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ORIGINAL ARTICLE

21st century economic development: Telework and its impact on local income

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Abstract

Telework, or telecommuting, is gaining increasing attention at the national level. However, the impact it has on local economies is not well understood. Theoretically, teleworking may result in higher levels of worker satisfaction and productivity, which in turn leads to increased income levels. In an effort to contribute to this important topic, this paper analyses census-tract level work from home statistics from the 2011–2015 American Community Survey. Results from a maximum likelihood regression using a spatial Durbin error model (SDEM) indicate that after controlling for various factors such as employment by industry, educational attainment, and broadband availability, the percentage of residents working from home in both salaried and self-employed jobs had a positive and significant impact on median household income. Importantly, spillovers from levels of telework in neighbouring communities are also shown to exist, although the direction of impact differs by worker category. The implications of this research support the need to modify current economic and workforce development policies to better nurture, attract, and retain teleworkers. A series of policy recommendations are discussed to help jumpstart this process.

KEYWORDS

economic development, telework, broadband, digital divide, local income

1 | INTRODUCTION

Recent analysis of data from the 100 largest metropolitan areas by the Brookings Institution found that US commuting patterns are changing (Kane & Tomer, 2015). Significantly more workers are choosing to work from home – a shift that research has shown can help lower transportation costs, increase levels of individual and firm productivity, and improve organizational outcomes (Bloom, Liang, Roberts, & Ying, 2015; Martin & MacDonnell, 2012). Between 2000 and 2014, 13% of new commuters worked from home, bringing the total to around 6.5 million (Kane & Tomer, 2015). The rate of growth of those working from home over this period surpassed those for any other commuting category. Despite this trend towards more people working from home, the academic literature has devoted little time to assessing the implications for local economic development.

It is important to note that there are distinct categories of people working from home (Mokhtarian, 1991; Scott & Timmerman, 1999). For instance, self-employed entrepreneurs with various degrees of technology use (interior designers, personal trainers, or freelance writers) may have different experiences and economic outcomes versus individuals who "remote in" to the office every day in conventional wage and salary jobs (account managers, engineers, or marketers). Therefore, this study distinguishes between those working from home as self-employed (including those with incorporated and non-incorporated businesses) and those working in wage and salary jobs (for profit, non-profit, and government). An important subset of those working from home can be described as "teleworkers." Teleworking is defined by the Office of Personnel Management as, "a work flexibility arrangement under which an employee performs ... from an approved worksite other than the location from which the employee would otherwise work" (OPM, 2010). While measures of those working from home are not perfect proxies for teleworking, work-from-home statistics are readily available from the US Census for a wide variety of geographies. These data can provide insight into the relationship between working from home (including most teleworkers) and local economic development.

Telecommuting research has led to conflicting and unclear outcomes mostly because it encompasses multiple disciplines (e.g., psychology, management, transportation, etc.) and has utilized multiple terminologies and conceptualizations over time (Allen, Golden, & Shockley, 2015). However, a predominant focus of this research has been on workers and / or organizations that employ it (Bloom et al., 2015; Martin & MacDonnell, 2012; Morganson, Major, Oborn, Verive, & Heelan, 2010; Pyoria, 2011). Another heavy emphasis has been on the availability of information technology (Allen et al., 2015; Nilles, 1975; Scott & Timmerman, 1999; Tung & Turban, 1996; Vilhelmson & Thulin, 2016). Therefore, access to faster broadband speeds and adoption of broadband applications and platforms play an important role in the viability of telework – and the economics literature has explored many aspects of broadband.

Alternatively, the larger-scale economic impacts associated with telecommuting have not been well-researched. For example, what impact does telework have on local economic indicators such as income? Theoretically, if teleworking leads to higher levels of worker satisfaction and increases in productivity, these will in turn lead to higher wages and overall levels of income. Such linkages have not been tested empirically. If telework does demonstrate a positive impact on income, it can become a viable alternative to more "traditional" work types that evolved during the industrial age and required working in an office or factory away from home. This type of shift, however, would require a change in workforce and economic development policies.

An important dimension to consider is whether teleworking has effects both within its unit of analysis (i.e. census tract) and for neighbouring areas. These "spillovers" have been shown to exist for other factors affecting economic development such as innovation (Shearmur & Bonnet, 2011) and levels of competition (Porter, 2000). Workers who telework for businesses in outside locations are hypothetically increasing the number of jobs available for local residents, as well as for residents of neighbouring areas who may commute in. Whether these spatial spillovers exist is relevant to policy discussions – for example, determining whether local or regional policies that promote telework might be appropriate. This paper adds to the literature by using recent, neighbourhood US data to provide evidence on the degree to which working from home (including teleworking) impacts household income – both for the local area and for neighbouring geographies.

2 | LITERATURE REVIEW

The primary question of interest is whether income is positively related to telework after controlling for other influential variables. The determinants of income are well established. Educational attainment, industrial structure, and age/race/employment status of the working class have all been shown to impact household income. A study by the Federal Reserve Bank of St. Louis is among the latest to demonstrate a strong correlation between education and income, particularly for higher levels of education (Wolla & Sullivan, 2017). Another recent report from the Bureau of Labor Statistics (2016) found that those with more education not only have higher earnings, but also have lower unemployment rates. Other studies show that the industrial composition of an area has a dramatic impact on wages (Brock, 2013; Krueger & Summers, 1986); that income levels vary significantly across race (Proctor, Semega, & Kollar, 2015); and that age is an important predictor of income (Hedstrom & Ringen, 1987). What has not been explored empirically, however, is the degree to which specific economic development measures (such as income) are impacted by the amount and type of teleworking taking place locally.

2.1 | A brief history of telework research

Before attempting to answer this question, some historical perspective may be helpful. The term "telecommuting" first appeared in a paper discussing phenomena impacting the traditional urban structure (Nilles, 1975). This original work defined telecommuting as a "network [that] has computational and telecommunications components which enable employees of large organizations to work in offices close to (but generally not *in*) their homes, rather than commute long distances to a central office" (Nilles, 1975, p. 1143). This definition did not place an emphasis on working from home because at that point in time information technology was not as sophisticated and widely adopted to even consider the possibility of using it to telework from home. Nonetheless, the author implied that this type of working arrangement had the potential to change the traditional urban structure resulting in decentralization. Note that the official 2010 OPM definition of telework listed above shares some characteristics with this early conceptualization.

Most of the early literature in this area focused on the individual worker's decision to telework. One study found that job category and gender played a major role in this choice, while age, years in organization, and computer skills were not major factors (Belanger, 1999). Other research uncovered that specifics of individual jobs such as self-perceived unsuitability to telework – and not general job traits – were better determinants of whether an individual decided to telework (Mokhtarian, 1998). For example, general job categories like information workers are assumed to be ripe for telework, yet individual workers may think their job cannot be done as well away from the office and thus choose not to telework. In addition, work-related factors such as a manager's willingness and workplace interaction also impact an individual's choice to telework (Mannering & Mokhtarian, 1995).

In a robust review of the early telework literature, Bailey and Kurland (2002) analysed more than 80 published academic empirical studies. They found that job satisfaction and productivity received the most attention in the telework literature. The authors found a handful of interview-based studies showing an increase in freedom and flexibility among those teleworking (Crossan & Burton, 1993; Duxbury, Higgins, & Neufeld, 1998). However, the overall evidence on job satisfaction was weak. Regarding worker output, the literature review identified a significant increase in effectiveness and productivity associated with teleworking. One important issue was that most of these studies were based on self-reported data of workers who volunteered to telework or requested it, thus opening the door for bias (Bailey & Kurland, 2002; Scott & Timmerman, 1999).

A more recent study examining the individual, social, and situational determinants of teleworker productivity found that teleworker beliefs and attitudes (as well as the quality of social interactions with family members and supervisors) strongly affected their productivity. In turn, social interactions with colleagues, supervisors, and family members strongly influenced teleworker's beliefs and attitudes (Neufeld & Fang, 2005). In other words, the perception of telework by friends and family members shaped the teleworker's beliefs, which in turn affected their own productivity. However, this study measured productivity through an interview with the teleworker, again raising the same bias issues associated with self-reported data. Additional research supports the notion that telework can increase productivity and improve performance in organizations, including a meta-analysis from 22 teleworking studies (Martin & MacDonnell, 2012). Surprisingly, however, no studies we are aware of have looked at the impact of telework on local measures of economic development, such as household income.

Research using an experimental design with employees of the largest travel agency in China found that those who teleworked four days a week for nine months were 13.5% more productive compared to those who stayed in the office during the same time period. In addition, the company saved $1,900 per employee in office space; and those teleworking reported higher job satisfaction, shorter breaks, fewer sick days, and took less time off. However, more than half of those who volunteered to telework later changed their mind about working from home, reporting they felt too isolated (Bloom et al., 2015).

In fact, one of the main concerns regarding telework is that it may lead to social isolation, since teleworkers do not engage with coworkers at the same level as non-teleworkers. One study found that the professional isolation from teleworking negatively impacted job performance (Golden, Veiga, & Dino, 2008), and another found that teleworkers experienced significantly more mental health symptoms than traditional office workers (Mann & Holdsworth, 2003). However, a study using European data found that telework was a community-friendly form of work where teleworkers reported higher voluntary/charitable and political/trade union activities compared to non-teleworkers (Kamerade & Burchell, 2004).

Some research suggests that work-family balance can be improved via telework. A study of the Chicago region found that telecommuting was associated with an increase in out-of-home activities (e.g., being able to take more non-work related trips) (He & Hu, 2015). This study also found that although low-income workers were less likely to telework, those that did also conducted a higher number of out-of-home trips compared to those that did not telework – resulting in higher work-family balance (He & Hu, 2015). Other studies also had findings suggesting that teleworking can help balance work-family conflict (Duxbury et al., 1998).

There are multiple other proposed benefits of telecommuting. One study found that due to participation in a State of California Telecommuting Pilot Project, the number of personal vehicle trips decreased by 27%, resulting in a 48% emission reduction of total organic gases, 64% for carbon monoxide, and 69% for nitrogen oxide (Koening, Henderson, & Mokhtarian, 1996). In a non-academic study, a report in early 2016 argued that telecommuting could save the US over $700 billion a year by saving on real estate, electricity, absenteeism, turnover and productivity, among other things (Global Workplace Analytics, 2016).

A more recent review of the telework literature concluded that a long-term research agenda and sustainable framework is needed that incorporates government policy, technology, and management (Blount, 2015). Hence, telework research has focused primarily on productivity, but there is a lack of research literature examining its impact on personal or household economic indicators – and minimal associated policy-oriented work.

2.2 | Broadband and economic growth

One important requirement for telecommuting is the availability of information technology, specifically broadband Internet access. As such, the empirical research on the relationship between broadband and general economic indicators is worth reviewing. Using national data from 22 countries, one study found a significant causal positive relationship between broadband infrastructure and growth (Koutroumpis, 2009). Further, a review of multiple broadband and economic growth studies between 2000 and 2009 concluded that broadband was positively associated with economic outcomes, although few studies delved into causality and none looked at the impact in rural areas (Holt & Jamison, 2009).

Other studies have focused specifically on what broadband means for rural areas (which can be important locations for telework). One study used propensity score matching techniques to find that higher levels of broadband adoption in rural areas resulted in higher income growth and lower unemployment rates compared to similar counties with lower broadband adoption (Whitacre, Gallardo, & Strover, 2014a). A second study used cross-sectional spatial and first-differenced regressions to untangle the impact of broadband adoption and availability on rural income and jobs. Results from the spatial regressions indicated that higher levels of broadband adoption were associated with higher number of firms and total employment levels. Results from the first-differenced regressions also pointed at a positive relationship between broadband adoption and median household income (Whitacre, Gallardo, & Strover, 2014b). Finally, a study of rural municipalities in Italy found that availability of ADSL2 broadband resulted in a significant 40 percent increase in annual sales and 25 percent in value added of rural firms over two years. No significant effects were found in terms of the number of employees (Canzian, Poy, & Schuller, 2015). The common theme of each of these studies was the positive impact of broadband on local economic indicators.

Most studies exploring the impact of broadband on economic growth focused on either broadband availability (e.g., percent of population without access to broadband – defined by set download and upload speeds) or broadband adoption (e.g., fixed broadband residential connections at download and upload speeds) at various geographic levels. The idea is that areas with higher levels of broadband availability or adoption should perform better economically. A similar concept, used in this study, is the "digital divide" which focuses on the inequality of Internet access and use.

The digital divide is a term used in multiple ways, mostly focused on illustrating disparities in access to and use of information technology (Gunkel, 2003). At the root of the digital divide concept are equality issues along technological (access to computers, devices, broadband), immaterial (life chances, freedom), material (capital, resources), social (position, power, participation), and educational (capabilities, skills) dimensions (van Dijk, 2006). National indices operationalize this concept similarly; however, most are constrained by data availability (e.g., DIDIX, Network Readiness Index, Digital Access Index, etc.). A digital divide index at a sub-national or sub-state level incorporating as many dimensions as possible is lacking.

For these reasons, this research uses a newly available digital divide index (DDI) score at the census tract level (Gallardo, 2017). The DDI directly operationalizes the technological dimension and indirectly captures the material and educational dimensions, and hence accounts for more than simple broadband availability/adoption. More information on this variable is available in the following section.

To summarize, previous telework research has looked at manager's and employee's attitudes, job satisfaction and productivity, impact on commute travel and residential relocation, work and family tradeoffs, quality of working life, mode of transportation, energy and air quality, legal and public policy issues, and organizational, behavioural, and social issues (Gupta, Karimi, & Somers, 1995). These topics can be organized in three levels: (i) *societal* including traffic congestion, opportunities for the disabled, etc.; (ii) *organizational* including cost savings, employee morale, control, etc.; and (iii) *individual* including flexibility, satisfaction, work-balance, etc. (Neufeld & Fang, 2005). What remains elusive, however, is analysis focused on whether telework has any impact on local economic development measures such as household income. It is crucial to begin answering this question in order to better position telework as an alternative to "traditional" community economic development strategies.

3 | DATA AND METHODOLOGY

To assess the impact that workers in place or teleworkers have on median household income, data from the 2011–2015 5-Year American Community Survey (ACS) were compiled at the census tract level. Median household income was chosen over *per capita* income because the median is a more representative measure than the average, which can be highly impacted by outliers. Census tracts offer more granular data than county level data, which can overlook critical dynamics such as proximity to towns or availability of roads. This is especially true for broadband access, which is highly sensitive to geography.

The dependent variable, median household income (MHHI), is in nominal dollars since the research design is cross-sectional, and is expressed in logarithmic form in order to obtain a normally distributed variable. The independent variables include a host of factors known to impact income. To control for urban/rural differences, the percentage urban variable (pURB10) was included from the 2010 Decennial census. This variable denotes the percent of the population within the census tract in 2010 living inside urbanized areas or urbanized clusters.[1] Race/ethnicity variables were obtained from the 2011–2015 ACS dataset and include percentage of black non-Hispanic (pBNH), percentage of Asian non-Hispanic (pASIAN), and percentage of Hispanic (pHISP). White non-Hispanic is the default

[1]Alternatively, we include a measure of population density using the 2010 population and census tract land area. The results are quantitatively and qualitatively similar between the percent urban variable and this alternative measure of density.

category. Since age and employment status are known to impact median household income, the percentage of the age group from 16 to 64 (i.e. working age) that are employed was included (pEMP1664).

To control for educational attainment, the percentage of those age 25 and over with a bachelor's degree or more (pBACH) was used from the 2011–2015 ACS. The percentage of those over 25 with less than a high school degree – also closely related to income – was not included, since this variable is part of the digital divide index discussed below. The type of employment in a region can also impact median household income. For this reason, the percentage of those employed in production industries (pPROD), including construction and manufacturing, was calculated using data from the 2011–2015 ACS dataset. To control for agricultural employment, which has also been found to impact income (Kusmin, 2016), the percentage of those employed in agriculture was included (pAG).

In terms of broadband variables, the analysis includes the digital divide index (DDI) score. The DDI is comprised of two elements: broadband infrastructure/adoption and socioeconomic characteristics known to impact technology adoption. The broadband infrastructure/adoption component includes Federal Communications Commission (FCC) data on the percentage of the population without access to fixed broadband 25 megabits down and 3 megabits upload (i.e. availability), the percentage of households with broadband connections of at least 10 megabits down and 1 megabit up (i.e. adoption), and fixed broadband average maximum advertised upload and download speeds.[2] The socioeconomic component includes the percent of the total population ages 65 and over, the percentage of the population 25 and over with less than a high school degree, the individual poverty rate and the percentage of the non-institutionalized population with any disability. Both elements were given equal weight and added up using z-scores. The DDI ranges from 0 to 100, where a higher number denotes a higher digital divide (Gallardo, 2017). *A priori* expectation is that there will be a negative relationship between the DDI and income – that is, tracts with poor levels of broadband availability/ adoption or more elderly/impoverished residents are expected to have lower incomes.[3]

The primary independent variable of interest is the percentage of workers age 16 and over working from home (pWFH) from the US Census (2011–2015 ACS). However, some areas with high levels of working from home are also predominantly agricultural locations as evidenced by "hotspots" in several Great Plains states. Including a control variable for agricultural production may be problematic given this link between working from home and agriculture. To account for this, we define a new working from home variable (pWFHnAg) by removing households classified as working from home that work in the agriculture industry (Figure 1). As an alternative measure, we calculate the percentage of workers age 16 and over working from home in wage and salary (pWFHWS) jobs and those working from home as self-employed (pWFHSE).[4] These two variables of interest do include farmers/agricultural workers, since the Census data does not allow us to pull out those working in agriculture from the wage & salary/self-employed numbers. The ACS estimates of home-based work only includes respondents that work much of the week from home and excludes those who work at home during off hours. Because of these reasons, the ACS home-based work estimates are more conservative than the Census' Survey of Income and Program Participation (SIPP) which defines an at-home worker as any respondent having worked only at home on a given workday (Mateyka, Rapino, & Landivar, 2012).

Census tracts from Alaska and Hawaii were removed (to conduct a spatial analysis), along with those that had a $0 median household income value, resulting in a total of 71,559 census tracts analysed. Figures 1 and 2 demonstrate the spatial nature of the independent variables of interest (pWFHnAg) and the dependent variable (MHHI). The highly statistically significant global measures of Moran's I are 0.68 for MHHI and 0.33 for pWFHnAg, suggesting that a spatial modelling approach may be needed.[5] There is a positive association between the two variables (Figure 3); however, more advanced statistical techniques such as multivariate regression are needed to isolate the relationship from other covariates.

[2]Includes satellite and fixed wireless connections.

[3]As an alternative specification, we include distinct measures of broadband availability and broadband adoption instead of the DDI. The results are similar to those for the DDI, with increasing availability / adoption being associated with higher levels of income.

[4]Note that pWFHWS and pWFHSE sum up to pWFH.

[5]Moran's *I* is a measure of spatial autocorrelation ranging from −1 to 1. Positive and significant numbers provide evidence of spatial autocorrelation.

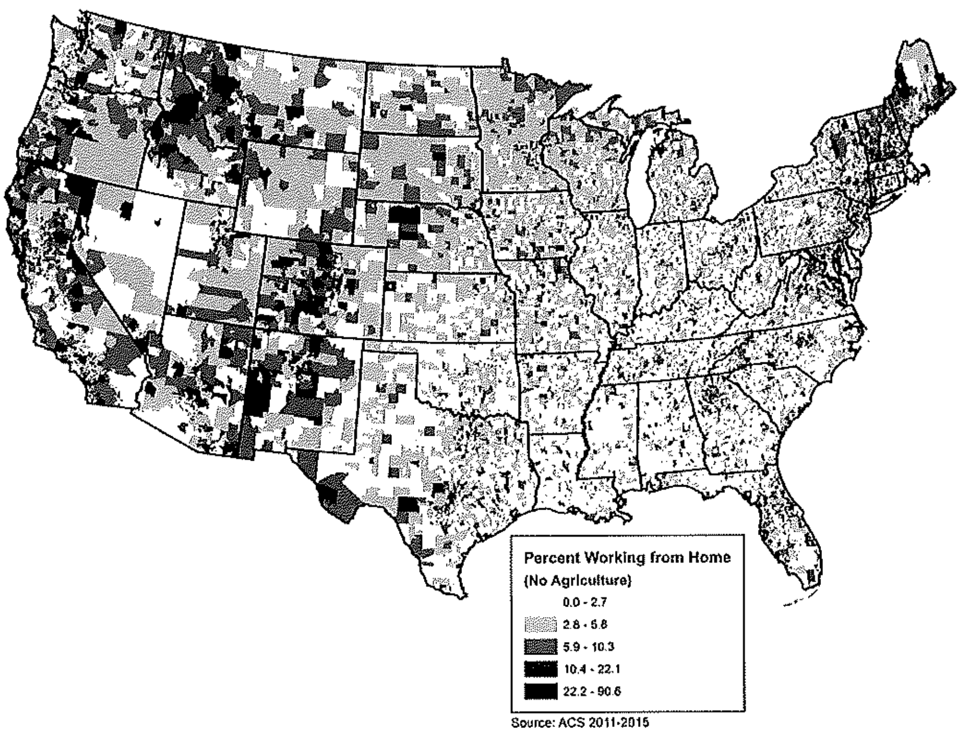

FIGURE 1 Percentage working from home (no agriculture) quintiles, by census tract

Table 1 provides a statistical summary of the variables involved in the analysis. Note that the mean value of the percentage working from home (pWFH) was 4.4%, but ranged from 0 to over 90%. Individuals working from home are nearly evenly split between those working for wage and salary (mean of 2.4%) and those that are self-employed (mean of 2.0%). A significant amount of variation exists in all the control variables, suggesting that if these variables do influence income, the resulting model will have high explanatory power.

Maximum likelihood regressions with spatial dependency were conducted using the census tract data. Spatial dependency models were incorporated given the patterns apparent in Figures 1 and 2, and because not accounting for spatial autocorrelation and/or spatial heterogeneity can cause inaccurate interpretation of the association between dependent and independent variables (Anselin, 1988; Anselin, Bera, Raymond, & Yoon, 1996; Voss, Long, Hammer, & Friedman, 2006). The presence of spatial dependence will cause traditional ordinary least squares estimators to be biased and unreliable (Anselin & Bera, 1998; LeSage, 2008; LeSage & Pace, 2009). However, the traditional models such as the spatial lag ($y = \rho Wy + X\beta + \varepsilon$, $\varepsilon \sim N(0, \sigma^2 I)$) or the spatial error ($y = X\beta + u$, $u = \lambda Wu + \varepsilon$, $\varepsilon \sim N(0, \sigma^2 I)$) account for the proximity of units through the spatial weight matrix W but do not allow for modelling of spatial spillovers between neighbouring units (Anselin, 1988; Elhorst & Vega, 2013). Alternatively, the spatial Durbin error model (SDEM) allows both the spatial dependency to be captured (via a lag or error term) but also explicitly estimates spatial spillovers by including lagged *independent* variables. The SDEM is written as:

$$y = X\beta + \theta WX + u,$$
$$u = \lambda Wu + \varepsilon,$$

and allows the parameters θ and λ to capture spatial elements in the data. Specifically, the value of θ associated with telework would estimate how the median household income in a census tract is influenced by the percentage of residents working from home in neighbouring tracts. As in the traditional spatial error model, λ captures heterogeneity

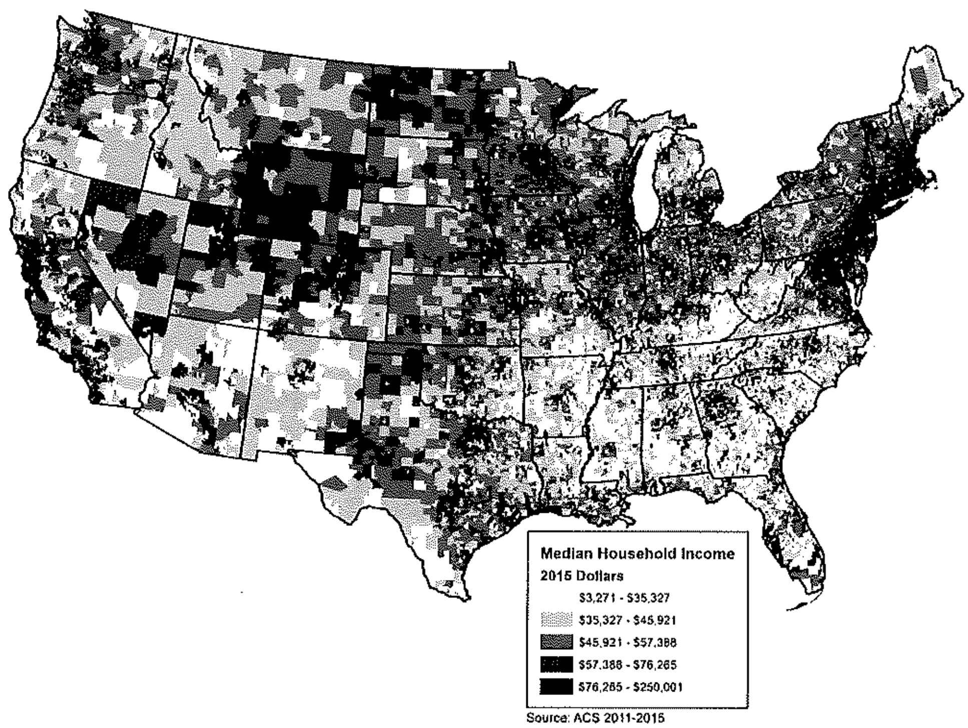

FIGURE 2 Median household income quintiles, by census tract

but is not easily interpreted. The SDEM's inclusion of the spillover effects (estimated by θ) represents a significant improvement over the more commonly used spatial lag or spatial error models (Elhorst & Vega, 2013).

Although the robust Lagrange multipliers (LM) for both the traditional lag and error models were statistically significant (see Table A1 in the Appendix), the robust LM coefficient for spatial error was much higher. In addition, an analysis of the residuals for the traditional lag and error models clearly showed the spatial error model to be a better fit.[6] Thus, the evidence suggests spatial heterogeneity is at work and the inclusion of a spatial error term (which is part of the SDEM specification) is appropriate. The final SDEM models were run using GeoDa software and a first-order queen contiguity spatial weights matrix to define the neighbourhood structure. Neighbours in queen contiguity are defined by any polygon that shares a common boundary or single point. Two variations of our model are run: one including the percentage of workers working from home after removing agricultural workers (pWFHnAg) and a second model including both the percentage of workers working from home in wage and salary jobs (pWFHWS) and those considered self-employed (pWFHSE). We include spatially lagged variables for education (pBACH_lag) and the work-from-home measures (pWFHnAg_lag, pWFHWS_lag, pWFHSE_lag) to assess potential spillover effects. Multicollinearity was assessed using variance inflation factors (VIFs); all resulting values were less than 3 suggesting no problems.

4 | RESULTS

Table 2 shows the results of several models demonstrating the relationship between working from home and income, ranging from the most parsimonious (simple OLS with no controls) to the preferred specification (the SDEM with a full host of controls). As discussed above, two versions of the independent variable of interest (percent working from

[6] Figures A1 and A2 in the Appendix show scatter plots and cluster-maps of the lag and error model residuals. The spatial error model has significantly fewer clusters of residuals, and the error model residuals also demonstrate a Moran's I measure closer to 0.

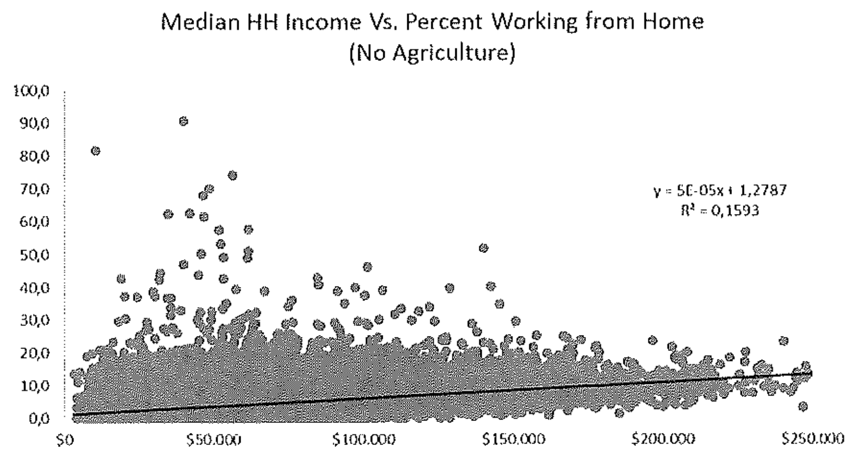

FIGURE 3 Median household income vs. percentage working from home (no agriculture) scatter plot
Source: 2011-15 ACS census tract data.

home) were used, one that excluded those working in agriculture, and a second that does include those working in agriculture but splits the data into wage/salary and self-employed components.

All results presented in Table 2 are for the nation although regional SDEM specifications are available in Appendix Table A2. Overall, the simplest model (OLS with no controls) suggests that the percentage working from home (not including working in agriculture) explains 12.7% of the variance in median household income (R^2). Adding controls to the OLS specification increases the explanatory power to about 71%. Spatial processes are clearly important, with the highly significant λ parameter resulting in an R^2 of 66% for the simplest SDEM. The final (and preferred) model, a SDEM with control variables added, explained about 84% of the median household income variance. Notably, the parameters on the percentage working from home not including agriculture (pWFHnAg) and in both wage and salary jobs (pWFHWS) and self-employed jobs (pWFHSE) are always highly significant and positive across the array of regressions. These parameter values decrease as control variables are added (as expected); however, the positive and significant relationship remains.

Several findings from the preferred SDEM specification (with controls) are worth discussing. Generally speaking, the results are similar regardless of whether the working from home variable includes agriculture (pWFHWS and pWFHSE) or not (pWFHnAg). As the share of those employed (pEMP1664), working in production (pPROD), working in agriculture (pAG), and with a bachelor's degree or more (pBACH) increase, so does median household income. Manufacturing employment has historically been related to higher incomes (Levernier, Partridge, & Rickman, 2000). Further, a recent report from the United States Department of Agriculture Economic Research Service found that although median household incomes in rural areas are still below 2007 levels, they increased more than 4 percent between 2007 and 2014 in farming-dependent counties (Kusmin, 2016). Results from this research support these findings.

On the other hand, several variables have a negative relationship with income in the final SDEM results. As the share of black non-Hispanics (pBNH), Asian non-Hispanics (pANH), and Hispanics (pHISP) increase, median household income decreases. The negative parameter on Asian households was unexpected; however note that it changes from positive in the OLS results to negative once a spatial modelling structure is incorporated. This switch is likely due to high levels of clustering displayed by Asian-American households (Hoeffel, Rastogi, Kim, & Hasan, 2012), which is subsequently captured by the spatial error component. Including a spatial lag on education is important, as tracts surrounded by high levels of education (pBACH_lag) find their incomes reduced. This may be caused by higher-education neighbours commuting across census tracts and taking higher-paying jobs, thus reducing the availability

TABLE 1 Statistical summary

Name	Description	Source	Obs.	Mean	Std. dev.	Min.	Max.
MHHI_LN	Median HH income (ln)	2011-2015 ACS	71,559	10.9	0.5	8..1	12..4
pURB10	Percentage of urban residents	2010 census	71,559	79.4	36.1	0.0	100.0
pEMP1664	Percentage aged 16-64 that are employed	2011-2015 ACS	71,559	66.7	10.9	0.0	100.0
pBNH	Percentage African-American	2011-2015 ACS	71,559	13.5	21.9	0.0	100.0
pASIAN	Percentage Asian	2011-2015 ACS	71,559	4.5	8.5	0.0	91.3
pHISP	Percentage Hispanic	2011-2015 ACS	71,559	15.9	21.3	0.0	100.0
pAG	Percentage employed in ag	2011-2015 ACS	71,559	2.2	4.7	0.0	70.0
pPROD	Percentage employed in production (mining, construction)	2011-2015 ACS	71,559	16.7	8.1	0.0	67.1
pBACH	Percentage with Bachelor's degree or more	2011-2015 ACS	71,559	28.6	18.7	0.0	97.3
pWFH	Percentage working from home (all)	2011-2015 ACS	71,559	4.4	3.7	0.0	90.6
pWFHnAg	Percentage working from home, no agriculture	2011-2015 ACS	71,557	4.1	3.6	0.0	90.6
pWFHWS	Percentage working from home in wage and salary jobs	2011-2015 ACS	71,557	2.4	2.5	0.0	90.5
pWFHSE	Percentage working from home in self-employed jobs	2011-2015 ACS	71,557	2.0	2.1	0.0	30.0
DDI	Digital divide index (0-100 range, larger = less availability / adoption)	FCC form 477; 2011-2015 ACS (Gallardo, 2017)	71,559	52.4	8.7	0.0	91.5

of those jobs within the tract. Additionally, as the digital divide increases (DDI), median household income decreases. Remember that the DDI consists of both broadband availability/adoption and socioeconomic characteristics known to impact broadband adoption (Perrin & Duggan, 2015), and that a higher DDI suggests lower levels of broadband availability / adoption. These findings were also expected.

Results also indicate that as the percent of the population living in urbanized areas (pURB) within the census tract increases, median household income *decreases*. This finding is somewhat counterintuitive, since rural areas generally have lower incomes than their urban counterparts. However, a likely explanation is that since the data is at the census tract level, this negative relationship is depicting inner-city low-income census tracts in large cities (Teitz & Chapple, 1998) that may be overlooked or aggregated when using county or state-level data. Notice the "doughnut" effect clearly seen in Figure 2 where low-income urbanized centers are surrounded by wealthier "rings."

The primary variables of interest are pWFHnAg and the two distinct categories of working from home, those working for wage and salary (pWFHWS) and those that are self-employed (pWFHSE). Notably, each of these variables shows positive and significant relationships (at the $p < .01$ level) with income. Perhaps surprisingly, the parameter on the self-employed variable is larger, implying that this category of teleworker has the largest impacts on income. The positive direct effects show that even after controlling for other characteristics known to influence income, higher proportions of residents working from home means that local median incomes will be higher. However, Figure 1 shows that the likelihood of working from home varies geographically, and it is possible that this result may vary by region. When separate regressions are run on the four primary Census regions (Northeast, South, Midwest, and West), the parameters on self-employed work (pWFHSE) remains positive and highly significant for all (Table A2). The parameter on pWFHWS loses statistical significance in the Midwest and the Northeast, demonstrating that regional differences do exist.

Interestingly, however, the spillover effects of working from home are mixed. If neighbouring tracts have a high proportion of self-employed teleworkers (pWFHSE_Lag), incomes in those home tracts will be *increased*.

TABLE 2 Cross-section model results comparison

Median household income (LN)	Simple OLS 1 (std. error)	Simple OLS 2 (std. error)	OLS controls 1 (std. error)	OLS controls 2 (std. error)	Simple SDEM 1 (std. error)	Simple SDEM 2 (std. error)	SDEM controls 1 (std. error)	SDEM controls 2 (std. error)
Constant	+10.65*** (2.5e-3)	+10.66*** (2.5e-3)	+11.63*** (1.5e-2	+11.65*** (1.6e-2)	+10.56*** (7.4e-3)	+10.57*** (6.6e-2)	+11.45*** (1.5e-2)	+11.46*** (1.5e-2)
pURB10	-	-	-0.003*** (3.7e-5)	-0.003*** (3.6e-5)	-	-	-0.002*** (3.9e-5)	-0.002*** (3.8e-5)
pEMP1664	-	-	+0.005*** (1.1e-4)	+0.005*** (1.1e-4)	-	-	+0.004*** (1.0e-4)	+0.004*** (1.0e-4)
pBNH	-	-	-0.002*** (5.3e-5)	-0.002*** (5.3e-5)	-	-	-0.003*** (7.5e-5)	-0.003*** (7.5e-5)
pASIAN	-	-	+0.001*** (1.2e-4)	+0.001*** (1.2e-4)	-	-	-0.002*** (1.6e-4)	-0.003*** (1.6e-4)
pHISP	-	-	+0.000** (5.3e-5)	+0.000*** (5.3e-5)	-	-	-0.001*** (8.5e-5)	-0.002*** (8.5e-5)
pAG	-	-	+0.006*** s(2.4e-4)	-	-	-	+0.004*** (2.6e-4)	+0.003*** (2.7e-4)
pPROD	-	-	+0.005*** (1.4e-4)	+0.004*** (1.4e-4)	-	-	+0.004*** (1.4e-4)	+0.004*** (1.4e-4)
pWFHnAg	+0.047*** (4.6e-4)	-	+0.009*** (3.1e-4)	-	+0.023*** (3.8e-4)	-	+0.005*** (2.6e-4)	-
pWFHnAg_Lag	-	-	-	-	+0.037*** (1.0e-3)	-	+0.000*** (2.2e-5)	-
pWFHWS	-	+0.037*** (6.8e-4)	-	+0.005*** (4.3e-4)	-	+0.015*** (5.2e-4)	-	+0.003*** (3.3e-4)
pWFHWS_Lag	-	-	-	-	-	+0.026*** (1.4e-3)	-	-0.001 (9.9e-4)
pWFHSE	-	+0.052*** (8.1e-4)	-	+0.013*** (5.1e-4)	-	+0.032*** (6.4e-4)	-	+0.010*** (4.4e-4)
pWFHSE_Lag	-	-	-	-	-	+0.039*** (1.7e-3)	-	+0.008*** (1.1e-3)
pBACH	-	-	+0.009*** (3.1e-4)	+0.009*** (8.7e-5)	-	-	+0.011*** (9.7e-5)	+0.011*** (9.8e-5)

(Continues)

TABLE 2 (Continued)

Median household income (LN)	Simple OLS 1 (std. error)	Simple OLS 2 (std. error)	OLS controls 1 (std. error)	OLS controls 2 (std. error)	Simple SDEM 1 (std. error)	Simple SDEM 2 (std. error)	SDEM controls 1 (std. error)	SDEM controls 2 (std. error)
pBACH_Lag	-	-	-	-	-	-	-0.001*** (1.4e-4)	-0.001*** (1.4e-4)
DDI	-	-	-0.029*** (2.0e-4)	-0.029*** (1.9e-4)	-	-	-0.023*** (2.0e-4)	-0.023*** (2.0e-4)
Lambda	-	-	-	-	+0.797***	+0.805***	+0.747***	+0.751***
R^2	0.127	0.118	0.709	0.707	0.664	0.668	0.842	0.842
Log likelihood	-43202.10	-43589.30	-3831.56	-4103.10	-14346.56	-14102.49	13443.20	13493.94
n	71559	71559	71559	71559	71552	71552	71552	71552

Note: *$p = 0.1$; **$p = 0.05$; ***$p = 0.01$.

Alternatively, if a census tract has neighbouring tracts with high proportions of wage & salary teleworkers, there is *no impact* on their own income levels (pWFHWS_Lag). This may be because the self-employed teleworkers are opening up jobs in their own tracts for people to commute into, either physically or via telework. The availability of these jobs in neighbouring communities may then raise local income levels. For wage and salary workers, however, no such pattern exists at the aggregate level. Note that for some regions (Northeast and Midwest), the impact of pWFHWS_Lag is actually negative (Table A2). This suggests that neighbouring wage and salary teleworkers may be working for companies in nearby tracts and taking higher-paying jobs, thus reducing local incomes. The overall pattern – that own-tract telecommuting has a positive relationship with income, while cross-tract telecommuting has potentially offsetting impacts – is a novel finding that is worth exploring further as the trend towards telecommuting continues.

5 | CONCLUSIONS

As telework continues to increase, it is critical that empirical studies are conducted to better understand this labour-related shift. This research attempts to contribute to the literature on this topic by documenting the existence of a positive relationship between teleworking and median household income. However, two main limitations exist. First, the measurement of the variable of interest – percentage of workers ages 16 and over working from home – is an imprecise proxy for telework. It likely includes individuals who do not fit the official OPM definition of teleworking, and does not include teleworkers that do *not* work from home. Some individuals may work from coffee shops, parks, co-working spaces, or even other countries. Second, this study is cross-sectional. In other words, it is only looking at one point in time – and therefore cannot make firm claims about causality. As such, the findings of the paper relate to correlations and do not imply a causal relationship, particularly because feedback effects make endogeneity a concern. Future research can look at changes over time and assess whether the positive relationship between teleworkers and income continues to hold. It may also attempt to deal with the endogeneity issue, perhaps by identifying an appropriate instrument (a variable that is correlated with telework, but not with income). Future research should also focus on the relationship between telework and the increasing "online gig" economy, whose employment grew at a faster rate compared to total employment between 2002 and 2014 (Gitis, Holtz-Eakin, & Rinehart, 2017).

Regardless, the main point made by this study remains that the nature of work is changing – moving from a centralized location to a more decentralized (mainly home-based) structure – and that working from home is positively related to median household income. The implications are multiple. First, it shows that the traditional economic development approach of industry attraction fails to consider other strategies, with telework potentially becoming more attractive as a community economic development tactic. Second, as teleworking continues to become a larger part of the workplace picture, its impact on local economies will continue to grow. Finally, future research may need to focus on specific categories of workers from home – since it seems that they may have measurably different effects on neighbouring communities.

Although understanding the physical and social environments that are preferred by teleworkers is beyond the scope of this paper, a reasonable hypothesis is that geographic clustering is not as relevant to teleworkers as it was for industrial clusters. Because of this, policy-makers need to make efforts to modify the existing industrial incentive system so it can more efficiently (and as a complementary alternative – not necessarily a replacement) focus on training and placing workers in telework jobs.

More research supporting the positive contribution of telework could potentially jumpstart discussions to expand economic development policy from offering industrial recruitment incentives towards recruiting and training teleworkers (Erard, 2016). This strategy is not only more aligned to the digital age, but also provides opportunities to rural communities that traditionally lack density of workers and customers, and have struggled to recruit industry. Rural communities continue to become more integrated into urban areas (Irwin, Isserman, Kilkenny, & Partridge, 2010;

Olson & Munroe, 2012), and encouraging telework may allow rural areas to effectively grow local opportunities for work while continuing to promote their historical advantages (natural amenities, housing costs).

To conclude, telework can be one of many digital-age related strategies that can level the playing field between urban and rural (Gallardo, 2016a). This paper found support for the argument that working from home can have positive impacts on local area income. Hopefully, this (and future) research will spur important conversations among policy-makers to better align economic and workforce development strategies to the digital age.

Federal policies that encourage telework do exist, such as the Telework Enhancement Act of 2010. This act promotes teleworking arrangements for federal employees and requires each executive agency to establish a policy for eligible employees to telework. Allen et al. (2015) note that as of 2014, 16 states had policies to encourage telecommuting for federal or state-employees. Even fewer states (roughly 6) had policies that offer some type of incentive for private companies to encourage telecommuting. For example, Georgia code 48.7.29-11 (passed in 2010) offers businesses tax deductions of up to $1,200 per employee for eligible telework expenses; similar legislation exists in Virginia but also allows tax credits of up to $50,000 for conducting a telework assessment. The findings of this research suggest that teleworking can have positive direct and spillover effects on income. As such, we argue that a state/community-related telework-friendly policy framework should look at the following areas (Gallardo, 2016b):

1. making it easier on existing businesses to offer telework through subsidies and tax credits, which help retain fast-growth companies that may otherwise leave due to lack of workers (and may also make the businesses more attractive to younger generations);
2. easing restrictions on out-of-state employers associated with hiring teleworkers in the state (this does not mean *physically* attracting businesses, rather, making it easy for non-resident businesses to hire state residents to telework for them);
3. modifying existing workforce development programmes to better align the workforce to telework-enhancing self-motivation, self-management, teamwork, and other soft skills – in addition to the actual skills required for the job (e.g., programming); and
4. improving broadband availability and access for teleworkers through multiple tax credit mechanisms (including subsidizing monthly access costs for teleworkers).

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APPENDIX

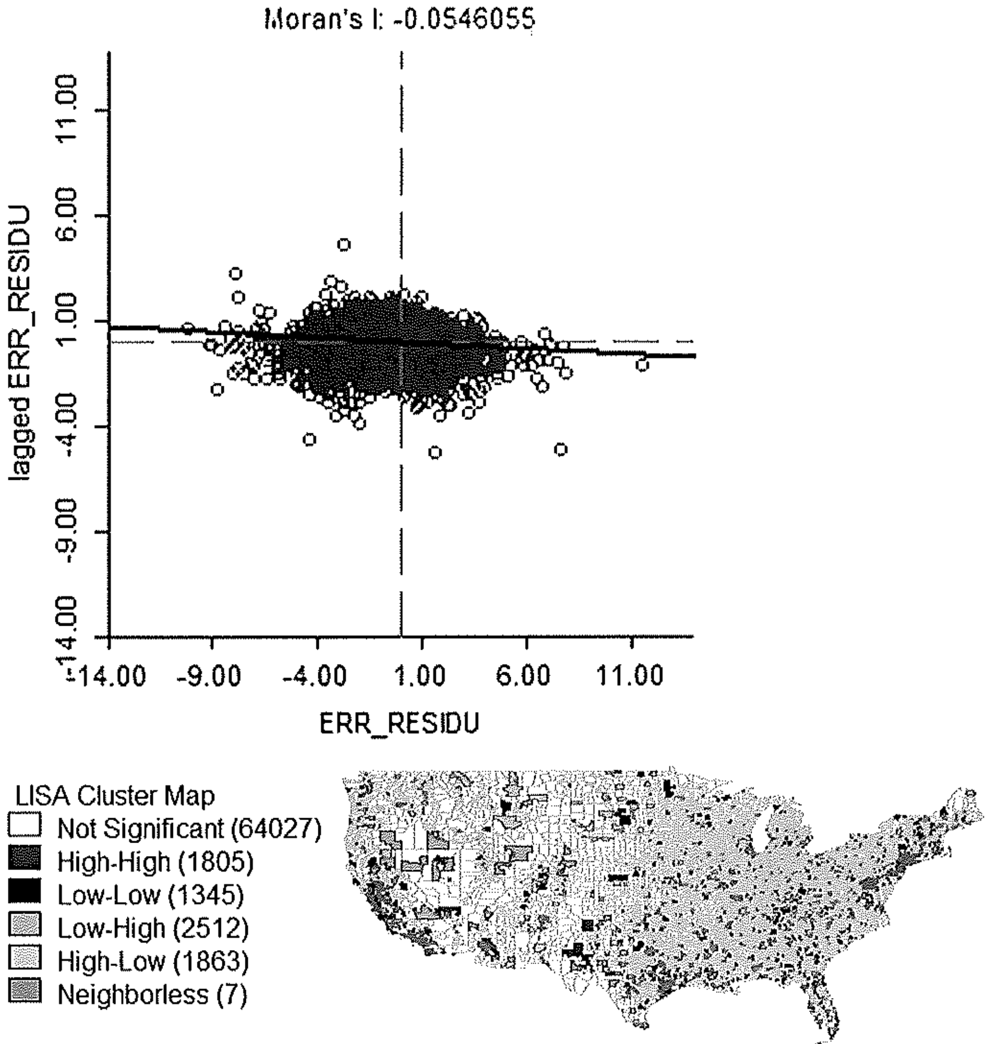

FIGURE A1 Local Moran's *I* spatial error residuals scatter plot and cluster map

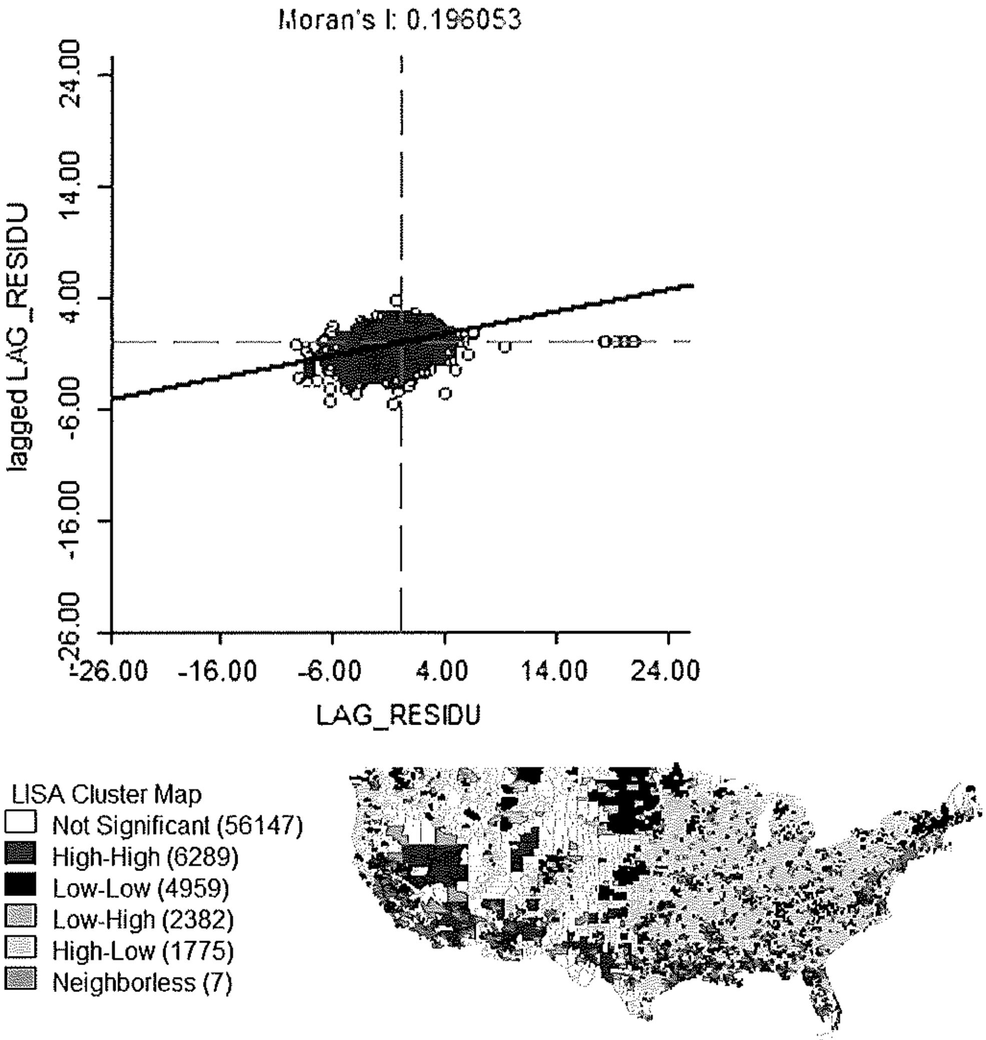

FIGURE A2 Local Moran's *I* spatial lag residuals scatter plot and cluster map

TABLE A1 OLS regression results with spatial dependence diagnostics

Median household income (LN)	Model A (std. error)	Model B (std. error)
Constant	+11.645*** (1.6e-2)	+11.657*** (1.6e-2)
pURB10	-0.003*** (3.7e-5)	-0.003*** (3.6e-5)
pEMP1664	+0.004*** (1.1e-4)	+0.005*** (1.1e-4)
pBNH	-0.002*** (5.3e-5)	-0.002*** (5.3e-5)
pASIAN	+0.001*** (1.2e-4)	+0.002*** (1.2e-4)
pHISP	+0.000** (5.3e-5)	+0.000*** (5.3e-5)
pAG	+0.006*** (2.4e-4)	+0.005*** (2.5e-4)
pPROD	+0.004*** (1.4e-4)	+0.005*** (1.4e-4)
pBACH	+0.009*** (8.4e-5)	+0.009*** (8.7e-5)
DDI	-0.028*** (2.0e-4)	-0.029*** (1.9e-4)
pWFHnAg	+0.000*** (1.0e-5)	-------------
pWFHWS	-------------	+0.005*** (4.3e-4)
pWFHSE	-------------	+0.012*** (5.1e-4)
R^2	0.708	0.707
Adjusted R^2	0.708	0.707
F-statistic	17387***	17304***
Robust LM lag	80.59***	54.56***
Robust LM error	48191***	49524***
n	71,559	71,559

Note: *p = 0.1; **p = 0.05; **p = 0.01.

TABLE A2 Cross-section spatial durbin error model results, by census region

Median household income (LN)	Northeast 1	South 1	Midwest 1	West 1	Northeast 2	South 2	Midwest 2	West 2
Constant	+11.655*** (3.6e-2)	+11.382*** (2.3e-2)	+11.180*** (3.3e-2)	+11.691*** (3.5e-2)	+11.663*** (3.6e-2)	+11.394*** (2.4e-2)	+11.213*** (3.3e-2)	+11.691*** (3.6e-2)
pURB10	-0.002*** (9.9e-5)	-0.002*** (6.3e-5)	-0.002*** (7.2e-5)	-0.002*** (1.0e-4)	-0.001*** (1.0e-4)	-0.002*** (6.3e-5)	-0.002*** (7.3e-5)	-0.002*** (1.0e-4)
pEMP1664	+0.004*** (2.3e-4)	+0.003*** (1.5e-4)	+0.005*** (2.2e-4)	+0.003*** (2.2e-4)	+0.004*** (2.3e-4)	+0.003*** (1.5e-4)	+0.005*** (2.2e-4)	+0.003*** (2.3e-4)
pBNH	-0.002*** (1.8e-4)	-0.003*** (1.0e-4)	-0.002*** (1.4e-4)	-0.006*** (3.9e-4)	-0.002*** (1.8e-4)	-0.003*** (1.0e-4)	-0.002*** (1.4e-4)	-0.006*** (3.9e-4)
pASIAN	-0.002*** (2.9e-4)	-0.003*** (3.8e-4)	-0.007*** (4.3e-4)	-0.001*** (2.7e-4)	-0.002*** (2.9e-4)	-0.003*** (3.8e-4)	-0.007*** (4.3e-4)	-0.001*** (2.7e-4)
pHISP	-0.003*** (1.9e-4)	-0.001*** (1.4e-4)	-0.001*** (2.2e-4)	-0.002*** (1.7e-4)	-0.003*** (1.9e-4)	-0.001*** (1.4e-4)	-0.001*** (2.2e-4)	-0.001*** (1.7e-4)
pAG	+0.005*** (1.1e-3)	+0.004*** (4.6e-4)	+0.005*** (5.9e-4)	+0.001*** (4.3e-4)	+0.005*** (1.1e-3)	+0.003*** (4.6e-4)	+0.003*** (6.3e-4)	+0.001*** (4.3e-4)
pPROD	+0.004*** (3.7e-4)	+0.003*** (2.2e-4)	+0.006*** (2.8e-4)	+0.005*** (3.3e-4)	+0.004*** (3.7e-4)	+0.003*** (2.2e-4)	+0.006*** (2.8e-4)	+0.005*** (3.3e-4)
pWFHnAg	+0.002*** (6.8e-4)	+0.006*** (4.5e-4)	+0.003*** (6.5e-4)	+0.006*** (5.5e-4)	-----	-----	-----	-----
pWFHnAg_Lag	-0.003** (1.8e-3)	+0.005*** (1.3e-3)	+0.000 (1.7e-3)	+0.003*** (1.3e-3)	-----	-----	-----	-----
pWFWS	-----	-----	-----	-----	+0.000 (9.0e-4)	+0.003*** (6.0e-4)	-0.000 (8.1e-4)	+0.003*** (7.4e-4)
pWFHWS_Lag	-----	-----	-----	-----	-0.007*** (2.4e-3)	+0.000 (1.5e-3)	-0.005** (2.2e-3)	-0.002 (1.9e-3)
pWFHSE	-----	-----	-----	-----	+0.005*** (1.1e-3)	+0.010*** (7.7e-4)	+0.009*** (1.0e-3)	+0.008*** (8.7e-4)
pWFHSE_Lag	-----	-----	-----	-----	+0.002 (2.9e-3)	+0.011*** (2.0e-3)	-0.003* (2.0e-3)	+0.011*** (2.2e-3)
pBACH	+0.010*** (2.1e-4)	+0.011*** (1.6e-4)	+0.011*** (1.9e-4)	+0.010*** (2.3e-4)	+0.010*** (2.1e-4)	+0.011*** (1.6e-4)	+0.011*** (1.9e-4)	+0.010*** (2.3e-4)

(Continues)

TABLE A2 (Continued)

Median household income (LN)	Northeast 1	South 1	Midwest 1	West 1	Northeast 2	South 2	Midwest 2	West 2
pBACH_Lag	+0.000***	-0.001***	-0.000***	-0.002***	+0.000***	-0.000***	-0.000*	-0.002***
	(3.1e-4)	(2.4e-4)	(2.9e-4)	(3.3e-4)	(3.1e-4)	(2.4e-4)	(2.8e-4)	(3.3e-4)
DDI	-0.030***	-0.021***	-0.022***	-0.025***	-0.030***	-0.021***	-0.022***	-0.025***
	(5.0e-4)	(3.1e-4)	(4.2e-4)	(4.4e-4)	(5.0e-4)	(3.1e-4)	(4.2e-4)	(4.4e-4)
Lambda	0.733***	0.723***	0.705***	0.769***	+0.732***	+0.724***	+0.703***	+0.769***
	(7.4e-3)	(5.5e-3)	(7.0e-3)	(6.3e-3)	(7.4e-3)	(5.4e-3)	(7.0e-3)	(6.3e-3)
R^2	0.863	0.838	0.832	0.821	0.863	0.838	0.833	0.821
Log likelihood	3085	4792	3835	2506	3090	4812	3880	2516
n	13,301	25,922	16,914	15,415	13,301	25,922	16,914	15,415

Note: $^*p = 0.1$; $^{**}p = 0.05$; $^{***}p = 0.01$.