An Exploratory Analysis Of Leisure Activity Variety As An Outcome Of Accessing Instrumental Social Resources

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INTRODUCTION

The need for travel is often perceived as demand derived from participation in various activities. From an activity-travel perspective, most trips are categorized by purpose such as mandatory, maintenance or discretionary/leisure travel. Differentiating it from the first two purposes, leisure travel is of a social and voluntary nature. In addition to offering freedom and satisfaction, leisure activities strengthen individual's relationships with families, friends, and create new connections.

Gathering evidence of the linkage between social networks and activity generation, Kim et al. (2018) reviewed transportation studies that analyzed the impacts of individuals' social network characteristics on the frequency of social activity participation using three measures:

(1) Network size: more frequent activity participation was associated with larger networks
(2) Relationship type: there was no clear consensus on its impact on ego-alter activity frequency due to varying methodologies and classification schemes
(3) Tie strength: higher social activity frequency was generated by stronger ties

Examining tie strength effects on activity generation, Maness (2017a) theorized that larger strong-tie networks and weak-tie diversification increases activity variety and frequency. Using a name generator for strong-tie characteristics and a position generator for weak-tie characteristics, the theory was confirmed by improved model fit. Maness' (2017a) study, however, was restrained by limited activity space as well as the lack of mobility data and directly accessible resources.

To address the limitations of existing literature, this paper proposed two research questions to test a theory that leisure activity variety is an instrumental outcome and thus mostly affected by instrumental social resources.

1. Do individuals with greater social capital (e.g.: more strong ties, direct and indirect accessible social resources) have more variety in their leisure activities?
2. What are the impacts of those social capital measures on leisure activity variety?
3. Does an individual's broader access to instrumental social resources significantly increase their instrumental outcome (i.e.: participation in diverse activities)?

The study aims at answering those questions using insights gathered from a self-administered web-based survey designed specifically to test differences in social capital and its relevance in a leisure activity context.

SOCIAL CAPITAL AND LEISURE ACTIVITY BEHAVIOR

The concept of social capital describes how individuals acquire beneficial assets and services by using social interactions. Among various definitions of social capital, Lin's formulation of social capital as embedded social resources has strong methodological rigor because this definition aligns well with the individual-level basis of most activity and travel research. Specifically, Lin (2001) proposes three primary elements of social capital: (1) resources embeddedness in social networks, (2) resource accessibility, and (3) resource use for action-oriented aspects. Lin (2001) defines three processes involved in the creation and use of social capital: (1) investment in social capital, (2) access to and mobilization of social capital, and (3) returns of social capital.

Häuberer (2011) schema (**FIGURE 1**) clarifies Lin's theory of the three processes and thus provides causal relationships between preconditions, social capital, and outcomes. Generally, smaller, denser networks promote continued access to group resources through trust and reciprocation which leads to expressive outcomes. Lin (2001) classifies expressive outcomes as mental health, physical health, and life satisfaction. In contrast, larger, wider social networks enable new contacts and thus access to new resources for profit or resource gain which leads to instrumental outcomes. Lin (2001) classifies instrumental outcomes as wealth, power, and status.

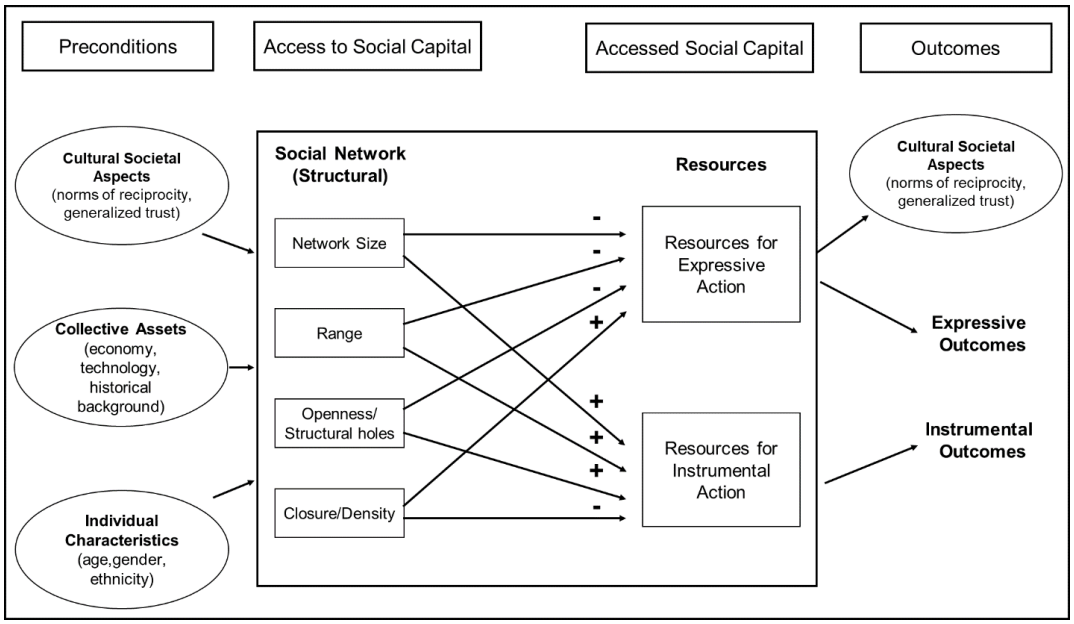

FIGURE 1 Häuberer (2011) Conceptual Diagram of Social Capital and Outcomes

Carrasco and Cid-Aguayo (2012) and Maness (2017b) attempt to link social capital to activity behavior through measuring social network characteristics. Parady et al. (2019) also links network size and club membership to social activity variety. But their efforts are limited by an unclear linkage between social resources and leisure activity preferences. By using Lin's social capital concept with the ability to measure structural and mobilized resources, the effects of leisure activity for enabling expressive and instrumental outcomes could be explored.

METHODOLOGY

Survey Design

A cross-sectional survey was designed to better understand social factors influencing the leisure activity participation. The survey instrument consists of questions on activity space, social capital, mobility/accessibility, individual and household characteristics. Leisure activity variety was asked over a list of 86 unique activity types – mostly adopted from Tinsley and Eldredge (1995).

Social capital was measured by 1) position generator, 2) resource generator and 3) core network size. The position generator, a list of 22 occupations proposed by Lin and Dumin (1986), was used to measure access to instrumental social resources. Respondents were asked to indicate if they personally knew someone (a relative, friend, or acquaintance) with that occupation.

In order to explore the availability of resources that individuals can access through their social network, a resource generator was included in the questionnaire. Respondents were advised: "This section is about who you would turn to for help, if you needed it, in different situations. For each situation, please choose who you would turn to first for help. (If there are several people you are equally likely to turn to, please choose the one who you feel is closest to you)." The list of 26 resources that respondents could access was refined from Joye (2019) and Foster and Mass (2016).

1. Help you for a household job that you cannot do yourself
2. Help you around the house if you were sick
3. Help you borrow a large sum of money
4. Help you with finding a job
5. Help you with computer problems
6. Help find a new place to live

7. Help look for information about a serious health issue
8. Give advice on legal matters
9. Be there if you felt down and wanted to talk about it
10. Give advice on family problems
11. Make you feel appreciated for who you really are
12. Be there if you wanted to talk about your day
13. Look after you if you were seriously ill
14. Pick you up from a social event
15. Is an elected official
16. Works at a government agency
17. Give advice on problems at work
18. Knows a lot about government regulations
19. Has good contacts at TV/radio/newspaper
20. Give advice about money problems
21. Can babysit others' children
22. Owns a car
23. Do shopping if you are ill
24. Watch your home or pets while away
25. Provide a place to stay for a week
26. Discuss politics

The core network size is an indicator of accessed social support and obtained by the question: "From time to time, most people discuss important matters with other people. Looking back over the last three months, think about the people whom you discussed matters that are important to you. How many people were you able to recall?" This core network size (count as the number of people who they discussed important matters over the last three months) was a generalized version of Burt's name generator in the General Social Survey (Burt 1984).

Survey Results

Data collection occurred from November to December 2019. The web-based survey was self-administered on computers or mobile phones. Non-probability samples were recruited from three sources: Amazon Mechanical Turk (46% of the data), Qualtrics Panel (46%), and Prolific (8%). After data cleaning, descriptive statistics of 1,297 survey respondents are provided in TABLE 1.

TABLE 1 Survey Descriptive Statistics

Age	Mean	46.9
	Median	44.0
	Standard deviation	16.9
Education	Less than high school	0.7%
	High school graduate/GED	12.2%
	Some college, no degree	18.4%
	Associate degree	9.5%
	Bachelor's degree	35.4%
	Graduate degree	19.6%
Employment	Full-time	57.0%
	Part-time	12.7%
	Retired	15.9%
	Student (not employed for pay)	1.9%
	Disabled (not employed for pay)	2.9%
	Not employed for pay	6.7%

Gender	Female	50.3%
	Male	49.2%
Household income	Under $15,000	5.5%
	$15,000–$24,999	9.6%
	$25,000–$34,999	10.6%
	$35,000–$49,999	16.0%
	$50,000–$74,999	22.3%
	$75,000–$99,999	14.1%
	$100,000–$149,999	12.5%
	$150,000–$199,999	4.9%
	$200,000–$249,999	2.2%
	$250,000 or more	2.0%
Household people	One	22.2%
	Two	38.2%
	Three or more	39.6%
Marital status	Married/domestic partnership	48.1%
	Widowed	4.0%
	Divorced	9.6%
	Separated	1.0%
	Living with a partner	7.2%
	Never been married	29.8%
Race/ethnicity	American Indian or Alaska Native	1.5%
	Asian	6.9%
	Black or African American	9.7%
	Hispanic, Latino or Spanish origin	0.6%
	White	82.0%
	Other race/ethnicity	2.5%
Household vehicles	No vehicle	7.8%
	One	37.2%
	Two	39.1%
	Three or more	15.7%

Leisure Activity Variety

Survey respondents reported participating in zero to 56 activities over the last three months as shown in FIGURE 2. About 50% of respondents participated in between 5 and 15 different activities over the three-month period.

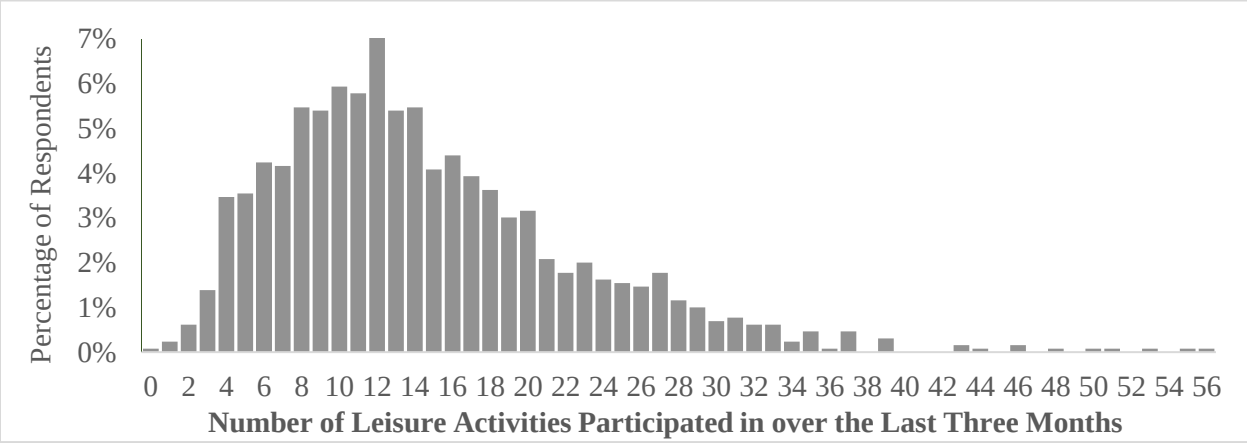

FIGURE 2 Activity Variety Distribution

Social Capital Measures

FIGURE 3 shows the distributional difference across three social capital measures.

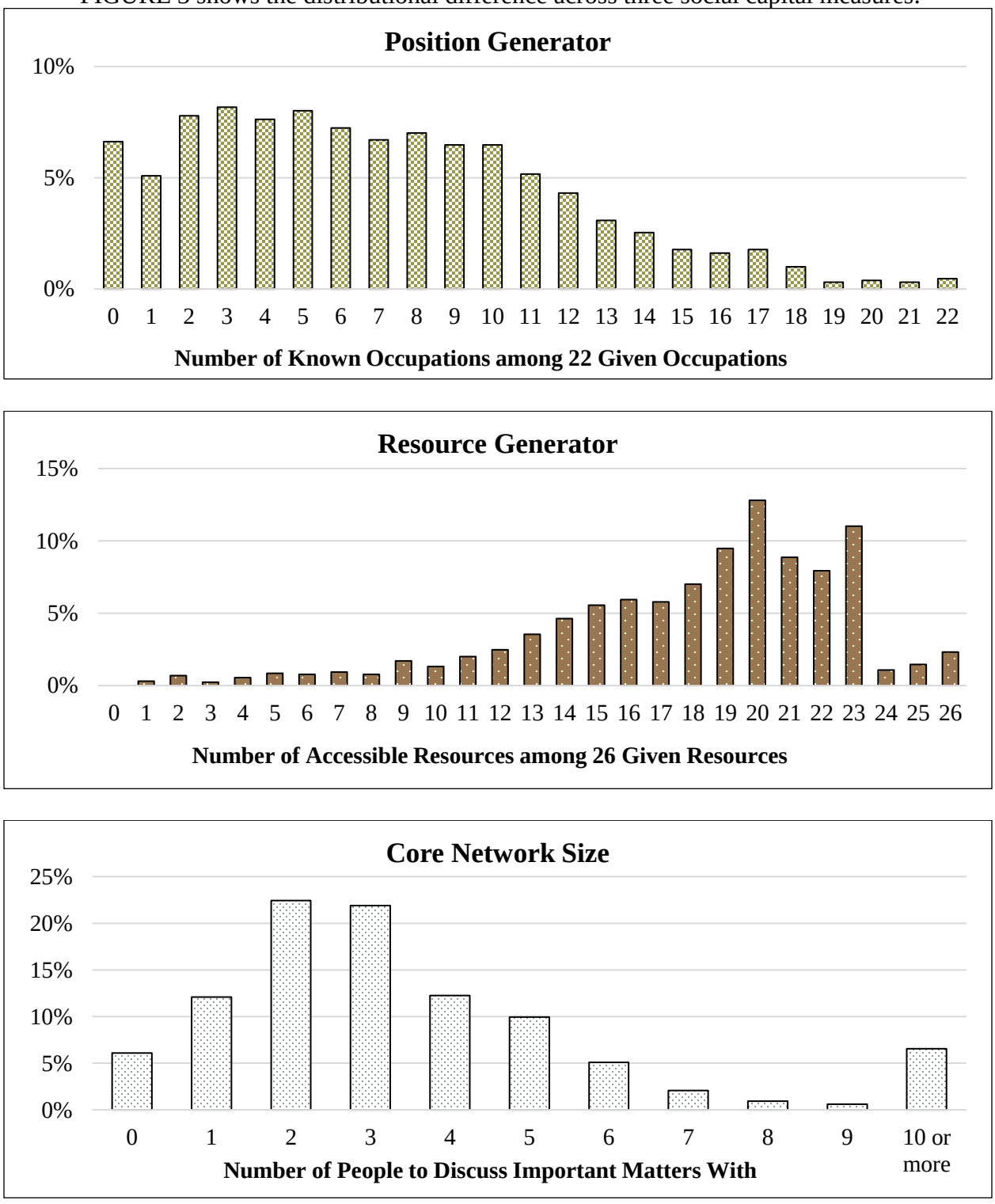

FIGURE 3 Distributions of Social Capital Measures

As an indicator for access to instrumental resources, the participants reported to know an average of 7.0 occupations and standard deviation of 4.8 occupations. It is expected to have a small portion of respondents who know people across more than 18 different professions.

Survey respondents indicate has a mean of 10.4 (standard deviation of 5.3) accessible resources via family, and a mean of 7.5 (standard deviation of 5.4) accessible resources via friend.

The core network size agrees with the assumed power law of relationship. That relationship mostly holds for many people having a few contacts and few people having many contacts, but there is a possible higher portion of respondents discussing important matters to 10 or more people.

LEISURE ACTIVITY VARIETY MODEL

Modeling Methodology

Activity variety was defined as the number of different leisure activities that survey respondents had participated in over the last three months. With a mean of 14.6 activities and standard deviation of 8.1 activities, the over-dispersion supported use of negative binomial regression. The model is specified through the following mathematical expectation:

$$E(y_n|x_n, s_n, p_n, r_n) = \exp(\beta x_n + \alpha s_n + \delta d_n + \theta r_n)) \quad (1)$$

where

$y_n =$ activity variety for individual *n*,

$x_n =$ individual and household characteristics for individual *n*,

$s_n =$ individual *n*'s core network size (number of strong ties),

$p_n =$ sum of the occupations known through individual *n*'s social network (measured by the position generator),

$r_n =$ sum of the accessible social resources in individual *n*'s social network (measured by the resource generator), and

$\beta, \alpha, \delta, \theta =$ model parameters.

In NB regression, an individual's probability $P(y_n)$ of participating in y_n different activities is defined as follows:

$$P(y_n) = \frac{\Gamma(1/\alpha + y_n)}{\Gamma(1/\alpha) y_n!} \left(\frac{1/\alpha}{(1/\alpha) + \lambda_n}\right)^{1/\alpha} \left(\frac{y_n}{(1/\alpha) + \lambda_n}\right)^{y_n} \quad (2)$$

where $\Gamma(\cdot)$ is the gamma function, $\lambda_n = \exp(\beta(x_n + s_n + d_n + r_n) + \varepsilon_i)$, and $exp\,(\varepsilon_n)$ is a Gamma-distributed disturbance term with unit mean and variance given by the dispersion parameter α. Model parameters were estimated using maximum likelihood estimation using the MASS package in R.

Leisure Activity Variety Model Results

The empirical estimation results of the factors correlated with the number of different participated activities over the last three months are provided in TABLE 2.

Social Capital Indicators

To clarify comparisons the impacts of social resources on activity variety, measures from the core network size, position and resource generator were normalized (ratio of reported measure to the maximum measure value) and their marginal effects were estimated. All three indicators have strong positive effects on activity variety, thus supporting the hypothesis of social capital's effect on one's activity participation. Of the three social capital indicators, the position generator had the greatest normalized impact followed by the resource generator with core network size having the smallest impact. The strongest effect of the position generator attests the hypothesis that leisure activity variety (being more an instrumental outcome than expressive outcome) is enabled through broader access to instrumental social resources (measured by the reported know occupations). Likelihood ratio tests determined that including social capital indicators significantly improved

model fit over a model with only sociodemographic factors. This shows that social capital indicators aid in reducing unobserved heterogeneity.

TABLE 2 Negative Binomial Model Estimation Results of Activity Variety

Variable Description	Parameter Estimate	Standard Error	Marginal Effect
Constant	2.198***	0.083	n/a
Core network size (number of strong ties divided by 10)	0.224***	0.054	3.11
Position generator (number of occupations divided by 22)	0.486***	0.068	6.75
Resource generator (number of resources divided by 26)	0.318***	0.082	4.42
Vehicle availability indicator (1 if there is no motorized vehicle in the household)	-0.096*	0.053	-1.28
Commute model indicator (1 if driving alone to work)	0.074**	0.031	1.03
Drive time to the closest sit-down restaurant indicator (1 if taking less than 5 minutes)	0.056**	0.026	0.78
Bicycle usage indicator (1 if never using a bicycle, or less than monthly, or not available)	-0.243***	0.033	-3.62
Transit usage indicator (1 if never taking a bus, light rail, metro/subway, or less than monthly, or not available)	-0.132***	0.039	-1.92
Ride-hailing service usage indicator (1 if using ride-hailing services at least 2-3 days a week)	-0.142**	0.063	-1.85
Disability indicator (1 if having a disability, condition, or illness that affects the ability to travel)	-0.135***	0.052	-1.78
Number of hours spent on cooking and chores per week	0.008***	0.002	0.11
Home type indicator (1 if living in a single-family house)	0.034	0.028	0.47
Marital status indicator (1 if being married)	-0.044	0.027	-0.61
Age group indicator (1 if being 55-64 years old)	-0.081**	0.037	-1.09
Household income indicator (1 if earning under $25,000)	-0.070*	0.039	-0.95
Employment indicator (1 if employed full-time)	-0.037	0.032	-0.52
Education indicator (1 if obtained a bachelor's degree or higher)	0.040	0.027	0.56
Race indicator (1 if identified as white)	0.060*	0.034	0.82
Gender indicator (1 if identified as women)	0.012	0.027	0.16
Sampling source indicator (1 if collected from Amazon Mechanical Turk panel)	0.277***	0.028	3.90
Number of observations	1297		
Log likelihood at convergence	-4140.1		
Log likelihood at constant	-4404.5		

* = estimate *p*-value ≤ 0.10 and > 0.05; ** = estimate *p*-value ≤ 0.05 and > 0.01; *** = estimate *p*-value ≤ 0.01.

Mobility/Travel Behaviors

Several mobility and travel behavior indicators show significant effects on leisure activity participation. Having no motorized vehicle in the household results in an average decrease of 1.28 activities. In contrast, people who drive alone to work participate in 1.03 more activities. These effects are as expected since auto availability/usage provide greater mobility, and thus increase out-of-home activity variety. A short drive time of less than 5 minutes to a nearest restaurant also

correlates positively with the activity variety. This variable indicates that individuals who live in an urbanized or dense neighborhood have higher accessibility to different activity locations.

Respondent's activity participation is also significantly correlated with their usage frequency of bikes, transit, and ridehailing services. Decrease in activity variety is observed in those who are generally not bikers, transits users, but are frequent ridehailing users. These findings are important to assess the effect of alternative modes of transportation on activity participation. Although the activity list has many activities that did not require travel, people with disabilities that limit travel were also limited in their activity space by an average of 1.78 less activities.

Sociodemographic Attributes

As individual's activity space is dependent on their available time budget. The model shows a strong effect of the total time spent on housework/chores and food preparation/cleanup: every hour of those tasks increases an average of 0.11 activities participated in over three months. The activity list has 40 activities that can be conducted at home, so individuals who spend more time on household tasks may also have higher indoor activity variety. The effects of living in single-family houses and marital status are not significant although the directions agree with the hypothesis that individuals may have self-selected into locations that support their preferred activities.

Individuals between 55-64 years old or earning less than $25,000 annually have significantly less activity variety. Lower income was expected to limit individuals' activity variety because the lack of disposable income limits the number of activities one can participate in and makes costly activities less affordable. Although not having significant effects, full-time workers averaged 0.52 less activities and educated individuals have higher activity participation. Joye et al. (2019) regarded education as cultural capital and emphasized its importance on social outcomes. White respondents participate in about 0.82 more activity than minorities. There is not a significant gender difference on activity variety.

Finally, results show that respondents in the Amazon Mechanical Turk panel reported more activity variety. It is unclear what unobservable factor may cause this differentiation between samples but perhaps may relate to differing participation motivations/needs.

CONCLUSION AND FUTURE WORK

This study answered the research questions and tested Lin's social capital theory. Using the survey data collected in online platforms, the effects of resources embedded in social networks on leisure activity outcomes were analyzed. With an expansive list of activities, respondents reported to have participated in an average of 14.6 different activity types over the period of three months. Those reported activity outcome was used as a basis for measuring an individual's instrumental actions.

With an average increase of 6.75 activities for every additional occupations known in one's social contacts, the results confirm the hypothesis that an individual's broader access to instrumental social resources (measured by the position generator) significantly increase their instrumental outcome (measured by the participation in diverse activities). Other highly significant positive correlations between leisure activity participation variety and resource generator and core network size were also confirmed. The inclusion of social capital measures significantly enhanced the model fit and show stronger effects on traditional sociodemographic and household attributes. To the authors' knowledge, this paper is the first in the transportation and activity literature to use both a position generator and resource generator to measure social capital.

The study's main limitation was the use of a retrospective survey for understanding leisure activity behavior. Leisure activities do not occur regularly enough for one-day or even week-long surveys to get a fair assessment of one's full activity space (particularly variety). This study asked respondents to recall over the past three months, but that time period may be too short to account

for seasonality effects. Additionally, the unit of analysis is at the activity type and frequency level. The activity type is counted based on the given activity list, though this list can never be exhaustive as the activity space is nearly limitless. Each activity also does not have equivalent commitment requirements or time scales. This analysis did not account for those differences without temporal and spatial data. Thus, long-term activity diaries would be useful for further exploring the leisure activity space and the corresponding changes in social capital.

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