Objective. The objectives of this study were to examine (1) the linkage from airports to regional talent distribution and (2) the effect of talent on regional economic development. Methods. Using the data collected in Wisconsin at the municipal level, a subcounty level, in a region of the North Central United States from 1970 to 2010 and the American Community Survey 2006–2010 five-year estimates, and random effects models and structural equation models, we employ descriptive and inferential statistics to examine the linkage from airports to talent to regional economic development. Results. We find that the farther a location is away from the airport, the lower its talent share tends to be, while greater passenger flow at the nearest airport increases a location’s talent share. Given the quantity of passenger flow, a longer distance from the airport also reduces a location’s talent share. The results furthermore suggest that economic development is impacted positively by passenger flow and talent share and negatively by distance to an airport. Conclusion. Our results underscore the intermediate role of talent between airports and regional economic development; building the linkage from airports to talent within the context of regional economic development provides important insights for local policy making aimed at attracting talented migrants.

As early as at the emergence of air transportation in the late 1930s and early 1940s, some sociologists recognized the potential role of aviation in economic activities and population interaction and distance (e.g., Ogburn, 1946; Ullman, 1941; Zipf, 1946). With the rapid increase of air transport for leisure trips, business travel, and goods shipment (Appold and Kasarda, 2013), air travel today is increasingly important for people and cities (Chi, 2012; Kasarda and Lindsay, 2011). In essence, accessibility of a location determines its centrality in a hierarchy of places and thereby its competitive position (Button and Lall, 1999; Hawley, 1986; Neal, 2010, 2012). In this article, we define centrality as the relative position of a location in a hierarchy of places near an airport. Airports, in effect, make a location a “favored position” in the global economy by providing “superior access to global flows of people, goods, money and information” (Bowen, 2002). Airports play an increasingly important role in regional development due to their capability of moving large
numbers of people over long distances within a short time frame (e.g., Brueckner, 2003; Florida et al., 2015; Green, 2007; Massey, 1988; Neal, 2012).

Owing to the key role of talent in economic development in the knowledge economy (e.g., Florida, 2002), factors attracting talent, that is, individuals with high human capital, defined as holders of higher education degrees (i.e., those with a bachelor’s degree or above), are taken as important indicators of the quality of a place in a modern economy. How the distribution of talent is determined has been widely explored across many disciplines because it plays an important role in regional economic development such as household income and unemployment rate (e.g., Chen, 2011; Chen and Chi, 2012; Clark, 2003; Florida, 2000, 2002, 2006; Florida et al., 2011; McGranahan et al., 2011; Mellander and Florida, 2007).

While the linkages from airport to economic development and from talent to economic development have already been established, the possible linkage from airport to talent has not been addressed in existing literature. This study attempts to fill the gap in the literature by investigating the dynamic relationship among the three elements. In particular, this study uses data from Wisconsin in five waves from 1970 through 2010 to advance our understanding of the effects of airports on talent distribution. Using random effects models and structure equation models, the longitudinal panel data allow us to examine the dynamics of talent distribution in different temporal contexts. Moreover, unlike most previous studies that used cities and metropolitan areas only, the data cover a spread of rural and urban areas at the municipal level. For these reasons, the data provide an excellent opportunity to explore the underlying relationships between airports and talent attraction by including urban, suburban, and rural areas. The study contributes to the theory of accessibility in a knowledge-based economy and the understanding of relationships between airports and talent distribution. Moreover, our findings that the airports play an important role in attracting talent imply that policymakers should consider airports as a significant factor in regional development.

**Literature Review**

The relationships between airports and regional economic development or between talent and regional economic development have been examined in a large body of literature. However, to our best knowledge, the linkage from airports to talent distribution is missing. In this section, we first review previous research on the impacts of airports and talent on regional economic development. We then attempt to build the conceptual framework for the analysis of the relationships among the three components and propose our research hypotheses.

**Airports and Regional Development.** A large body of literature analyzes and justifies the relationship between a city’s airport and its population and economic activity (Irwin and Kasarda, 1991; Brueckner, 2003; Button et al., 1999; Green, 2007). Irwin and Kasarda (1991) found that position in the airline network has pervasive effects on metropolitan employment growth, and changes in an airline network were a cause rather than a consequence of this employment growth. Centrality within air traffic networks allows some cities to deliver business services more effectively to increasingly global hinterlands (Neal, 2010). Button et al. (1999) found that proximity to an airport hub has important structural advantages for the local economy and showed that hubs create employment rather than follow employment trends, that is, airlines selecting cities as hubs simply because such places
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are already economically dynamic. Airports Council International ([ACI] 2004) studied the social and economic impact of Europe’s airports. Its report demonstrated the benefits of airports on regional development. Airports as regional economic motors increase regional accessibility and enhance the development of tourism.

Brueckner (2003) confirmed that good airline service is an important factor in urban economic development, especially for the service-related industries. Every 10 percent gain in passenger traffic in a metropolitan area is related to a 1 percent gain in service employment. Green (2007) found that boardings, originations, and hub status are good predictors of an increase of population and economic activity while cargo is not. Kasarda (2008) suggested that major airports are evolving in form and function. He created the airport city model based on the fact that major airports have developed significant nonaeronautical facilities, services, and revenue streams. Florida et al. (2015) found that airports are equivalent to human capital in regional economic development.

**Talent and Regional Development.** Places with high levels of human capital enjoy fast economic growth and high productivity. Ullman (1958) noticed the role played by human capital or talent in regional development about half a century ago. Glaeser et al. (1995) found a strong relationship between the population’s education level and city growth. They deduced that schooling was a generator of growth and that higher education levels influenced later growth by influencing the growth of technology. Simon (1998) found that cities with higher average levels of human capital enjoyed faster employment growth. Desrochers (2001) noted that the ability to incubate and nurture creativity and to attract creative people plays a central part in regional development. Florida (2002) confirmed that talent is a key intermediate variable in attracting high-technology industries and generating higher regional incomes. Recent evidence supporting the relationship between human capital and regional development can be found in different disciplines (e.g., Chen, 2011; Gennaioli et al., 2012; Lengyel and Ságvári, 2011; Florida et al., 2010; McGranahan et al., 2011).

**The Distribution of Talent: The Role of Airports.** There are many factors that affect the distribution of talent. Glaeser et al. (2000) noted that both market and nonmarket forces affect the location of people and firms. Economists traditionally supposed that places attract people by offering them high wage income and employment (Florida, 2002). Given that talented people tend to have more job opportunities relative to people who receive less education, the former enjoy relative advantages in terms of the chance to choose attractive regions to live and work. Three kinds of nonmarket factors play a role in attracting talent: amenities, openness, and universities. Several studies have examined the role of natural, recreational, and lifestyle amenities in affecting a place’s ability to attract talent (e.g., Chen and Chi, 2012; McGranahan et al., 2011). Community aesthetics and community satisfaction can affect a person’s decision where to live (Florida et al., 2011; Mellander et al., 2011; Chen and Chi, 2012). Florida (2000) confirmed that service amenities and environmental quality are vital to the attraction of talent. Talent is also attracted to diversity or openness of a place (Florida, 2002; Florida et al., 2008, 2010; Mellander and Florida, 2007; Chen, 2011; McGranahan et al., 2011). Regions that are open and possess low barriers to entry for human capital would gain a distinct economic advantage in the competition for talent or human capital (Florida, 2002). The university is a central hub institution of the talent-driven creative economy and is crucial to attracting talent, technology, and regional development (Mellander and Florida, 2007; Berry and Glaeser, 2005; Florida, 2006; Qian, 2008). In sum, amenities, openness, and universities
affect the distribution of human capital through different ways and play complementary roles in the geographic distribution of talent (Mellander and Florida, 2011).

As we reviewed above, talent and airports significantly contribute to regional development, and a wide range of factors affect the location of talent. However, to the best of our knowledge, it remains unclear whether airports play a role in attracting talent, and if they do, how that works. Although research appears to move toward empirically exploring the effect of airports on the movement of talent, few studies have actually done so (for one exception, see Florida et al., 2015). Florida et al. (2015) found that airports have a bigger effect on regional economic development by moving people than by moving cargo, and moving people rather than cargo is positively associated with talent share. In examining the causal effects between creative jobs and airport activities, especially the volume of air passengers, Neal (2012) found that, during economic upswings, creative jobs follow airport activity, while airport activity follows creative jobs during economic downturns. However, Neal's study focused on metropolitan areas and did not include rural areas.

In this study, we examine the possible linkage from airports to talent within the regional economic development context. Our conceptual framework is illustrated in Figure 1. Solid lines represent what has been already examined in previous research, and the dotted line represents what we focus on in this study: the possible impact of airports on talent distribution. The direction in which arrowheads point indicates the causal direction we assumed. The empirical relationships among the three components are analyzed with structural equation models.

Local-level (municipal-level) panel data are used to examine the effect of airports on attracting talent. The assumption of this study is that talent mostly works on creative activities, and the key features of many creative activities are that information is imperfect, rapidly changing, and not easily codified, and therefore face-to-face contact is practically important (Storper and Venables, 2004; also see Florida, 2002). In addition, in our global economy, transnational interactions between people are increasing and very important, such as academic interaction and negotiation of business. Therefore, creative people are more likely to choose a location that is easily accessible through airports. In other words, the position of a location in a system of territory is important in shaping competitive advantage (Irwin and Kasarda, 1991). Locations in central places are more competitive in attracting and retaining people and their economic and social activities. Thus, measuring a location's centrality based on its access to airports, our main research hypothesis is:
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The higher a location’s centrality is, the higher will be the location’s share of talent in a region.

Unlike previous studies, we use data covering urban, suburban, and rural areas in Wisconsin, not just data limited to cities or metropolitan areas. This approach benefits our study in revealing the general pattern of talent distribution across different types of places. More importantly, these longitudinal data in combination with the use of a random effects modeling strategy allow us to make causal inferences (Halaby, 2004). Moreover, to make the causal analysis more robust and to stress the whole picture of the relationships from airports to talent and to regional economic development, after having examined the hypothesis above, we will estimate a structural equation model as Figure 1 shows.

Data and Methods

Data

We use a panel data analysis to examine the effects of airports on talent distribution in Wisconsin, a region of the North Central United States. This analysis is conducted at the minor civil division (MCD) level. MCDs are the smallest governmentally functioning units in Wisconsin that collect tax revenues and provide services; thus conducting the analysis at the MCD level captures social and political functions, giving our study an advantage over studies of census-defined geographic units, such as census tracts, that are delineated for population enumeration, and have no social and political implications.

Table 1 provides definitions and descriptive statistics for the variables used in our analysis. The talent data were derived from decennial censuses from 1970 to 2000 and the American Community Survey 2006–2010 five-year estimates. Talent is measured by the percentage of population (age 25+ with bachelor’s degrees) in each MCD. In order to ascertain the causal direction from airports to talent share, we used talent \((t+1)\) as a dependent variable, and talent at time \(t\), as the control variable. In this study, the average percentages of talent share from 1970 to 2010 are 5.32, 9.73, 11.43, 15.35, and 18.51, respectively (see Figure 2).

Airport data are from a variety of federal and state aviation offices and airports located in Wisconsin and surrounding states, including Michigan, Illinois, Iowa, and Minnesota. In total, 16 major commercial airports that provide passenger services were selected for this study, including seven located in Wisconsin and nine in surrounding states (Figure 3). We used two variables to measure airports in terms of determining a location’s centrality in the system of places: one is the distance to the nearest airports and the other is boarding passenger flow. For a location, closer proximity and greater passenger flow in an airport mean greater centrality. In new economic geography (NEG), it is widely recognized that firms and high-skilled workers agglomerate in a particular region (i.e., a hub city), and NEG often theoretically and empirically argues the importance of a hub (Neal, 2013). Neal (2013) describes three types of hub cities and how their effects on urban economies differ. The three types of hub cities parallel three measures of the centrality of networks: degree, closeness, and betweenness. Degree has the strongest effect on the creative economy

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1Our measures of centrality are different from Irwin and Kasarda’s, whose measures followed the network analysis of the Bonacich (1987) measure. They focused on U.S. metropolitan areas, each of which has its own airports and can use network centrality measure of that; but our unit of analysis is a MCD, which would not necessarily have an airport.
and betweenness the least. Our measure of passenger flow includes both the volume of passengers for whom the city is a final destination and those for whom it is a connecting stop, thereby mixing both the degree and close types of hub city centrality. As a result, our study contributes to the literature on the role of hub cities in the knowledge economy.

The average numbers of passenger flows from 1970 through 2010 are 35.96, 48.17, 72.59, 111.11, and 119.79 (all in 10,000), respectively (see Figure 2). From the graph, we can see the general trend in the relationship between talent share and passenger flow over the past several decades. Logically, if no airline frequents a city, the presence of an airport in that city would not be useful in attracting talent. When an airport has a sufficiently large airline network, talent increasingly accumulates in those cities. To address this point,
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FIGURE 2
Trend of Talent Share and Passenger Flow in Wisconsin from 1970 to 2010

for each airport in question, we use the number of connections with other airports to examine the correlation of airline networks and talent distribution.

Data for the control variables are from a variety of federal and state governmental agencies. Demographic and socioeconomic data are from the U.S. Bureau of Census and Wisconsin Blue Books. Natural amenity data are from the Wisconsin Department of Natural Resources. Transportation data are from the Wisconsin Department of Transportation. Land developability data were extracted from the land developability index project (http://www.landdevelopability.org). For natural amenity conditions, water area is measured by the percentage of water coverage, and forest area denotes the percentage of forest coverage. Economic conditions are measured by income (median household income; $1,000) and the unemployment rate (percent). Other control variables include population (size of population in the area in 10,000s); county seat (whether a MCD is a county seat or not); demographic factors such as the proportion of young people (the percentage of the population who are 12–18 years old), elderly people (the percentage of the population who are 65 and older), and black population (the percentage of the population who are black); public transportation (the percentage of workers using public transportation to get to work); highway density (the total length of main highways over MCD areas [km/km²]); regional characteristics such as rural areas (yes = 1, no = 0) and proximity to metro cities (×10,000, the inverse distance to the centroid of a metro cities); a land developability index (measured by the proportion of lands available for development); and agricultural workers (the percentage of workers in agricultural industries).

2We collected current data about their direct connections with other airports from airline websites. We were unable to obtain historical data about direct connections and therefore were unable to perform a panel analysis for those data.
Methods

We use random effects modeling (Bell and Jones, 2015) to analyze the effect of airports (both distance to the airport and passenger flow) on the talent share in a MCD, measured at four occasions (level 1) for all 1,837 MCDs (level 2) in Wisconsin. The variables in the model include time-variant terms, such as passenger flow (one of the variables of interest that generally increases over time); variables that change rarely, such as public transportation; and time-invariant variables, of which the distance to airport is one; others include water areas, forest areas, county seat status, rural, development index, proximity to metro cities, and so on. Using ordinary least-squares (OLS) regression to model an occasion-level outcome as a function of time-specific-level and individual-level variables would overlook characteristics of the error structure resulting from the commonalities of time-specific cases within individual-MCDs, which violates the assumptions of the OLS regression model. Hierarchical models, on the other hand, explicitly incorporate both occasion-level and individual-MCD-level errors. In addition, they account for the
correlations among a region’s repeated observations over time (Raudenbush and Bryk, 2002). Because the distance to an airport is a time-invariant variable, the fixed effect model is not appropriate. Therefore, we adopt a random effect model that properly specifies the within and between effects and provides identical results to a fixed model (Bell and Jones, 2015). In this model, following a between and within random model strategy (Bell and Jones, 2015), we group all time-varying variables into two new variables: occasion-level, \((x_{it} - \bar{x}_i)\) and individual-MCD level, \(\bar{x}_i\) as a time-invariant variable. The equations estimated for our base model are as follows:

\[
y_{it} = \beta_0 i + \sum_{k=1}^{k} \beta_k x_{kit} + \sum_{m=1}^{m} \gamma_m z_{mi} + \mu_i + e_{it} \\
\mu_i \sim N(0, \sigma_u^2) \\
e_{it} \sim N(0, \sigma_v^2) 
\]

Equation (1) characterizes talent share in a MCD over time. The response variable \(y_{it}\) for MCD \(i\) at time \(t\) is modeled as a function of airport passenger flow, distance to airport, and other control variables for MCD \(i\) at time \(t\). \(x\) represents time-variant variables, calculated by \((x_{it} - \bar{x}_i)\), such as passenger flow within, our variable of interest. \(Z\) represents all time-invariant variables, including all \(\bar{x}_i\), such as the distance to airport and passenger flow between. The coefficients \(\beta_{0i}, \beta_{1i}, \text{ and } \beta_{x_i}\) represent the parameters to be estimated for, respectively, intercept, passenger flow, and control variables. The term \(e_{0i}\) represents the model’s error. \(\mu_i\) is the individual-MCD-level residual for individual MCD \(i\), allowing for differential intercepts for individual MCDs, and \(e_{it}\) is the occasion-level residual for occasion \(t\) of individual MCD \(i\). Both \(\mu_i\) and \(e_{it}\) are assumed to be normally distributed.

To capitalize on the advantages of random effect models, we use the random coefficient model (Bell and Jones, 2015; Raudenbush, 2009). This model allows the effects of \(\beta\) coefficients to vary by the individual MCDs (Bell and Jones, 2015). We will allow the effect of passenger flow to vary by the individual MCDs. This does not require us to assume homoscedasticity but explicitly models the heteroscedasticity at each level (Bell and Jones, 2015). Equation (2) is the same as Equation (1) with the addition of the random part of the effect of passenger flow variables.

\[
y_{it} = \beta_0 i + \sum_{k=1}^{k} \beta_k x_{kit} + \sum_{m=1}^{m} \gamma_m z_{mi} + \mu_{0i} + \mu_{1i} \chi_{1it} + e_{it} 
\]

with the following distribution assumptions:

\[
\begin{pmatrix} \mu_{0i} \\ \mu_{1i} \end{pmatrix} \sim N\left\{0, \begin{pmatrix} \sigma_{u0}^2 & \sigma_{u0,1} \\ \sigma_{u0,1} & \sigma_{u1}^2 \end{pmatrix}\right\} \\
\begin{pmatrix} e_{0it} \\ e_{1it} \end{pmatrix} \sim N\left\{0, \begin{pmatrix} \sigma_{e0}^2 & \sigma_{e0,1} \\ \sigma_{e0,1} & \sigma_{e1}^2 \end{pmatrix}\right\} 
\]

To test our research hypothesis, we estimated two random coefficient models. In Model 1, we included all variables but the interaction terms between passenger flow and the distance to airports, with the passenger flow within as the random part. Model 2 is the same as Model 1 with added interaction terms. To perform this analysis, we used MLwiN (Rasbash et al., 2009) via Stata’s runmlwin command (Leckie and Charlton, 2013).

The importance of the effects of airports on talent lies in the major role of talent in regional economic development. To make the whole picture complete as Figure 1 shows,
we estimate a structural equation model to analyze the effects from airports to regional economic development through talent distribution and from airports directly to regional economic development.

Results

Airport Effects on Talent Distribution

The results from Model 1 show that, with all controls,\(^3\) distance to airports has a significant effect on talent share: the longer the distance to airports, the lower the talent share (Table 2). The passenger flows both between and within are positive; the former is statistically significant at the 0.05 level, and the latter at the 0.10 level. Lagged talent share is positive and significant only for the in-between effect; it does not matter for the within effect. Water and forest areas as natural amenities have a positive effect. Income in a region can attract more talented people; for this factor both within and between effects are significant and positive. At the same time, the unemployment rate has a negative effect on talent share, but is only significant for the between effect. As expected, public transportation and highways are also positively associated with a higher talent share. At level 2, the positive covariance term tells us that, conditional on the variables in the fixed part of the model, variance in talent share between MCDs increases according to the within component of passenger flow; MCDs diverge a little as they increase passenger flow over time.

In Model 2, which adds the interaction terms of the distance to airports with passenger flow, the passenger flow has a significant effect on talent share in a region, and the magnitude of the main effects becomes stronger while the effect of distance to airports is a little weaker. Significant effects of interaction terms either between or within suggest that, given the passenger flow, the greater the distance of a MCD from its nearest airport, the lower its talent share will be. Natural amenities effects change little. Model 2 also shows that economic factors have significant positive effects on talent share. In addition, other control variables remain more or less consistent with Model 1.

From Models 1 and 2, we can also see that, regardless of whether within or between, the variable “old” (the proportion of the population aged 65+) positively affects the talent share in that region, whereas the “young” variable (the proportion of the population aged 12–18) has a negative effect on a MCD’s talent share. These results imply that talent share is driven by the elderly population, especially retirees. Table 2 also shows that, with all control variables including lagged talent share, rural areas have a greater share of talent. That means that, with a greater number of people holding bachelor or higher degrees, the rural areas also benefit from this trend of increasing talent.

In order to demonstrate the different effects both within and between MCDs, following Model 2, we graph the relationships between predicted talent share and passenger flow both between and within (see Figure 4). Figure 4 clearly shows that, with the increase of passenger flow, the within effect is much stronger than the between effect. These interesting and substantive findings could not be revealed with a fixed effect model; this is one of the reasons for our random effects modeling strategy. Therefore, whether within or between MCDs, more centrality (higher passenger flow) contributes to talent share in that area.

\(^3\)For raw results without control variables, the trends are substantively the same except that the magnitude of the coefficients is smaller after controlling for those variables (Results not reported to save space and available from the authors upon request.)
### TABLE 2  
The Extended Within-Between RE Model for the Effects of Airport on Talent Share

<table>
<thead>
<tr>
<th></th>
<th>Model 1 (Between)</th>
<th>Model 1 (Within)</th>
<th>Model 2 (Between)</th>
<th>Model 2 (Within)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Fixed Part</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Airport</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Distance to Airport Index</td>
<td>$-0.488^{***}$</td>
<td>$(0.121)$</td>
<td>$-0.366^{**}$</td>
<td>$(0.123)$</td>
</tr>
<tr>
<td>Passenger Flow Index</td>
<td>$0.015^*$</td>
<td>$(0.007)$</td>
<td>$1.014^{***}$</td>
<td>$(0.204)$</td>
</tr>
<tr>
<td>Distance $\times$ Passenger Flow (within)</td>
<td>$-0.059^{***}$</td>
<td>$(0.008)$</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Distance $\times$ Passenger Flow (between)</td>
<td>$-0.045^{***}$</td>
<td>$(0.009)$</td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Control Variables</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Economic Factors</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Income</td>
<td>$0.870^{***}$</td>
<td>$(0.025)$</td>
<td>$0.846^{***}$</td>
<td>$(0.026)$</td>
</tr>
<tr>
<td>Unemployment Rate</td>
<td>$-0.144^{**}$</td>
<td>$(0.047)$</td>
<td>$-0.149^{***}$</td>
<td>$(0.047)$</td>
</tr>
<tr>
<td><strong>Demographics</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Talent Share (lag)</td>
<td>$1.180^{***}$</td>
<td>$(0.075)$</td>
<td>$1.189^{***}$</td>
<td>$(0.075)$</td>
</tr>
<tr>
<td>Young (%)</td>
<td>$-0.326^{***}$</td>
<td>$(0.059)$</td>
<td>$-0.312^{***}$</td>
<td>$(0.059)$</td>
</tr>
<tr>
<td>Old (%)</td>
<td>$0.243^{***}$</td>
<td>$(0.031)$</td>
<td>$0.242^{***}$</td>
<td>$(0.031)$</td>
</tr>
<tr>
<td>Black (%)</td>
<td>$-0.057$</td>
<td>$(0.107)$</td>
<td>$-0.066$</td>
<td>$(0.107)$</td>
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<tr>
<td>Population (10,000)</td>
<td>$-0.079$</td>
<td>$(0.107)$</td>
<td>$-0.092$</td>
<td>$(0.107)$</td>
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<tr>
<td>Agricultural Workers (%)</td>
<td>$-0.020*$</td>
<td>$(0.010)$</td>
<td>$-0.020*$</td>
<td>$(0.010)$</td>
</tr>
<tr>
<td><strong>Natural Amenities</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Water (%)</td>
<td>$0.031$</td>
<td>$(0.018)$</td>
<td>$0.038^*$</td>
<td>$(0.018)$</td>
</tr>
<tr>
<td>Forest (%)</td>
<td>$0.080^{***}$</td>
<td>$(0.006)$</td>
<td>$0.081^{***}$</td>
<td>$(0.006)$</td>
</tr>
<tr>
<td><strong>Accessibility</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Proximity to Metro Cities (x10,000)</td>
<td>$1.389$</td>
<td>$(1.584)$</td>
<td>$1.861$</td>
<td>$(1.589)$</td>
</tr>
<tr>
<td>Public Transportation</td>
<td>$0.617^{***}$</td>
<td>$(0.109)$</td>
<td>$0.558^{***}$</td>
<td>$(0.110)$</td>
</tr>
<tr>
<td>Highway</td>
<td>$0.362^{***}$</td>
<td>$(0.098)$</td>
<td>$0.309^*$</td>
<td>$(0.098)$</td>
</tr>
<tr>
<td>County Seat</td>
<td>$1.435^*$</td>
<td>$(0.642)$</td>
<td>$1.652^{**}$</td>
<td>$(0.641)$</td>
</tr>
<tr>
<td><strong>Land Use and Development</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Developability Index</td>
<td>$-2.414^{***}$</td>
<td>$(0.696)$</td>
<td>$-2.064^{**}$</td>
<td>$(0.701)$</td>
</tr>
<tr>
<td>Rural ( = 1)</td>
<td>$0.808^*$</td>
<td>$(0.326)$</td>
<td>$0.858^{**}$</td>
<td>$(0.326)$</td>
</tr>
<tr>
<td>Constant</td>
<td>$0.834$</td>
<td>$(2.891)$</td>
<td>$-1.670$</td>
<td>$(2.945)$</td>
</tr>
</tbody>
</table>

continued
TABLE 2

<table>
<thead>
<tr>
<th></th>
<th>Model 1 (Between)</th>
<th>Model 2 (Within)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Random Part</td>
<td>(Between)</td>
<td>(Within)</td>
</tr>
<tr>
<td>Level 2: id</td>
<td>19.651 (0.749)</td>
<td>19.576 (0.746)</td>
</tr>
<tr>
<td>σ²(u0)</td>
<td>0.104 (0.025)</td>
<td>0.111 (0.028)</td>
</tr>
<tr>
<td>δ(u0u1)</td>
<td>0.104 (0.025)</td>
<td>0.111 (0.028)</td>
</tr>
<tr>
<td>σ²(u1) (flow wi)</td>
<td>0.001 (0.000)</td>
<td>0.002 (0.0006)</td>
</tr>
<tr>
<td>Level 1: yearid</td>
<td>11.989 (0.232)</td>
<td>11.839 (0.229)</td>
</tr>
<tr>
<td>σ²(e0)</td>
<td>0.043 (0.016)</td>
<td>0.074 (0.020)</td>
</tr>
<tr>
<td>δ(e0e1)</td>
<td>0.043 (0.016)</td>
<td>0.074 (0.020)</td>
</tr>
<tr>
<td>σ²(e1) (flow wi)</td>
<td>-0.001 (0.001)</td>
<td>0.0005 (0.0009)</td>
</tr>
<tr>
<td>Log Likelihood</td>
<td>-21406.47</td>
<td>-21381.09</td>
</tr>
<tr>
<td>Number of Observations</td>
<td>7,348</td>
<td>7,348</td>
</tr>
</tbody>
</table>

Note: Standard errors in parentheses; !p < 0.10, *p < 0.05, **p < 0.01, ***p < 0.001 (two-tailed tests).

FIGURE 4

The Predicted Talent Share by Between and Within Effects of Passenger Flow on the Individual MCDs’ Talent Share

To address the importance of airport networks, we use the number of current airport connections to perform a supplementary analysis. We use the mean of airport domestic connections as the cutoff point to determine talent distribution change from 1990 through 2010. The average percentage of talent in MCDs with airport domestic connections above
the cutoff point was 17.50 percent in 1990, 22.98 percent in 2000, and 27.03 percent in 2010. If we use the criterion of whether the airport is international to examine the talent distribution change, the trend is the same. An example is the Minneapolis–Saint Paul International Airport (MSP). Neal (2013) found that Minneapolis–St. Paul was a top 10 hub city for both betweenness and closeness among his three measures of centrality. Of the MCDs for which MSP was the closest airport, those that were the farthest had talent distributions of 13.02 percent in 1990, 13.24 percent in 2000, and 15.50 percent in 2010. In contrast, the MCD closest to that airport had talent distribution of 15.18 percent in 1990, 21.42 percent in 2000, and 20.20 percent in 2010. The former showed very little increase in talent percentage, whereas the latter showed an increase. This example demonstrates that distance to an airport is an important factor in a MCD having a higher share of talent.

Reverse Causality

We assume that airport passenger flow and the distance to airports are causes of talent share. But this assumption may not necessarily be appropriate. As Neal (2012) found, in different economic conditions, creative jobs and airport activities may have opposite causal relations. Florida et al. (2015) also suggest that more talent is also more likely to have an airport in the first place. However, to address this reverse causality problem, we used talent share in t+1 as a dependent variable, and within our observation period, no new airports were built in any of the MCDs we observed. This finding makes us more confident that the causal relation we established between airport factors to talent share is robust. But we still need to be cautious in drawing causal inferences.

The structural equation model results suggest that, through the distribution of talent, airports have significant effects on regional economic performance (see Figure 5). The distance to the nearest airport from a MCD does have a negative effect (−0.008), but is not statistically significant at the conventional level. All other coefficients have the expected signs and are statistically significant at the 0.001 level. Talent share significantly increases regional income (0.588) and reduces unemployment (−0.104). Greater distance to the nearest
airport clearly reduces talent share in a MCD, and greater passenger flow promotes talent share (0.266). Overall, airports have significant effects on regional economic development through talent attraction and retention. Identifying this causal link thus advances our understanding of the relationship between airports and regional development (ACI, 2004).

**Discussion and Conclusion**

The results of the panel data analysis demonstrate that, after controlling for natural amenities (water and forests) and economic factors (household income and unemployment rate), airports have a significant effect on attracting talent, which is consistent with Florida et al. (2015). Using a random effects modeling strategy, we found both within and between effects. Distance to airports has obvious negative effects on talent share in a region; and in terms of passenger flow, longer distance to airports was related to lower talent share. At the same time, the increase of passenger flow has a greater effect within a MCD than between MCDs, and, through talent attraction and retention, an airport has significant effects on regional economic performance. Therefore, talent share is an important intermediate factor between airports and regional economic development.

This study has both theoretical and practical implications. Theoretically, our study brings the link between airports and economic development using talent as an intermediate factor, and thus contributes to the mechanism of the function of airports in economic development by attracting and retaining talent. This study also contributes to the literature of the new geography economy by addressing the important role of hub cities in the knowledge economy. More importantly, the structural equation model results suggest the causal relation from airport to talent share and then to local economic development.

Beyond their theoretical implications, the findings have troubling implications for the future of low-income areas in the United States. Airports play an important role in attracting talent and places with high levels of talent/highly educated individuals enjoy robust economic growth and high productivity (Chen, 2011; Florida, 2002; McGranahan et al., 2011; Rauch, 1993). Places without access to airports experience a deepening brain drain—more talent moving out and less moving in—and the advantages associated with human capital concentration flow disproportionately to those places with high centrality positions in the airport traffic network (i.e., hub city). Success breeds success, and brain drain stimulates further brain drain. These patterns may create a vicious cycle for disadvantaged areas and may make regional inequality worse within the state of Wisconsin as well as within the United States as a whole.

This research could be extended into at least four future directions. First, do the effects of airports on talent distributions differ along the life course of talents and if so, how? Variation of the effects is possible along the life course because the motivations and patterns of migration differ across age groups. Future research could partition the data samples by age groups and estimate the models for each group. Second, how individuals make decisions in choosing places to live is still unclear. Our findings are based on aggregated data analysis. Because of the ecological fallacy that occurs if we ignore the individual-level observation and only rely on higher-level units of analysis (Robinson, 1950), we should be cautious in interpreting our results. The micromechanism of the individual decision-making process and the determinants of mobility of knowledge workers (Miguélez and Moreno, 2014) could be addressed in future research. Third, the measurement of airports is limited in this study, as we considered only the airport nearest a city or location and ignored others nearby. Fourth, the generalization of our findings to other regions of the United States is limited, as
our study is focused on Wisconsin, which lacks major talent-attracting metropolitan cities. Conducting the analysis in other regions might provide more robust and generalizable findings.

REFERENCES


