factors contribute to the intensity of program participation within counties including the intensity of neighbors' participation in the program, the county unemployment rate, and agricultural production levels.

Our finding that intensity of program participation within each US county is significantly and positively affected by program usage in adjacent counties has important implications for program administrators and farm labor researchers who seek to expand program participation and forecast usage levels. Some relevant findings from this research include:

1) A contagion effect suggests that agricultural producers have incomplete information regarding the H-2A visa program. Many producers only begin using the program after they observe others in their professional and geographic networks using it. Anecdotal evidence suggests these benefits include access to a reliable and legal workforce and higher production levels (Roka, Outlook on Agricultural Labor in Florida, 2012-13, 2014). Additionally, some producers wait to begin using the program because learning how to navigate it is a substantial opportunity cost in terms of their time. Thus, producers first learn how to use the program through observing their neighbors and then rely on those neighbors' shared advice about how to navigate the certification and visa processes. This gap in potential users' knowledge of the H-2A program suggests program administrators may be able to increase participation in under-served areas. Program advocates may be able to expand participation by strategically targeting underserved regions. More specifically, program administrators can work with extension educators to identify those employers that are likely to benefit from the program in the short term and hold enough influence within their professional/geographic networks to stimulate subsequent adoption of the program by their peers.
2) By demonstrating the presence of contagion effects, we set a precedent for future research oriented towards forecasting program expansion. The H-2A visa program is a primary focus in contemporary discussions of U.S. agricultural labor policy. Frequent news articles

and academic reports discuss the program and its rapid growth, including in regions where usage was previously minimal (Carlson, 2018) (Mohan, 2017) (Pellechia, 2015) (Arcury, Summers, Talton, & Nguyen, 2015) (Martin P. , 2017). Although it is not yet clear to what extent the specialty crop sector will become reliant on H-2A workers, present trends suggest that guest workers will eventually be the majority across crop categories. Taylor and Charlton (2012) predicted that although U.S. agricultural will remain dependent on foreign workers in the years ahead, demand will eventually exceed supply, as the already waning surplus of crop workers in Mexico suggests. To better anticipate changes in program usage at the national and regional level, program administrators and policy analysists can forecast through econometric modeling techniques. Our findings suggest that subsequent attempts to predict program usage at the regional level should consider and control for contagion effects.

3) It has been proposed that interruption of migration flows from Mexico due to tightened border security and interdiction have caused the agricultural labor supply to become less elastic in recent years. Tightened border security may lead to more apprehensions of undocumented migrants and programs such as e-verify implemented at the state level discourage employers from hiring migrants without work authorization. A decrease in the elasticity of the domestic agricultural labor supply is likely to correspond with an uptick in demand for H-2A workers thus, we control for enforcement against undocumented migration (apprehensions of illegal aliens) and e-verify. Our failure to find significant correlation between interdiction of undocumented migration and intensity of program participation at the county level, suggests that the flow of migrants and e-verify programs are weaker determinants than has been postulated.

The remainder of this paper is structured in the following manner: First, we provide background on the H-2A program and conduct a short literature review on the role of social learning in technological diffusion. Next, we describe the data and detail the empirical model used in this estimation. We then discuss the results of the analysis. Lastly, we summarize our findings with some concluding remarks.

2 Background

We develop the rationale for this research by providing a brief review of the history of the H-2A temporary agricultural worker visa program. We describe how the program is administered, explain important program rules, and review some of the research on H-2A workers and related agricultural labor topics. We conclude this section with a review of the literature on social learning and social contagion as it relates to our modeling approach.

2.1 Agricultural Labor Policy

The agricultural workforce in the United States has undergone major changes over the last century, with the general trend being movement out of agriculture and into the manufacturing and service sectors. For the most part, this shift has been a natural consequence of technological advances making agricultural production less labor-intensive (Mankiw, 2017). The fact that there are fewer farmworkers available today than in decades past is not a problem for most capital-intensive industries (e.g. grain farmers), however, labor shortages frequently reported with labor intensive specialty crop industries (Oliveira, Effland, Runyan, & Hamm, 1993).

In 1920, an estimated 30% of the U.S. workforce was employed in the agricultural sector, the majority working in small-scale labor-intensive agriculture (Lebergott, 1966) (Dimitri, Effland, & Conklin, 2005). By this time, however, a "regular exodus" from agriculture had already begun with hired farm workers (many of them African American) leaving crop-work in the rural South for better paying jobs in urban centers (Wilkerson, 2011). Improvements in technology had also begun displacing farming families, as their small operations became less competitive against rapidly expanding large-scale capital intensive agricultural. Additionally, restrictions placed on immigration during World War I lead to farm labor shortages, prompting the U.S. government to enter into a bilateral agreement with Mexico: the "braceros program". Although relatively short-lived, the "braceros program" (1917-1921) set a precedent for labor relations between the United States and its southern neighbor, with Mexican migrants under the program receiving temporary authorization to work for U.S. agricultural producers (Philip, 2003). This first "braceros program" was discontinued due to the Mexican governments' dissatisfaction with the treatment and inferior wages its people received in the United States (Rural Migration News, 2006).

During World War II, labor shortages once again became a significant problem in the US. agricultural sector. In response, the federal government reinstated the braceros program (1945-1964), allowing for the controlled entry of Mexican migrant workers on a seasonal basis. This second iteration of the "braceros program" is credited with establishing the migration flows that persist to this day from Mexico to the United States and helping to institutionalize U.S. dependence on labor from Mexico (Taylor & Thilmany, 1993). The "braceros program" was eventually replaced by the H-2 visa program in 1964, which was in turn converted to the current H-2A visa program in 1986. Although individuals from diverse nationalities can be hired through the H-2A visa program, the majority of visa recipients are from Mexico. Thus, one can argue that the current H-2A visa program is only the most recent iteration of a long-standing tradition of the U.S. federal government facilitating the transfer of Mexican human resources to United States employers.

Today, the percentage of Americans employed in the agricultural sector is only a small fraction of what it was in 1920, yet production levels in the U.S. have grown substantially. This increase in crop output from a century ago is mostly due to technological advances including higher yield crop strains and mechanization (e.g. tractors and combines) (Dimitri, Effland, & Conklin, 2005). Despite this trend, the cultivation and harvest of specialty crops in the United States remains highly dependent on manual labor (Huffman, 2005); specialty crops, which include most fruits and vegetables as well as ornamentals, where mechanization damages soft tissue and opportunities to sell into a fresh produce market. It is often difficult for producers to find enough workers who are willing to work at the wage rates they can offer. While the wage rate for farm labor varies by location and industry, average self-reported earnings of workers interviewed in the 2013 national agricultural workers survey were $10.19. The federal minimum wage in 2013 was $7.25 per hour. Nineteen states and the District of Columbia set higher minimum wage rates, ranging from $7.35 in Missouri to $9.19 in Washington (GovDocs, 2013 https://www.govdocs.com/2013-state-and-federal-minimum-wage-rates/, accessed July 6, 2018).

It is not uncommon for employers to further increase wage rates during labor shortages, but the evidence suggests these wage hikes are met with mixed success (Morris, 2017). The labor supply appears to be inelastic within the threshold of wages that agricultural producers are able to offer their employees. This inelasticity of the agricultural labor supply is likely a symptom of waning interest in agricultural work among the low-skilled workforce (Clemens, 2013).

Even among the US foreign-born workers, occupational migration out of agriculture is common. Research on the effect of an IRCA (1986) policy providing legal work-authorization to many of the nations' undocumented migrants, confirms that a significant number of farm-workers leave agriculture for the service sector when given the opportunity (Martin P. , 1994; Taylor &

Thilmany, 1993; Tran & Perloff, 2002). Nonetheless, agricultural labor economist Philip Martin (2007) suggested that labor shortages in the agricultural sector are much less frequent than the media portrays, and often amount to momentary delays in the adjustment of wages to shifts in the labor supply curve (Martin P. , Farm Labor Shortages: How Real? What Response?, 2007). Whether labor shortages in the agricultural sector are best solved through natural market mechanisms (e.g. wage hikes) or through increasing the supply of low-skilled workers via institutionalized migration is a matter of debate among politicians and policy analysts. It is notable, however, that despite labor shortages, farm-work remains among the lowest paid occupations in the United States, with estimated mean average hourly wages of $11.41 and mean annual earnings of $23,730 for full-time crop-workers in 2017 (BLS, 2017).

Official figures from the Bureau of Labor Statistics for the year 2017 indicated that less than 2.45 million people were employed in agriculture and related industries: less than two percent of the workforce (150 million). This figure includes individuals employed in industries related to agriculture, such as sales of agricultural products and food processing. Data disaggregated at the occupational level reveals that an even smaller fraction of those employed in the agricultural sector work directly in crop and livestock production.

Table 1 | Number of Hired Farm Workers Employed in U.S. Agriculture

Year	Av. # of Hired Farm Workers	# of H-2A Positions Certified	# of H-2A Visas Issued	% Farm Work Positions Filled by H-2A
1997	879,000	--	16,011	2%
1998	879,500	--	22,676	3%
1999	923,250	--	28,568	3%
2000	887,750	--	30,201	3%
2001	873,250	--	31,523	4%
2002	884,500	--	31,538	4%
2003	836,000	--	29,882	4%
2004	824,750	--	31,774	4%
2005	777,750	--	31,892	4%
2006	751,250	59,110	37,149	5%
2007	789,667	76,814	46,432	6%
2008	730,750	82,099	64,404	9%
2009	739,250	86,014	60,112	8%
2010	762,500	79,011	55,921	7%
2011	754,667	77,246	55,384	7%
2012	775,250	85,248	65,345	8%
2013	777,250	98,821	74,192	10%
2014	712,500	116,689	89,274	13%
2015	737,250	139,832	108,144	15%
2016	730,750	165,741	134,368	18%
2017	731,250	200,049	161,583	22%

1. Source USDA NASS Farm Labor: average calcuated from quarterly employment estimates
2. Source US DOL H-2A Disclosure Data: total number of H-2A positions for the calendar year
3. Source US Department of State Non-Immigrant Visa Statistics

H-2A positions are certified only for jobs that work directly in production, such as crop-workers, livestock workers and ranchers. By program rules H-2A positions must be seasonal in nature and cannot last for an entire year. An individual H-2A visa recipient can be certified to perform more than one job as long as the sponsoring employer files a separate application for each position the worker is to perform. The total number of H-2A positions certified by the DOL each year, generally exceeds the aggregate number of H-2A visas issued by the U.S. department of state because in many cases a single H-2A visa corresponds to multiple certified H-2A agricultural positions. The USDA National Agricultural Statistics Service (NASS) provides quarterly estimates of the number of hired farm workers in the United States (annual averages are presented in column 2 of the Table 1). One can roughly estimate the impact of the H-2A program on hired farm labor at national level by comparing the number of H-2A visas issued by the Department of State each year with the corresponding annual estimates of total hired farm workers in the U.S. In column 5 of Table 1 we express the number of H-2A visa recipients as a percentage of total hired farm workers since 1997and a clear trend emerges: the percentage of hired farm workers in the United States who are H-2A has increased substantially over the last 20 years. As the NASS data are aggregate estimates of hired farm workers in all occupational and crop categories one can assume that the influx of H-2A workers is even more pronounced in certain occupational categories. Other evidence suggests H-2A workers are rapidly becoming the majority of harvest workers in certain industries. Results from a survey of Florida a citrus workers suggest that as many as 80% of citrus harvest workers in the state were H-2A by 2016 (Simnitt, Onel, & Farnsworth, 2017).

The H-2A visa program is administered by the U.S. Department of Labor (DOL). By design the program provides agricultural employers access to foreign workers given the employers were unable to fully staff their work crews with labor from the domestic workforce. The application process from start to finish can last several months, as employers need to demonstrate they already sought to hire domestic workers and offered jobs to all domestic workers who would accept. Program rules dictate that applicants (employers) submit a separate application for each job type they plan on filling with H-2A workers and for each city where the work will take place. These application data are publicly available on the DOL website, and include employers' names, their contact information, the types of crop/task they are hiring workers to perform and the compensation they will pay each worker.

In addition to the filing fee ($460) for each application, sponsoring employers incur significant costs per H-2A worker. Additional costs for each H-2A worker include paying for transportation for the worker from and to their country of origin, providing housing for the worker during the contract of employment, and providing meals when cooking facilities are not available. Roka et al (2017) estimated that the additional cost associated with employing each worker through H-2A program is approximately $2000 per worker. Further, sponsoring employers are required to pay their H-2A workers for at least 75% of the duration of their contract regardless of unforeseen changes in production. This rule mandating employers to keep paying their workers for at least 75% of the compensation stipulated in the contract, barring 'an act of God', is referred to as the three-quarter guarantee rule.

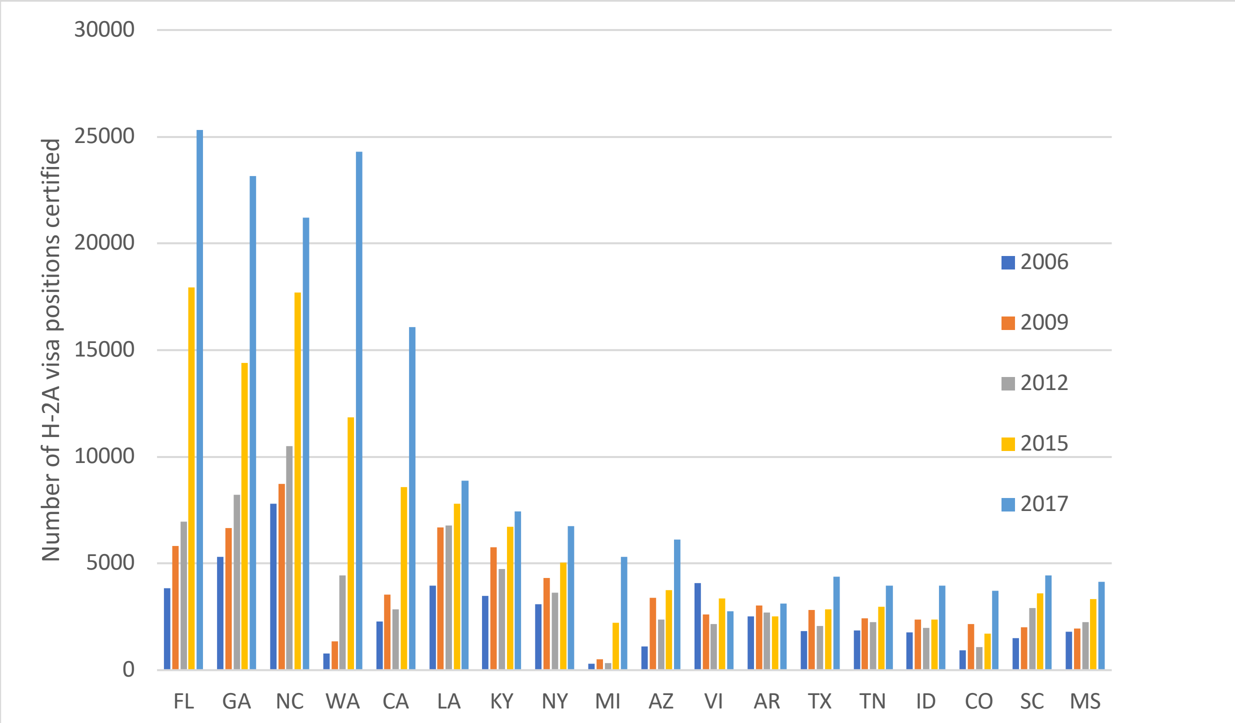
In 2012 program administrators implemented a new rule, commonly referred to as the '60 minute rule'. The '60 minute rule' mandates that employers work their H-2A employees at jobsites only within a 60 minute drive from their workers' housing (Fritz, Simnitt, & Farnsworth, 2017).

Thus, employers who have work sites beyond a 60-minute driving radius of their existing housing, have to provide a second housing complex within the 60-minute radius of those sites. A firm must submit a separate job order for each housing location, because each application is tied to only a single housing address. Roka et al (2017) found that the '60 minute rule' resulted in higher costs to many employers due to multiple application fees per worker.

It is understandable that some employers have been reticent to use the program, given these additional costs and regulations. Additionally, potential users have indicated that they find the program bureaucratically cumbersomeness and difficult to navigate (ISIM, 2014). Nonetheless, the growth of participation in the H-2A program suggests that a growing number of producers experience a net benefit from employing H-2A workers.

The US Department of Labor publishes an annual report detailing program participation by state and other descriptive statistics, including the names of the top ten employers hiring the largest number of workers, and principal crops for which workers were hired. Also published is a list of the top ten visa requesting states. While some states including Florida and North Carolina consistently place among the top 10 in number of H-2A visa positions certified, there is considerable movement in the ranking of visa requesting states over the last decade. Only in the last two years (2016–2017) has California placed among the top ten visa requesting states. California leads the nation in specialty crop production, which suggests H-2A program usage levels do not necessarily coincide with production levels (USDA NASS, 2012). Figure 1, shows the variation in the number of visas requested across years for 18 states.

Figure 1 | Top 18 H-2A Visa Requesting States (2006-2017)



Demand for H-2A workers is especially pronounced in the U.S. Southeast, which included six of the top ten H-2A visa requesting states in 2017, however, usage is growing within virtually all regions of the country. The number of H-2A positions certified by the U.S. Department of Labor has increased every year since 2011, with an overall increase of 158% between 2011 and 2017 (OFLC, 2017). Data for the second quarter of 2018 shows the number of certified H-2A positions surpassing the second quarter from the previous year by 16% (OFLC, 2018). Present trends suggest that program participation is not only increasing but accelerating. Researchers propose this growth in program demand is driven by a shrinking domestic labor supply and possible employer preference for legally documented workers (Charlton, 2017; Pullano, 2017).

There was considerable change in the allocation of H-2A workers among crop categories between the years 2012 and 2017. The percentage of total H-2A positions certified for work with berries (blueberries, strawberries, blackberries, raspberries etc.) increased from 5% to 12% of all

H-2A positions certified during this period. Similarly, the percentage of H-2A positions certified for work with apples increased from 4% in 2012 to 8% in 2017. Apple and berry farmers' increased demand for H-2A workers, may help explain the ascension of Washington and Michigan states to among the top 10 H-2A visa requesting states in 2017.

U.S. agricultural policy is of special concern to researchers interested in migration issues. García-Colón (2017) found that from the late 1970's to early 1980's, Puerto-Rican migrants that moved to the U.S. mainland to work in apple production were disadvantaged by the H-2 guest-worker program. He concluded that the H-2 program gave employers access to Mexican labor, the growers' 'preferred class of worker', despite a growing pool of legally authorized workers from Puerto-Rico (García-Colón, 2017). Onel and Goodwin (2014), modeled inter-sectoral migration (migration out of agriculture) using a real options value model. They found that land appreciation values are a significant predictor of migration out of agricultural. They also found that wage differentials are a significant predictor of migration out of agriculture after a given threshold. Based on their findings, mandated wages rates (e.g. the adverse effect wage rate), and government policies which indirectly affect land values are two examples of policies that may influence migration. In their assessment of trends in the North American agricultural labor market, Taylor and Martin (2012) reported growing demand among U.S. growers for workers with legal authorization. At the same time, they note diminishing local labor supplies and increased reliance on foreign workers. They predict that the future supply of labor in Mexico and Central America will eventually be inadequate to meet North American growers demand, thus U.S. producers may turn to Asia for additional labor sources.

There are only a handful of studies to date that use quantitative methods in their analysis of H-2A visa program. Apgar (2015) used an OLS regression to examine wage differentials between guest workers (including H-2A workers), undocumented Mexican migrants, and Mexican immigrants with legally protected status (LPS). She found that, while guest-workers earn significantly less than LPS workers, they earn more than their undocumented counterparts. This difference in the compensation received by H-2A workers and undocumented workers is even more pronounced after one factors in the additional housing benefit H-2A workers receive.

Wu and Guan (2016) proposed a model for estimating the optimal labor decisions in agriculture. They estimate demand for H-2A workers vs. the demand for domestic workers among strawberry farmers within a dynamic optimization framework. They find that relaxing the three-quarters guarantee rule will significantly increase strawberry farming profitability. They also find that an increase in the minimum wage rate to AEWR levels will eliminate the demand for domestic workers, as domestic workers lose their cost competitive advantage over H-2A workers.

The H-2A temporary agricultural workers program institutionalizes a long-standing economic relationship between the United States agricultural sector and human resources in less developed countries. For reasons that are not entirely clear, the number of H-2A visa positions requested by producers has surged over the last decade. While there are numerous studies that examine agricultural labor in the United States, few directly address the H-2A program.

2.2 Contagion

Social contagion in the behavioral and political sciences denotes when an individual's level of knowledge, behavior, or opinion is affected by that of his or her closest associates, often resulting in partial or total conformity to external influences. Just as a disease spreads from one individual to another, so too do social and behavioral phenomena spread among network nodes. Researchers have examined contagion effects in applications as diverse as marketing, political science, sociology, and economics. Social learning, a specific type of social contagion, occurs when knowledge is passed from one individual to another along network paths. Imitation occurs when an individual in a network copies the behavior of one of her peers without direct knowledge sharing. Social learning is distinct from imitation albeit difficult to separate (Andrew, 2017). In the present application we broadly interpret our findings of contagion to include both imitation and social learning. We begin this section by describing how social contagion has been modeled in the general literature and then move to more specific applications in agriculture.

Perhaps the most classic representation of contagion models in the economic literature is the study of how covariate shocks diffuse among financially codependent nations (Aloui, Safoune Ben Aissa, & Nguyen, 2011; Forbes & Rigobon, Measuring Contagion: Conceptual and Empirical Issues, 2017). Similarly, contagion has been modeled in the diffusion of political initiatives across regions. Pacheco (2012) modeled the diffusion of anti-smoking legislation across U.S. states using a logistic regression model. She observed that individual states were more likely to adopt anti-smoking legislation given one of their adjacent neighbors had adopted similar legislation in the preceding period. She found the effect to be significant irrespective of other covariates.

Williams and Whitten (2014), estimated the effects of spatial contagion on political parties' performance during parliamentary elections. They use a spatial autoregression model to estimate the change in the percentage of votes for each party between election cycles. They compare results from a pre-spatial regression with those of their SAR model. They find evidence of strong contagion effects in party competition during low-clarity elections.

From a theoretical perspective contagion effects also exist in the context of technology adoption by farmers. Once a new technology becomes available, and potential adopters are informed, the cost to benefit ratio at the individual level is usually unknown. Thus, while a producer may have a relatively clear idea of the costs associated with a new technology the potential benefits to her own operation are less apparent. Thus, an individuals' decision to adopt may be based in part on the assessment of the observed benefits to similar peers within her network.

Studies have considered how agricultural producers' decisions to adopt technologies are influenced by social interactions. Most of this research, examining technology adoption by agricultural producers, has looked primarily at interactions within the family unit (Ramirez, 2013) (Smith, et al., 2007). Feder and Slade (1985) and Smith et al (2007) are among those to examine the influence of extended peer networks on agricultural producers' adoption decision. They found that agricultural producers were more likely to adopt improved irrigation technologies, after acquiring knowledge by word of mouth from peers in their network. In a study examining the role of networks in technology adoption among farmers Ramirez (2013) found that once a tenant successfully implemented a new technology other tenants who leased from the same landowner were likely to implement the new technology. Additionally, she found that participation in external clubs and associations encouraged the adoption of technology as farmers acquired the requisite knowledge through other network members.

In his study of social learning among Kenyan farmers, Crane-Droesch (2017) modeled diffusion rates of biochar adoption among small scale agricultural producers via a Generalized Additive Model. He developed an equation to model the individual firm's adoption decision, wherein he expresses the binary decision of whether to adopt in terms of a two-moment utility function. We reproduce Crane-Droesch's adoption equation here, given its usefulness in the present conceptual framework.

$$(1) \quad Adopt_i = \mathbf{1}(\alpha + \hat{\mu}^{\theta_1} - \hat{\sigma}^{\theta_2} + \boldsymbol{Z\Gamma} + \epsilon > 0)$$

Where μ and σ are beliefs about the expectation and standard deviation of the profitability, and θ_1 and θ_2 define risk preferences. The matrix $\boldsymbol{Z\Gamma}$ represents other covariates contributing to the producer's decision. If the summation of the covariates $\alpha + \hat{\mu}^{\theta_1} + \boldsymbol{Z\Gamma} + \epsilon$ exceeds the variability in profits based on the individual's risk preferences, $\hat{\sigma}^{\theta_2}$, the producer adopts the technology. We assume producers' beliefs regarding future profitability (μ) are firmly rooted in observation of their early adopting neighbors' outcomes. Thus, producers who observe their neighbors achieving higher yield with adoption are more likely to adopt the technology themselves. Ultimately, Crane-Droesch found that the strength of social linkages between primary and secondary adopters was a major determinant of whether the latter began applying biochar to their fields in subsequent harvests.

Although not a physical technology, the H-2A agricultural workers program is a process designed to improve both administrative and production outcomes at the firm level. Thus, one can consider the H-2A program in the same vein as other technological improvements. While a firm can estimate the additional costs associated with contracting and employing workers through the H-2A visa program in a straightforward manner, it is less clear how benefits derived therefrom translate to revenue and profit. There is reason to suspect that potential users look to other individuals in their network prior to using the program. While the data in this analysis do not allow us to directly represent social networks, we use geographic closeness as a proxy for social proximity, wherein contiguous US counties are treated as connected nodes within a larger network.

The measurement of contagion is related to the spillover effects inherent in many causal models. Spillover occurs when one individual's outcome due to a treatment is inadvertently affected by the treatment status of other nearby individuals. Miguel and Kremer (2004) provided a clear example of spillover effects in their study of deworming efforts at primary schools in

Kenya. They showed that many students in attendance at schools in the control group, indirectly benefitted from deworming treatments at nearby schools, because the deworming of their neighbors in the treatment group reduced the overall incidence of infected individuals within their geographic environment. As spill over-effects can lead to biased estimates of the explanatory variables, researchers have developed methods to eliminate spill-over from parameter estimates, including controlling for proximity to other treated individuals (Sinclair, McConnell, & Green, 2012; Miguel & Kremer, 2004). By design, spatial econometric approaches allow for the control and estimation of spill-over effects. Contagion models are structured to isolate and then decompose the contagion effect into direct and indirect effects to interpret the magnitude of the contagion. Imai and Jiang (2017) demonstrate how to decompose direct and contagion effects from the average spill over effect in their study examining the influence of family relationships on voter turnout.

In summary, we consider the H-2A visa program akin to other forms of technology designed to improve production outcomes for U.S. agricultural producers. As with other types of technology, where adoption is voluntary, producers decide on whether to begin using the program based on their assessment of its net benefit to them. We suspect that contagion effects factor into the individual firm's decision to use the program. How we go about controlling for and estimating contagion effects is explained in greater detail in the following section.

3 Data and Methods

We begin this section by presenting the empirical model methods used in the analysis. We detail the steps followed to arrive at the selection of the dynamic spatial Durbin model, and explain its components. Thereafter we provide a description of the data.

We justify our model selection based on other scholarship and best recommended practices in the spatial econometrics literature. In the decades since Jean Paelinck (1974) introduced the term, spatial econometrics has grown in popularity in the quantitative social sciences. The main tool of the spatial econometrician is the spatial weights matrix. This weights matrix, which is included in the functional form of the model, allows for the control of spatial relationships between data points. In practice, the weights matrix is used to compute the spatial lag of the dependent variable, error term or a combination of both (Anselin L. , 1988).

A diversity of weights matrices are represented in the spatial econometric literature, but most fall into one of two categories: contiguity matrices or distance matrices. In our analysis, we select between a row-standardized queen contiguity matrix and an inverse squared distance matrix (Getis & Aldstadt, 2004). Distances were computed between county centroids in the latter, then squared to emphasize nearest neighbor relationships.

We first engage in exploratory analysis to confirm that spatial autocorrelation exists in the data set (Anselin, 1988). We check for spatial autocorrelation by estimating Global Moran's I statistics for individual cross-sections of the data (for a description of how Moran's I is computed see Appendix B). Thereafter we calculate and present the Local Moran's I (LISA) statistic in the form of a cluster map as demonstrated by Luc Anselin (1995). Anselin recommends the Local Moran's I as it provides a more nuanced view of autocorrelation among regions.

Upon detecting spatial autocorrelation we proceed with estimation of the main model of our analysis, a spatial Durbin model of the form:

$$(1)\ \mathrm{y_{it}} = \tau \mathrm{y_{it-1}} + \eta \mathrm{wy_{jt-1}} + \rho \mathrm{wy_{it}} + \beta \mathrm{x_{it}} + \theta \mathrm{wz_{it}} + \mu_\mathrm{i} + \varepsilon_{it}$$

where y_{it} is the dependent variable to be explained, y_{it-1} is the time-lagged dependent variable, $wy_{it-1}$is a space-time lagged variable, wy_{it} is the spatially-lagged dependent variable, x_{it} is a matrix of explanatory cofactors, wz_{it} is a spatially lagged matrix of explanatory cofactors, μ_i is a vector or matrix of individual effects and ε_{it} is the stochastic error terms. The parameters $\tau, \eta, \rho, \beta, and\ \theta$, correspond to coefficients that accompany each set of righthand side explanatory variables.

The spatial Durbin model is preferred for the present analysis as it contains the space-time lagged variable wy_{it-1}among its regressors. We operationalize contagion as the effect of intensity of neighbor's participation in the program in the past on own participation intensity in the present. Thus, we interpret the direct effect of the space-time lagged variable wy_{it-1}, on the dependent variable (intensity of program usage) as the contagion effect. Another advantage of the SDM is that it contains the Spatial Autoregressive (SAR) and spatial error (SEM) models nested within it. For a more detailed explanation of how to select from among these models see the appendix.

Due to the presence of feedback effects the coefficients $\tau, \eta, \rho, \beta, and\ \theta$ cannot be directly interpreted as the effect of a unit increase in the explanatory variable on y_{it}. For this reason, we calculate the marginal effects for each explanatory variable while holding others at their mean.[2] We decompose these marginal effects into their direct and indirect effects. Asymptotic t-statistics are computed via a bootstrapping method. The spatial Durbin model is estimated via a bias corrected quasi-maximum likelihood (QML) procedure. We apply Yu and Lee's (2010) first-difference transformation to the model equation to eliminate unstable elements.[3]

[2] Marginal effects for the coefficients derived in the SDM were estimated in MATLAB using a code adapted from Paul Elhorst (2013).

[3] Yu and Lee have demonstrated that the condition $\rho + \tau + \eta < 1$ in the estimation of dynamic spatial panels otherwise the model is non stable. As estimation of instable models is more complicated they recommend the removal of unstable elements by applying a first-differences transformation.

For interpretation of direct and indirect effects in spatial models, we look to the explanation put forth by Braz Golgher and Vass (2015). Direct effects are interpreted as the effect of a unit increase in a county's own explanatory variable x on its own dependent variable y. Indirect effects are interpreted as a unit increase in neighboring counties' explanatory variable x on the county's own dependent variable y.

We did not include a time-invariant variable controlling for each counties' distance from the border with Mexico. Whether a county's distance from Mexico has a significant effect on the number of H-2A workers is relevant for forecasting diffusion of the program. Nonetheless, best recommended practices preclude the inclusion of time invariant factors in fixed effects models (Elhorst, Zandberg, & De Haan§, 2013). Additionally, we exclude a variable controlling for the Hispanic proportion of the population in each county. The lack of variation in such a variable over time periods lead to convergence problems in estimation.

The approach for detecting and measuring the effect of social contagion on diffusion is contingent on data availability. In an ideal scenario, one would test for contagion within a clearly defined social network made up of program users and non-users. To our knowledge, no such data exists. Thus, we use program certification data aggregated at the county level and geographical proximity as a proxy for professional networks. Data are compiled from several sources: visa application data are from the Office of Foreign Labor Certification of the U.S. Department of Labor, demographic data are from the U.S. Census and Department of Labor and Agricultural production data are from U.S. Census Bureau.

Individual units of observation are all contiguous counties in the lower 48 United States (3107 individual counties and townships). Each county is observed over a 12-year period (2006-2017), bringing the total number of observations to 37,284. Each observation includes variables at the county year level, such as total H-2A positions certified by firms in each county, unemployment data, wage data, and crop production in terms of acres cultivated.

Intensity of program participation is defined as the number of H-2A positions certified by the US Department of Labor in a given county for that year. The data are disaggregated at the US county level, rather than at the individual firm level. Thus each unit of observation most often corresponds to the aggregate usage of multiple firms. Because the data are disaggregated at the county level, we are unable to precisely observe the entry of additional firms into the program in a given year. An increase in the number of total workers requested at the county level therefore may indicate that additional firms are beginning to use the program or previous participants are expanding their usage.

Contagion effects are of primary concern to this study. By demonstrating that the intensity of program participation within a county is positively correlated with intensity of program participation in neighboring counties, while controlling for other relevant variables, we aim to demonstrate the significance of geographic networks on program usage. To control for social-contagion effects we include several spatially and temporally lagged dependent and independent variables.

Critics of the H-2A program and other guest worker programs have argued that imported foreign workers depress wages and contribute to unemployment (Manzo IV, 2017). We test these assertations by including control variables for wages and unemployment in the regression model. We control for the county level average unemployment rate for all occupations. We also control for county level wages in the agricultural and construction sectors to test if program usage might inadvertently depress wages. If we find significant negative correlation between intensity of program participation at the county level and average county wage rates this lends support to allegations that the H-2A program may depress wages. Further, if we find significant positive correlation between unemployment rate and program participation rates this may lend credibility to the hypothesis that growth of the H-2A program contributes to unemployment, and thus warrant further investigation.

Median home price at the county level was included in the analysis in an attempt to control for the effect of housing availability on employer preferences for the program. According to H-2A program rules, sponsoring employers must provide their temporary workers with housing free of charge. We expect that this requirement for employers to provide free lodging to all H-2A employees raises total program costs precluding the participation of the most price-sensitive producers. Thus, agricultural producers in areas where low cost housing is harder to find may be among those less likely to employ H-2A workers.

Research has shown that there is a negative relationship between individuals' willingness to work as farm laborers and legal status, with undocumented migrants making up a plurality if not the majority of the U.S. domestic agriculture workforce. Thus, a substantial drop in the flow of undocumented migrants into the United States may lead to a decrease in the agricultural labor supply. We attempt to control for the flow of undocumented migrants by including a variable for the number of apprehensions by immigration enforcement agents as disclosed by the U.S. Customs and Border Patrol (CBP). The number of deportable aliens has been shown to track fairly well undocumented migration (Espenshade, 1995). The CBP reports annual totals of apprehensions for each of its 44 sectors across the country. In an effort to control for migration flow at the regional level we included total number of apprehensions at the nearest CBP sector for each given county and year.

There is evidence that a growing number of agricultural employers prefer legally authorized workers (Martin & Taylor, Ripe with Change: Evolving Farm Labor Markets in the United States, Mexico, and Central America, 2013). It is not entirely clear why there has been a shift in preference towards a legally authorized workforce, but government interdiction of hiring undocumented workers may play a role. Implementation of e-verify and similar programs designed to prevent employers in the public and private sectors from contracting workers without work authorization are examples of such interdiction. We attempt to control for government interdiction of illegal employment activities by controlling for the implementation of e-verify at the state level. A total of 20 U.S. States have implemented e-verify to date, with the Colorado being the first state to adopt the program in 2006 and Pennsylvania the most recent adopter in 2013 (Pennsylvania Department of Public Services, 2018) (Colorado Secretary of State Wayne Williams, n.d.).

We include variables to control for specialty crop production at the county level. We also include variables to account for the production of the following field crops: hay, cereals, corn, and soybeans. Further, we include a variable corresponding to the number of estimated crop worker positions for the given county in each year. We suspect that changes in production levels are positively correlated with the number of crop workers in the county, including H-2A workers. We expect higher specialty crop production levels to correspond to increased demand for workers, save in the case of citrus. Citrus production levels are declining across the country with the unabated spread of citrus greening disease. Roka (2012) suggested there is an inverse relationship between citrus production levels and demand for H-2A guest workers because greening disease makes the trees less resilient to mechanized harvesting techniques.

Annual production data at the individual state and county levels were gathered from the USDA's Cropscape project, a publicly available data source with crop acreage estimates at the county level. Cropscape data is compiled from satellite images of land cover in the lower 48 states and includes acreage estimates for over one-hundred different categories of vegetation. Also included in the model are the climate variables, average annual precipitation levels (in 0.10 mm units) and number of days per year where the temperature dropped below freezing (< 0 degrees Celsius). Minimum temperature and rainfall levels were included given the effect of climate on both yield and crop variety, which are important elements of production.

We seek to detect the presence and estimate the magnitude of social contagion on intensity of program participation within U.S. counties. We demonstrated that the spatial Durbin model is an appropriate approach given it allows for the estimate of direct effects of intensity of neighbors' participation in the preceding time period on own intensity of participation. Furthermore, the SDM allows for the simultaneous control of multiple cofactors, such as crop production, unemployment, wages, interdiction and migration flows and time effects. We have assembled data from various public sources for this research, always disaggregating at the county level when possible.

4 Results

In this section we present our primary research findings. We begin by describing and interpreting the results from tests for spatial autocorrelation. We then proceed with a discussion of the model estimation process and present the regression results. This is followed with a presentation and interpretation of the marginal effects computed from the preferred model: dynamic SDM with first-difference transformation. We conclude this section with a discussion of the potential policy ramifications of these findings.

The primary motivation behind this research is to identify which factors influence U.S. agricultural producers' usage of the H-2A temporary workers' visa program, and model diffusion of the program across U.S. counties. Specialty crop producers continue to remain dependent on manual labor for the bulk of their harvesting, thus, expansion of the program promises to be among the best methods for allowing growers to secure much needed workers. For reasons that are not entirely clear, certain regions in the country use the program at higher rates than elsewhere. Such is the case of North Carolina which led all other US states until 2016 in the number of H-2A positions therein. This was despite North Carolina having lower total agricultural output levels than Florida, California, and several other states.

We apply the same conceptual framework used in studies of technology diffusion to U.S. agriculture producers' decision to use the H-2A visa program. Upon identifying which factors contribute to individual firms' participation and usage rates, policy makers and program developers can implement strategies to increase participation in the H-2A program.

4.1 Test for Spatial Autocorrelation

The global Moran's statistic suggests strong spatial autocorrelation for intensity of program participation among US counties. In Table 2, Global Moran's I statistics are presented for the years 2008, 2011, 2014 and 2017. Randomized reference distributions were created with 999 permutations for each data year. All values generated with the nearest neighbor weight matrix are statistically significant. This finding is unsurprising given the natural clustering of agricultural counties in rural portions of the country. Conversely, urbanized counties with few farms and few or no agricultural workers often share borders. These global Moran's I provide strong evidence that program usage is not random among US counties. However, they reveal little about the nature of correlation between neighbors.

Local Moran I's clusters displayed in Figures 2–5 illustrate the nuances of spatial autocorrelation. Visual analysis of these local Moran's I statistics for the individual counties suggests strong directional correlation between units in terms of intensity of program participation. These clusters show especially pronounced usage of the program in the southeastern U.S. and Pacific states (California and Washington). As indicated in the key, bright red denotes positive autocorrelation among high intensity usage counties, while dark blue indicates positive autocorrelation among adjacent counties with low program usage levels. Chronological comparison of these cluster maps shows the relative growth of intensity of program participation within states.

Table 2 | Intensity of Program Participation: Number of H-2A Positions Certified per U.S. County (Global Moran's I Statistics for the Years (2008, 2011, 2014, and 2017)

Year	I	E(I)	SD(I)	Z-stat	Pseudo-p.value
2008	0.186	0.00	0.01	18.389	0.0000
2011	0.158	0.00	0.01	15.221	0.0000
2014	0.119	0.00	0.01	14.16	0.0000
2017	0.2	0.00	0.01	20.556	0.0000

Figure 2 | Intensity of Program Participation Local Indicators of Spatial Autocorrelation Moran's I (2008)

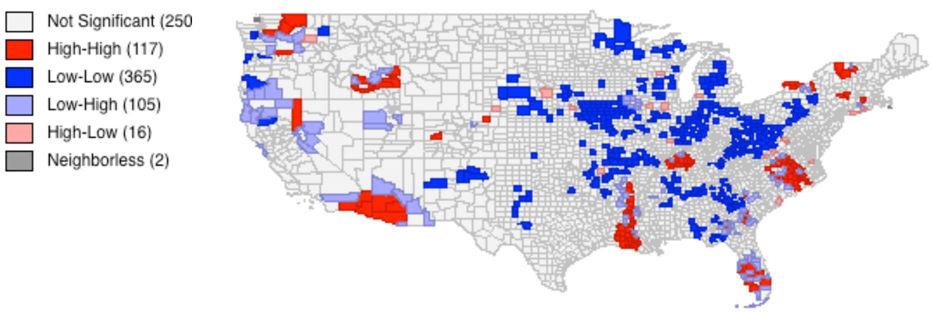


Figure 3 |
Intensity of Program Participation Local Indicators of Spatial Autocorrelation Moran's I (2011)

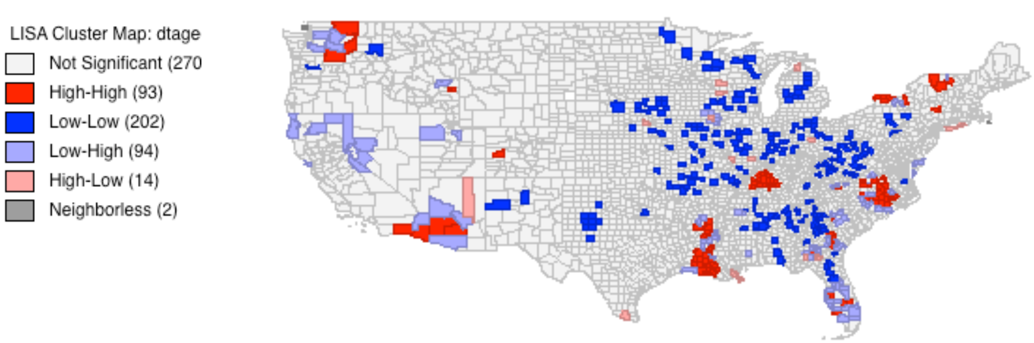


Figure 4 |
Intensity of Program Participation Local Indicators of Spatial Autocorrelation Moran's I (2014)

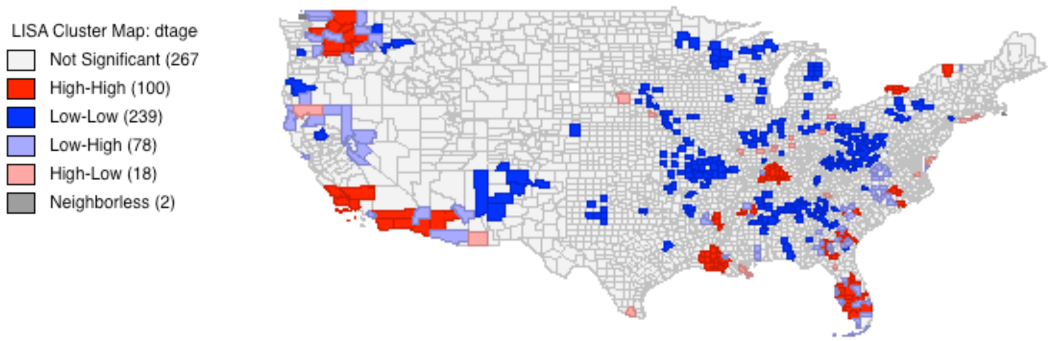
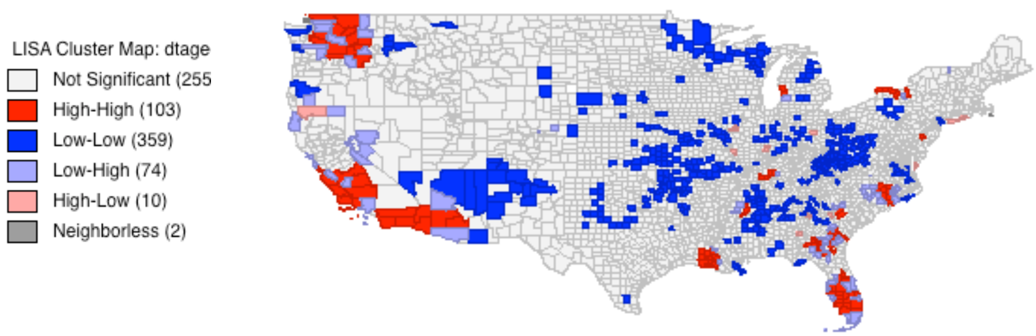


Figure 5 |
Intensity of Program Participation Local Indicators of Spatial Autocorrelation Moran's I (2017)



4.2 Model

Upon confirming the presence of spatial autocorrelation we move to model estimation. All SDM regressions were performed via bias-corrected QMLE. We only display and interpret the results for the final preferred model, but detail the steps leading to its selection.

Our first decision about model selection concerns *W*, the spatial weights matrix. To choose between weights matrices we perform two initial estimations; one with the nearest neighbor contiguity weights matrix, the other with the inverse-distance squared weights matrix. We select the weights matrix that provided for estimation with the smallest log likelihood value: the inverse-distance matrix (Elhorst, Spatial Econometrics From Cross-Sectional Data to Spatial Panels, 2014). Given that the spatial Durbin model has the SAR and SEM models nested within, we perform a series of statistical tests and confirm that the SDM provides the best fit among these models.

We check the model for stability by testing the assumption $\rho + \tau + \eta < 1$ with an F-test. The computed F-value suggests the model is non-stable. We subsequently apply the first-difference transformation recommended by Lee and Yu (2010) and re-estimate the model. After this transformation we continue to detect non-stability in the model, suggesting bias may remain.

Results for the dynamic SDM with inverse distance squared weights matrix and applied first-difference transformation are displayed in Table 3. We control for time effects, given the evident trend of increasing intensity of program participation over time at the aggregate level. We use time effects to control for any time variant variables we failed to include in the model. The lagged dependent variables are significant in the dynamic spatial Durbin model, as is unemployment, specialty crop acreage, and several of the spatially lagged production variables. Due to feedback effects inherent in spatial models, we are unable to interpret the coefficient estimates as direct effects on the dependent variable: intensity of program participation. For this reason, we compute marginal effects for each regressors while holding all other regressors at their respective means; we compute the asymptotic t-statistics via bootstrapping.

Table 3| Dynamic Spatial Durbin Model: Intensity of Program Participation at the County Level. Bias-Corrected QMLE (First Difference Transformation)

Variable	Coefficient	Asymptotic T-Stat	
Y(t-1)	0.94	270.464	***
w.Y(t-1)	0.06	5.962	***
unemployment rate	32.13	13.620	***
log av. weekly wage crop workers	3.61	0.890	
log av. weekly wage construction workers	-0.33	-0.080	
log av. weekly wage (all combined)	-0.58	-0.138	
log av. # of crop workers in county	2.41	0.469	
citrus acreage[a]	0.00	-0.675	
specialty crop acreage[b]	0.00	3.832	***
field crop acreage[c]	0.00	1.047	
e-verify	0.00	-1.268	
border apprehensions	-5.46	-1.086	
median home price	0.00	1.046	
precipitation (rainfall 0.10 mm)	0.00	-0.476	
# of freeze days (annual)	0.00	0.062	
w.unemployment rate	-5.32	-1.113	
w.log av. weekly wage crop workers	1.20	0.135	
w.log av. weekly wage construction workers	-5.73	-0.648	
w.log av. weekly wage (all combined)	3.10	0.319	
w.log av. # of crop workers in county	9.00	0.898	
w.citrus acreage	0.00	-0.167	
w.specialty crop acreage[a]	0.00	5.902	***
w.field crop acreage[b]	0.00	-3.163	***
w.e-verify	0.00	1.601	
w.border apprehensions	6.05	1.101	
w.median home price	0.00	-1.973	**
w.precipitation (rainfall 0.10 mm)	-0.03	-1.263	
w. # of freeze days (annual)	-0.01	-0.405	
w.Y	0.02	2.569	***

a. citrus was included separate from specialty crops because of citrus greening disease
b. specialty crops include, fruits and vegetables (see appendix for comprehensive list)
c. field crops include grains and soy
* signf. p-value ≤ 0.10
** signf. p-value ≤ 0.05
*** signf. p-value ≤ 0.01

We chose to model intensity of program participation with a dynamic spatial model because it includes the space-time lag of the dependent variable, w.y(t-1). The direct effect of this space-time lagged dependent variable indicates how intensity of neighboring counties' participation in the past effects own intensity of program participation in the present. Thus, we view the direct effect of the space-time lagged dependent variable as the contagion effect. Standard interpretation of the short term direct effect of the space-time lag suggests that a unit increase in the intensity of neighbors' program participation in the previous year, results in an increase in own intensity of program participation by 0.06 certified positions (Table 4). All long term direct effect estimates however are insignificant. This is likely due to the inclusion of time-effects in our model given that excluding time effects lead to significant long term direct effects estimates.

Table 4 | Direct and Indirect Effects of Explanatory Variables on Intensity of Program Participation in the Short Term

Variable	Direct Effect	Asymptotic T-stat		Indirect Effect	Asymptotic T-stat	
w.Y(t-1)	0.064	5.804	***	0.066	6.262	***
unemployment rate	32.140	13.746	***	33.431	13.458	***
log av. weekly wage crop workers	3.693	0.952		3.841	0.951	
log av. weekly wage construction wor	-0.487	-0.124		-0.507	-0.124	
log av. weekly wage (all combined)	-0.590	-0.142		-0.612	-0.141	
log av. # of crop workers in county	1.987	0.387		2.066	0.386	
citrus acreage[a]	0.000	-0.632		0.000	-0.633	
specialty crop acreage[b]	0.001	3.945	***	0.001	3.943	***
field crop acreage[c]	0.000	1.171		0.000	1.171	
e-verify	0.000	-1.233		0.000	-1.233	
border apprehensions	-5.692	-1.142		-5.923	-1.142	
median home price	0.000	1.099		0.000	1.098	
precipitation (rainfall 0.10 mm)	-0.005	-0.535		-0.006	-0.535	
# of freeze days (annual)	0.001	0.060		0.001	0.059	
w.unemployment rate	-5.323	-1.123		-5.542	-1.123	
w.log av. weekly wage crop workers	0.807	0.089		0.842	0.090	
w.log av. weekly wage construction w	-5.542	-0.615		-5.764	-0.615	
w.log av. weekly wage (all combined)	3.366	0.333		3.490	0.332	
w.log av. # of crop workers in county	10.042	1.009		10.448	1.010	
w.citrus acreage	0.000	-0.245		0.000	-0.245	
w.specialty crop acreage[a]	0.002	5.793	***	0.002	5.772	***
w.field crop acreage[b]	0.000	-3.407	***	0.000	-3.402	***
w.e-verify	0.000	1.575		0.000	1.574	
w.border apprehensions	6.340	1.170		6.598	1.170	
w.median home price	0.000	-1.975	**	0.000	-1.972	**
w.precipitation (rainfall 0.10 mm)	-0.029	-1.300		-0.031	-1.301	
w. # of freeze days (annual)	-0.009	-0.368		-0.009	-0.367	
w.Y	0.024	2.519	***	0.025	2.438	***

a. citrus was included separate from specialty crops because of citrus greening disease
b. specialty crops include, fruits and vegetables (see appendix for comprehensive list)
c. field crops include grains and soy
* signf. p-value ≤ 0.10
** signf. p-value ≤ 0.05
*** signf. p-value ≤ 0.01

The direct effect of the average unemployment rate is significant and positive (Table 4) suggesting that counties experience an increase in intensity of program participation in the short term amid growing unemployment. Interpretation of this direct effect suggests that a unit increase in the unemployment rate within a county corresponds to 32 more H-2A visa positions certified within the county. This finding is inconsistent with the stated goal of the H-2A program, which is to provide growers with foreign workers in the case of labor shortages in the domestic market. This interpretation of the unemployment variable should be regarded with caution, however, given the model includes unemployment across all occupations and sectors, not just agricultural work alone. We detect no significant relationship between county level wages and intensity of H-2A program participation.

The marginal effects computed for specialty crop acreage within counties are significant in the short term. The direct effect of specialty crop acreage on intensity of program participation is 0.001 suggesting that an additional H-2A worker is hired for each 1,000 acre increase in specialty crops. The short term direct effects of neighbors' specialty crop acreage on intensity of own program participation is also significant with a thousand acre increase corresponding to a 2 more H-2a positions.

Despite our efforts to control for and estimate the effects of interdiction of undocumented migration on H-2A program participation we find no significant effect of the number of apprehensions at CBP sectors on intensity of participation in the H-2A program. Empirically, migration flows within individual U.S. counties may not correspond to aggregate migration flows at the CBP sector level. Additionally, we detect no significant effect of e-verify at the state level on intensity of program participation. Few of the states that currently implement e-verify require that private employers use it and, in practice, usage by agricultural employers may be hard to enforce. While we cannot rule out that enforcement of migration policies and work-authorization laws influence producers' demand for H-2A workers, we are unable to estimate any such effect in the present model.

We find strong evidence that intensity of program participation at the county level is positively influenced by the intensity of program participation in neighboring counties. This result in turn suggests that social contagion plays a role in individual firms' decision to participate in the program. Relevant economic theory suggests that an agricultural producer will model her own business decisions after those of other producers within her network if she is pleased with their results. Knowledge sharing can also play a role as information is passed among producers within a network either actively or through passive observation.

Our detection of social contagion at the county level strengthens the argument that U.S. agricultural producers lack adequate information about the program prior to deciding to participate. Many are unable to accurately evaluate the benefits of program participation without first observing outcomes of their neighbors who already employ H-2A workers. Some producers may also be late adopters of the program due to a gap in their understanding of how to use it. Such producers may learn how to use the program through observing their neighbors, or through consulting with experienced program participants in their professional networks. There is little doubt that the H-2A visa program is becoming many producers' best option for meeting their labor demands with a legally authorized workforce. Thus, it is in best interest of the federal and local governments to facilitate the program's continued expansion. Program administrators can reduce present gaps in knowledge between program users and non-users with targeted outreach and education. Specifically, state governments can work with extension educators to help agricultural producers better assess the benefits of program participation, and with managing the application process.

5 Conclusion

The H-2A temporary agricultural workers program is rapidly becoming U.S. specialty crop producers preferred method for sourcing their labor needs. Although it is relatively more expensive for producers to employ H-2A workers than domestic workers, participation levels have increased substantially throughout the country since at least 2006. There are considerable differences in growth patterns across regions, however, and there remains much we do not know about the adoption decision of individual firms. This research investigates the diffusion of the H-2A program by modeling intensity of program participation across U.S. counties via spatial econometric techniques.

For conceptual purposes we have likened the H-2A program to other production technologies, wherein the agricultural producer weighs the benefit of the technology (returns in profit) against the risk of failure. The producer's decision is contingent on an outcome she has not yet observed therefore, she suffers from incomplete knowledge. We have posited that many of the producers, who eventually begin using the program, first observe the participation of peers in their network. Subsequently, they opt to use the program if they are satisfied with their neighbors' results and have gained additional knowledge in how to manage their own participation. We have termed this effect of network peers' past usage on own program participation as the contagion effect.

We estimate intensity of program participation at the county level with a dynamic spatial Durbin model, and interpret the direct effect of the space-time lagged dependent variable as the contagion effect. We find that intensity of neighbor's program participation in the previous year has a significant positive effect on own intensity of program participation in the short term. Additionally, we find that specialty crop acreage within counties is positively correlated with program usage in the long term, as is the average unemployment rate within the county. These findings, particularly the detection of contagion effects, have significant implications for future applications.

Contagion effects suggest that many U.S. agricultural producers lack sufficient knowledge about the program, and that program administrators and other interested parties can increase participation through educational targeting of agricultural producers. Additionally, our finding of contagion effects sets a precedence for future models meant to forecast program usage levels whether at the local or national level. Furthermore, the techniques applied in the research can be extended to similar policy questions, such as other guest-worker programs (H2-B, H1-B etc.)

Three possible extensions on the present research include (1) estimation of program participation at the firm rather than the county level, (2) using a censored or double-hurdle estimation technique to remove any downward bias due to the inclusion of strictly non-agricultural counties in the data set, (3) the inclusion of additional explanatory variables such as climate data, controlling for the numbers of firms that operate within the county, controlling for whether the adopting firm is a farm labor contractor of grower.

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Appendix A:

Crop Categories Summed into the Variables Specialty Crop Acreage and Field Crop Acreage

Specialty Crops	Field Crops
Melons	Sorghum
Lettuce	Millet
Onions	Rye
Herbs	Soybeans
Carrots	Wheat
Celery	Durum Wheat
Strawberries	Rice
Blueberries	Hay
Raspberries	Corn
Blackberries	
Cranberries	
Plums	
Peaches	
Apricots	
Cherries	
Apples	
Grapes	
Tobacco	

Appendix B: Spatial Panels

Spatial econometric approaches can be applied to both stationary data such as cross-sections, or panels; wherein individual units are observed over multiple time periods. Many of the best recommended practices for panel data analysis can be applied to spatial panels. This includes the model selection process wherein one chooses between fixed and random effects.

While model selection is a somewhat arbitrary process, best recommended practices often include exploratory analysis, to first establish the presence of spatial autocorrelation, after which various linear and non-linear models can be applied in regression analysis. The Moran's I remains one of the most popular statistical tests for detecting spatial autocorrelation. One computes the Moran's I by multiplying the weights matrix W by the variable of interest, summing, and dividing as such:

$I = \frac{n}{W} \frac{\sum_i \sum_j w_{ij}(x_i - \bar{x})(x_j - \bar{x})}{(x_i - \bar{x})^2}$, where n is the number of observations, w_{ij} is the matrix of spatial weights, x_i is the variable of interest for observation i, $\bar{x}$ is the sample mean of the variable of interest, and W is the sum of all the weights.

Moran's I is only useful for detecting spatial autocorrelation in large datasets if there is a null value for comparison. One can construct a reference distribution via boot strapping and subsequently calculate pseudo p-values based on the number of times each reference Moran I computed via bootstrapping exceeds the Moran's I derived empirically. The same method can be applied to subsections within the greater spatial network to detect local spatial autocorrelation. This is frequently referred to in the literature as LISA (local indicators of spatial autocorrelation).

Upon detection of spatial autocorrelation, the researcher can select from a number of spatial auto-regression models, spatial autoregressive model (SAR), spatial error model (SEM), spatial Durbin model (SDM) etc. One can approach the process of model selection haphazardly by deriving the AIC (Akaike information criterion) for each model and then comparing these to determine which model provides the best fit for the data, however, Belotti et al (2016) provide a better way. They recommend beginning with the Spatial Durbin Model. As the Spatial Durbin model nests the SEM, SAR and spatial autocorrelation (SAC) models within it, comparison is relatively straightforward.

To determine between the SEM and SDM model one need only test the hypotheses $0 = \theta$ and $\rho \neq 0$, where θ is the vector of coefficients derived for the lagged explanatory variables and ρ is the coefficient from the spatially lagged dependent variable. Upon rejecting both nulls the SDM is preferred over the SEM. Additionally should one fail to reject the hypothesis $\theta = -\beta\rho$, the SAR is the better model (Belotti, Hughes, & Mortari, 2016).

As in with standard panels one can decide between random and fixed affects by applying the Hausman test (1978), wherein one computes a chi-statistic of the form $\hat{\xi} = \hat{\delta}'\hat{V}_o^{-1}\hat{\delta}$, where $\xi = (\hat{\beta}_{fe} - \hat{\beta}_{re})$. An important assumption of the Hausman test is that the joint variance covariance matrix $\hat{V}_o^{-1}$be positive-definite, an assumption which frequently fails in the context of spatial panels. Thus, a modified version of the Hausman statistics the Robust Hausman can be derived by applying a sandwich formula to the joint variance covariance matrix to assure positive definiteness. Upon rejecting of the null of sameness between the two models the fixed effects model is preferred, as it provides more robust estimates.

Much as panel models can be adapted to dynamic scenarios, by including a lagged dependent variable term among the regressors, one can adapt spatial temporal panel models. A dynamic spatial panel includes one or more variables that are lagged in both space and time such as the form $y_{it} = \tau y_{it-1} + \eta w y_{jt-1} + \rho w y_{it} + \beta x_{it} + \theta w z_{it} + \mu_i$, where y_{it-1} is the time lagged dependent variable and $w y_{jt-1}$is the dependent variable lagged in both space and time.

In his review of dynamic spatial panels, Elhorst (2014) presents the three primary methods used for estimation of spatial lag madols: bias corrected Maximum Likelihood and Quasi Maximum Likelihood (QMLE), Instrumental Variable or Generalized Method of Moments estimation (IV/GMM), and the Bayesian Markov Chain Monte Carlo (MCMC) approach. A review of the bourgeoning literature on dynamic spatial panels suggests that QMLE and IV/GMM are the most common methods used in empirical work with several different canned software programs/toolboxes available to the general public for the estimation of dynamic spatial panels.

To our present knowledges all publicly available programs designed for the estimation of dynamic spatial panel models are designed for long panels ($t > 25$), as they presume the inclusion of fixed effects (Belotti, Hughes, & Mortari, 2016; Elhorst et al, 2013). Lee and Yu (2010) explain, the inclusion of fixed effects in a dynamic spatial panel model without first removing them via an appropriate transformation, can results in biased estimates. Dynamic spatial panel models with random effects have also been proposed although to a lesser extent. Unfortunately, already written software programs for their estimation are not currently published.

Explanatory Variable	Short term effects					
	Direct Effect	Asymptotic T-test	Indirect Effect	Asymptotic T-test	Total Effect	Asymptotic T-test
w.Y(t-1)	0.064	6.431	0.066	6.942	0.130	6.685
unemployment rate	32.267	13.398	33.540	13.141	65.807	13.329
log av. weekly wage crop workers	3.091	0.772	3.213	0.772	6.304	0.772
log av. weekly wage construction workers	-0.714	-0.175	-0.744	-0.175	-1.458	-0.175
log av. weekly wage (all combined)	-0.552	-0.134	-0.577	-0.135	-1.129	-0.135
log av. # of crop workers in county	3.629	0.677	3.776	0.678	7.405	0.678
citrus acreage	0.000	-0.527	0.000	-0.528	0.000	-0.528
specialty crop acreage[a]	0.001	3.693	0.001	3.684	0.002	3.690
field crop acreage[b]	0.000	1.017	0.000	1.015	0.000	1.016
apprehensions at nearest CBP sector	0.000	0.111	0.000	0.111	0.000	0.111
e-verify implemented at state level	-0.344	-0.221	-0.356	-0.220	-0.700	-0.221
w. unemployment rate	-5.244	-1.072	-5.451	-1.070	-10.695	-1.071
w. log av. weekly wages (crop workers)	2.058	0.219	2.136	0.219	4.194	0.219
w. log av. weekly construction wage	-8.832	-0.988	-9.172	-0.987	-18.004	-0.987
w. log av. weekly wages (all combined)	1.550	0.160	1.613	0.160	3.163	0.160
w. log av. # crop workers	7.980	0.769	8.293	0.769	16.273	0.769
w. citrus acreage	0.000	-0.174	0.000	-0.176	0.000	-0.175
w. specialty crop acreage	0.002	6.189	0.002	6.195	0.005	6.199

w. field crop acreage	0.000	-3.441	0.000	-3.429	0.000	-3.436
w.Y^c	0.023	2.631	0.024	2.540	0.048	2.584