

6-14-2019

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Recommended Citation

Ruiz, Linda D., "Socioeconomically disadvantaged neighborhoods, stroke risk, and cognition in older adults: A focus on violent crime" (2019). *College of Science and Health Theses and Dissertations*. 302.
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Socioeconomically disadvantaged neighborhoods, stroke risk, and cognition in older adults:

A focus on violent crime

Wednesday, January 16, 2019

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Word Count: 3761

References: 52

Number of Tables and Figures: 3

Abstract

Living in socioeconomically disadvantaged neighborhoods, i.e., neighborhoods with lower incomes, lower education/occupational levels, and/or higher crime, increases one's risk of developing chronic health problems, including cardiovascular disease risk factors and stroke. These health problems are associated with reduced cognition and dementia and may help to explain disparities in brain aging. We investigated the association of neighborhood socioeconomic characteristics on stroke risk and cognitive outcomes hypothesizing that stroke risk mediates the association between the socioeconomic environment and cognitive functioning. Participants were non-demented community-dwelling older adults (N=121), ~67 years of age (50% male, 44% non-Latino Black) who underwent cognitive and medical assessments. Stroke risk was measured using the 2017 Framingham Stroke Risk Profile Score (FSRP). Neighborhood socioeconomic characteristics were quantified at either the census tract (income, education, and employment) or the point (violent crime) level. We focused on cognitive domains most vulnerable to pathological aging and stroke risk including memory, attention/information processing, and executive functioning. Structural equation modeling (SEM) evaluated whether FSRP mediated the relationship between neighborhood socioeconomic characteristics and cognitive performance. SEM results accounting for neighborhood income, education, and employment levels revealed that higher rates of violent crime were associated with higher FSRP scores, and higher FSRP scores were associated with reduced attention/information processing performance. Neighborhood-level crime had a significant effect on individual health, which, in turn, impacted individual cognition independent of other socioeconomic neighborhood factors typically investigated. Taken together, results suggest that clinicians working with older adults should query individual *and* neighborhood health.

Introduction

The quality of an individual's neighborhood may be characterized by social and economic factors. For example, the density of violent crimes, expressed as crime per capita, is one neighborhood characteristic often used to describe social disorganization (Shaw & McKay, 1949). The economic environment is often characterized by rates of poverty, educational attainment, and unemployment. Taken together, these aspects of the socioeconomic environment have been found to impact a broad range of individual outcomes among adults. For example, there is strong evidence of geospatial patterns in mental (e.g., cognitive functioning/decline) and physical (e.g., cardiovascular disease risk factors) health disparities based on neighborhood physical, social, and economic characteristics (Besser, McDonald, Song, Kukul, & Rodriguez, 2017; Kruger, Reischl, & Gee, 2007; Diez Roux, 2003). However, there is little research that considers all of these factors simultaneously.

While most research has focused on the impact of physical characteristics of the neighborhood environment on health (i.e. walkability, transportation, aesthetics) there is evidence to suggest that the state of the socioeconomic neighborhood environment also has a significant impact on health outcomes (Diez Roux & Mair, 2010; Diez Roux, Mujahid, Hirsch, Moore, & Moore, 2016). For instance, in a prospective study of a socioeconomically heterogeneous sample of approximately 13,000 adults between the ages of 45 and 65, findings indicated that individuals living in the most disadvantaged neighborhoods based on income, education, and occupation were, on average, at 60% higher risk for developing coronary heart disease (Diez Roux et al., 2001b). The association between neighborhood environment and risk of heart disease has been replicated by several researchers, and persists even after controlling for individual socioeconomic status (SES) and race/ethnicity (Diez Roux, 2001b; Murray et al.,

2010; Sundquist, Malmstrom, & Johansson, 2004). These findings suggest that neighborhood-level socioeconomic characteristics explain variance in health outcomes above and beyond individual-level factors.

Socioeconomic disadvantage at the neighborhood level is also associated with increased rates of cognitive decline even after controlling for individual-level SES (Besser, McDonald, Song, Kukull, & Rodriguez, 2017). For example, low neighborhood-level SES seems to be the strongest and most consistent predictor of cognitive health outcomes for older adults (Besser et al., 2017). Furthermore, neighborhoods that are higher in psychosocial hazards including social disorganization, public safety concerns, physical disorder and economic deprivation are associated with lower cognitive performance among residents (Besser et al., 2017). One potential mechanism to explain the impact of the neighborhood-level socioeconomic environment on individual-level cognition is through changes in health (Duron & Hanon, 2008; Fryar, Chen, & Li, 2012; Gorelick, Scuteri, & Black, 2013), e.g., cardiovascular disease and associated risk factors, as described above. Research is needed, however, that considers all of these factors simultaneously.

The present cross-sectional study aims to investigate the effects of the neighborhood-level socioeconomic environment on individual-level health and cognitive outcomes in non-demented community-dwelling older adults. Based on the literature linking neighborhood socioeconomic to health (Diez Roux, 2003; Diez Roux & Mair, 2010; Diez Roux, Mujahid, Hirsch, Moore, & Moore, 2016; Sundquist, Malmstrom, & Johansson, 2003) and health to cognition (Duron & Hanon, 2008; Elias, Elias, Sullivan, Wolf, & D'Agostino, 2005; Gorelick, Scuteri, & Black, 2013), our hypotheses are multi-factorial. Thus, we hypothesized that neighborhood-level psychosocial hazards in the form of violent crime will be positively

associated with cardiovascular disease factor related stroke risk. Further, we hypothesized that disadvantaged neighborhoods based on lower neighborhood-level socioeconomic resources of income, education, and occupation would be also be positively associated with stroke risk after adjusting for violent crime. Lastly, we expected that cardiovascular disease risk factor related stroke risk is associated with cognitive functioning and would mediate the relationship between socioeconomic environment/violent crime and cognition: i.e., the socioeconomic environment would be negatively associated with stroke risk, violent crime would be positively associated with stroke risk, and stroke risk, in turn, would be negatively associated with cognition.

Methods

This study was funded by the National Institute on Aging to investigate individual cardiovascular disease risk factors and neighborhood ‘health’ factors that may negatively contribute to health disparities in cognition and brain aging. The study was approved by the University of Illinois at Chicago Institutional Review Board (IRB) as well as the Rush University Medical Center IRB. It was conducted in accordance with the Declaration of Helsinki with written informed consent obtained on all participants.

Participants

Individuals aged 60 or older from one of three self-identified ethnic/racial categories (i.e., non-Latino White or Black, and Latinx) were recruited via community outreach (e.g., advertisements and fliers) and word of mouth. An initial telephone screen conducted in participants’ language of choice (English or Spanish) determined study eligibility. At this screen, exclusion criteria consisted of a positive self-report of any of the following: current or past history of neurological conditions including Alzheimer’s disease or any other form of dementia or mild cognitive impairment, Parkinson’s disease or any other movement disorder, stroke, or

seizure disorder, current or past history of Axis I or II psychiatric disorders (e.g., depression or bipolar disorder), a history of head injury or loss of consciousness, a present or past history of substance abuse or dependence, psychotropic medication use or contraindications for magnetic resonance imaging (MRI) including metallic implants, cardiac pacemaker/defibrillator, and claustrophobia. A self-reported history of stable (e.g., diabetes) or remitted medical illness (e.g., cancer) was not an exclusionary factor. Individuals were not eligible if they had received cognitive testing within the past year, or if they reported current involvement in a study with cognitive testing.

Following successful completion of the telephone screen, eligible individuals were scheduled for a more detailed evaluation including cognitive, i.e., the Mini-Mental State Examination (MMSE) (Folstein et al., 1975), and psychiatric, i.e., the Structured Clinical Interview for DSM-IV-TR (SCID) (First et al., 2002) screens for final inclusion and exclusion determination. Screening measures were administered by a trained research assistant fluent in either English or Spanish and followed by an evaluation by a psychiatrist who completed the 17-item Hamilton Depression Rating Scale (HAM-D) (Hamilton, 1960). All raters were blind to telephone screen information. Final inclusion criteria consisted of an absence of a psychiatric symptoms based on the SCID, a score ≤ 8 on HAM-D and an MMSE score ≥ 24 , as well as a lack of subjective memory complaints.

One-hundred and twenty-one participants met all inclusion and exclusion criteria and were enrolled in the study. We excluded 10 participants who were administered Spanish-language versions of cognitive measures given concerns about comparability of some test measures and 6 individuals who either evidenced incidental findings during MR imaging or lacked information on key variables in our analyses. Thus, the final sample utilized in the current analyses was 105 participants.

Neighborhood-Level Socioeconomic Assessment

Participants provided their current address and duration of residence at their current address. If the stated duration of residence was less than 5 years ($n = 21$), participants were asked to provide their immediately prior address and duration of residence at that location for geocoding. For the purposes of this study, participant data was associated with the characteristics of the area immediately surrounding their current address.

Geospatial information systems (GIS) was utilized to analyze participants' addresses as related to the socioeconomic environment (i.e., income, education, and employment). The address for each participant was geocoded as a point based on coordinates. A buffer area with a radius of 1,600 feet was created around each participant's address coordinates, which was then associated with social and economic environment data respectively. Data were collected either at the census tract level from the U.S. Bureau of the Census (e.g., income, education, housing, and employment) or at the point level (i.e., all violent crime data) from the Chicago Police Department's Citizen Law Enforcement Analysis and Reporting (CLEAR) database.

In accordance with methods outlined by Messer and colleagues (2006), a standardized index of neighborhood deprivation was constructed based on variables representing the following domains: income (variables included percent of the population with income below poverty level and median household income), occupation (variable included percent of the eligible, civilian workforce population classified as unemployed), and education (variables included percent of population with more than 16 years of education and percent of population with less than 12 years of education). These 5 variables were subjected to a principal component analysis (PCA), and the first principal component, which accounts for the largest proportion of total variance in any unrotated PCA, was retained. This composite score represented the individual standardized weighted coefficients of all 5 variables thought to represent neighborhood deprivation based on neighborhood-level

socioeconomic environmental resources of income, education, and occupation (higher values indicated greater socioeconomic resources).

While crime statistics have not traditionally been included in indices of neighborhood disadvantage, the link between crime and poverty is well established (Bourguignon, 2001; Pratt & Cullen, 2005; Sampson & Lauristen, 1994). Subsequently, crime variables representing per capita rates of homicide, robbery, assault, and sexual assault (separately) were quantified and combined using the same PCA procedure outlined above in order to construct a psychosocial hazards composite score that accounted for differences in homicide, robbery, assault, and sexual assault. Higher values on this composite reflect greater psychosocial hazards associated with neighborhood disadvantage (Besser et al., 2017).

Cardiovascular Disease Risk Factor and Stroke Assessment

Participants received a medical screen, history and physical conducted by trained staff and a registered nurse, respectively, from the UIC Clinical Research Center (CRC). This evaluation included two seated blood pressure measurements separated by 5 minutes, anthropometrics including height, weight, and waist circumference, a confirmed 12-hour fasting blood draw for health-related variables such as glucose and hemoglobin A1c, as well as an electrocardiogram and medication review. Portions of this evaluation allowed for an assessment of the 2017 revision of the Framingham Stroke Risk Profile score (FSRP) (Dufouil et al., 2017). The 2017 FSRP score (higher score indicates higher risk) is based on age, sex, systolic blood pressure, anti-hypertensive medication use, diabetes mellitus, diabetes medication, current cigarette smoking, cardiovascular disease, and atrial fibrillation.

Cognitive Assessment

Participants underwent a comprehensive neuropsychological assessment conducted by trained research assistants fluent in Spanish or English. For the current study, we focused on three specific cognitive domains shown to be particularly vulnerable to increased cardiovascular disease risk factors and associated stroke risk in older adults (e.g., Lamar et al., 2015): (a) verbal learning, memory, and recognition (LMR); (b) attention and information processing (AIP); and (c) executive functioning (EF). These domains and the test variables that reflected them are outlined below.

The LMR domain was based on three variables from The California Verbal Learning Test-II (CVLT-II) (Delis, 2000). This 16-item list learning task consisted of a 5 trial learning phase followed by a distractor list as well as short- and long-delay free and cued recall as well as recognition testing. The specific components chosen for measurement of this domain included total recall across Trials 1-5, Long Delay Free Recall, and recognition discriminability calculated with the following equation: $[1 - (\text{false positive errors} + \text{misses}) / 48] * 100$, max=100.

The AIP domain consisted of three variables: time to completion for Trail Making Test (TMT) Part A (Army Individual Test Battery, 1944) that represents how long participants took to connect 25 numbered circles in order as quickly as possible; time to completion for Motor Trails that requires participants to connect open circles following a dotted line 'trail' as quickly as possible; and the Wechsler Adult Intelligence Scale, Fourth Edition (WAIS-IV) Digit Symbol Coding where participants must write, as quickly and as accurately as possible in a 90-second period, the missing number that corresponds to a provided symbol given a code key of number/symbol pairs.

The EF domain included 4 test variables: a score for TMT B minus A that derived from TMT Part B in which participants connect dots by switching back and forth between numbers

(lowest to highest) and letters (alphabetical order) as quickly as possible minus TMT Part A described above for a score that reflected mental manipulation and working memory without processing speed or visual search; the Wechsler Abbreviated Scale of Intelligence, Second Edition (WASI-II) Matrix Reasoning score was based on the total correct final items chosen in a series or matrix when presented with an incomplete matrix; total correct on the WAIS-IV Letter-Number Sequencing subtest in which participants must re-order a verbally presented and disorganized string of letters and numbers into the correct numeric and then alphabetic order; and Verbal Fluency, i.e., total correct number of words produced in 60-seconds for the letters F, A, and S (separately) summed across all three letter trials.

We created continuous, composite measures of the three cognitive domains outlined above by averaging z-scores for test items comprising each domain. For the AIP and EF domains, relevant test scores were recoded such that higher values equated with worse performance (e.g., multiplied Digit Symbol Coding variable by -1). Cronbach's alpha (based on standardized values) for each domain is as follows: LMR=0.89, AIP=0.64, EF=0.73. A global cognitive score was also created by averaging all z-scores from all test items regardless of domain.

Statistical Analyses

Structural equation modeling (SEM) was employed to evaluate whether stroke risk mediates the relation between neighborhood socioeconomic environment and cognitive performance. Four models were tested, examining stroke risk as a mediator between neighborhood characteristics (SES, crime) and (a) global cognition, (b) LMR, (c) AIP, and (d) EF, separately. In order to assess the extent to which the model fit the data the Chi-squared (X^2) statistic and several practical fit indices were utilized to evaluate the model including the root

mean square error of approximation (RMSEA), comparative fit index (CFI) and Tucker-Lewis index (TLI). While the chi-squared is sensitive to sample size bias, it is considered an adequate metric for samples between 75 and 200 with suggested cut-off values greater than $p=.05$ representing better fit (Kenny, 2015). RMSEA is less influenced by large sample sizes with suggested cut-off values of .01, .05, and .08 indicating excellent, good, and mediocre fit respectively (MacCallum, Browne, and Sugawara, 1996). CFI values approaching 1 and TLI values over .90 are indicative of acceptable fit (Moss, 2016; Moss, 2016). Despite our consideration of fit indices reflective of our sample size, we also followed up SEM analyses with multiple regression modeling. All statistical analyses were completed using Mplus (Version 8).

Results

Participants

Participants included in these analyses (N=105) were on average 67 years of age, equally split by sex (48.6% male), racially and ethnically diverse (49.5% non-Latinx Black, 42.9% non-Latinx White, 7.6% Latinx), and attained an average of 16.3 years of education. The average MMSE score was 28.6 and the average FSRP score was 6.1 (Table 1).

Structural Equation Modeling

Mediation models, in which stroke risk mediated the relation between predictors (crime and SES) and the outcome variables (global cognition, LMR, AIP, and EF, separately), were tested using SEM. The model was initially run with all paths freely estimated. The direct effects between the predictor and outcome variables were consistently non-significant so they were constrained to zero subsequently.

Cognition— Analyses were repeated with several outcome variables including Global Cognition as well as individual cognitive domain composite scores of LMR, AIP, and EF. The

Global Cognition model had poor overall fit ($X^2 (12, N = 99) = 4.23, p = 0.12; RMSEA = 0.11; CFI = 0.72; TLI = 0.31$) as did the EF model ($X^2 (12, N = 102) = 3.53, p = 0.17; RMSEA = 0.09; CFI = 0.74; TLI = 0.36$). Model fit was adequate for the LMR model ($X^2 (12, N = 106) = 1.81, p = 0.41; RMSEA < 0.01; CFI = 1; TLI = 1.25$) and the AIP model ($X^2 (12, N = 105) = 2.62, p = 0.27; RMSEA = 0.05; CFI = 0.91; TLI = 0.78$). However, stroke risk was not significantly associated with ($\beta(106) = -0.004, p = .86$). Stroke risk was significantly correlated with AIP in the hypothesized direction ($\beta(105) = 2.18, p = .03$): the higher the stroke risk the higher the scores on AIP measures, which indicates lower performance. The final model is described graphically in Figure 1.

Post-hoc Analyses

In order to investigate the positive correlation between SES and stroke risk, the SES variable was divided into its component indicators and each indicator was tested within the model to pinpoint whether there was a specific aspect of SES driving the result. It was revealed that the education variables (i.e. percent of the population with greater than 16 years of education and percent of the population with less than 12 years of education) were the only variables significantly correlated with stroke risk such that lower educational attainment at the neighborhood level was associated with lower stroke risk ($\beta(105) = -2.35, p = .02$), and higher educational attainment at the neighborhood level was associated with higher stroke risk ($\beta(105) = 2.67, p < .01$).

Discussion

The purpose of this study was to investigate the effects of neighborhood factors, specifically violent crime and SES, on stroke risk and, in turn, the effects on cognition. Of the cognitive domains tested, attention/information processing was the sole domain significantly

associated with stroke risk in a constrained model. Furthermore, results suggest that higher rates of violent crime were associated with higher stroke risk and higher stroke risk was associated with poorer performance on measures in the AIP domain. While aspects of the model ran counter to expectations, e.g., higher levels of socioeconomic resources were associated with higher stroke risk, our overall SEM results suggest that stroke risk may mediate the relationship between neighborhood-level violent crime and individual-level attention/information processing performance.

The literature suggests that chronic exposure to stressful environments has a negative impact on health including an increased risk for developing cardiovascular disease risk factors like hypertension, diabetes, and coronary heart disease, all of which are associated with increased risk for stroke (Needham et al., 2014; Nilsson, Tufvesson, Leosdottir, & Melander, 2013). An underlying assumption of this study is that living in neighborhoods with higher crime is stressful. In fact, there is evidence that living in such environments is associated with greater cortisol dysregulation, which is a biomarker of increased stress (Hajat et al., 2015; Needham et al., 2014; Nilsson et al., 2013). While stress (or cortisol) is not directly measured in this study, our data support the assertion that stressful environments matter for individual-level health beyond stroke risk in a relatively healthy community-dwelling population and that dangerous environments may also be indirectly associated with cognitive health through stroke risk.

While the association between our measure of socioeconomic resources and stroke risk was significant, the direction was contrary to our hypotheses, and the majority of extant literature which suggests that living in more impoverished, socioeconomically disadvantaged neighborhoods has an adverse effect on individual health (Diez Roux & Mair, 2010; Hajat et al., 2015). Post-hoc analyses suggest that the aspect of the socioeconomic resources driving our

counter-intuitive result was neighborhood-level educational attainment; i.e., individuals living in neighborhoods with low educational attainment had significantly lower stroke risk and vice versa. A recent study examining the relationship between race, SES, and neuroimaging markers of structural brain integrity revealed that higher SES was associated with greater total brain, gray and white matter volumes in non-Latino Whites but not non-Latino Blacks (Waldstein et al., 2017). These investigators hypothesized that differential exposure to contextual stressors, particularly relevant for non-Latino Blacks with higher SES may explain their results. While the current study does not specifically explore racial differences, it is possible that disparities in contextual stressors unique to non-Latino Blacks and Latinos – who comprised approximately 60% of our sample – may have influenced the direction of the association between SES and stroke risk in our study. We are currently working to understand these complex relationships.

Results of this study contribute to the literature in several ways. First, this study represents a growing body of literature that aims to draw connections between neighborhood-level factors and individual-level health outcomes (Besser et al., 2017), extending this work to include the fact that geographic location matters for stroke risk and that stroke risk matters for cognitive functioning. Second, a recent systematic review of the literature regarding the neighborhood environment and cognition in older adults advocated for more work studying mediators to elucidate the underlying mechanisms linking neighborhood-level factors and cognition (Besser et al., 2017). Results of this study highlight the need to investigate the interplay between neighborhood-level crime and individual-level stroke risk as it may contribute to cognitive functioning in older community-dwelling adults.

While the cross-sectional nature of our study does not allow for an understanding of causality per se, we did require that participants provide an address that denoted at least a 5-year

duration of exposure to their neighborhood environment. It is documented in the literature that individuals are likely to live in socioeconomically similar regions throughout their life (Brenner, Diez Roux, Barrientos-Gutierrez, & Borrell, 2015; Diez Roux et al., 2016; Murray et al., 2010), adding to our assumption that participants in this study had at least a reasonable duration of exposure to the socioeconomic characteristics and violent crime stressor of their current environment. Ultimately, whether the data represents a longitudinal effect, or more of an acute effect, the results may support the underlying theory that ecological risk factors have an impact on cardiovascular and brain health.

Additional study limitations should be considered. For example, participants in this study were relatively healthy and even evidenced a relatively low stroke risk. While this may have introduced bias into the sample such that the average participant may or may not be representative of the population in their surrounding area, the fact that we had signal to detect an effect suggests future work in less healthy populations may also reveal these associations. It should be noted, however, that confirmatory regression analyses of crime, stroke risk, and attention/information processing did not support our modest SEM results. This may be due, in part, to a lack of power to detect these associations given that most studies of this kind are conducted within a large-scale epidemiological investigation (e.g., Besser et al., 2018).

In conclusion, this study demonstrated that neighborhood-level characteristics such as higher amounts of violent crime have a negative impact on stroke risk and, in turn, attention and information processing. While work is ongoing to clarify the role of socioeconomic disadvantage, more specifically neighborhood-level educational attainment, on individual-level physical and cognitive health outcomes, our findings with neighborhood-level crime have clinical practice implications. Specifically, the neighborhood represents an important context that

should be considered by clinicians as part of the diagnostic interview and case conceptualization process. While it may not be common for clinicians to specifically ask about the neighborhood in which their patients live, doing so may provide a wealth of information about daily, chronic stressors that have implications for symptom presentation and possibly even long-term prognosis.

Acknowledgments

The authors would like to thank the participants of this study. This research was supported by the National Institutes of Health, National Institute on Aging: K01 AG040192 (ML) and R21 AG048176 (ML). Additionally, aspects of this project were supported by the National Center for Advancing Translational Sciences through UL1TR002003.

The authors have no conflict of interest to report.

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Table 1. Characteristics of all eligible participants (N = 105).

Age <i>M (SD)</i>	67.84 (6.64)
Gender <i>n (%)</i>	
Male	51 (48.6)
Female	54 (51.4)
Race <i>n (%)</i>	
Black	52 (49.5)
White	45 (42.9)
Latino	8 (7.6)
Education	
Degree years <i>M (SD)</i>	16.13 (2.89)
Less than 12 years of ed. <i>n (%)</i>	2 (1.9)
High School diploma <i>n (%)</i>	10 (9.6)
Some College <i>n (%)</i>	30 (28.6)
16 or more years of ed. <i>n (%)</i>	63 (60.2)
MMSE <i>M (SD)</i>	28.60 (1.45)
FSRP <i>M (SD)</i>	6.14 (4.87)

Abbreviations: MMSE = Mini Mental Status Examination; FSRP = Framingham Stroke Risk Profile

Table 2. Correlation table – final model variables.

	1.	2.	3.	4.
1. SES	--			
2. Crime	-.62**	--		
3. FSRP	.09	.02	--	
4. Cognition – AIP	-.10	-.13	.20*	--

Abbreviations: SES = Neighborhood Socioeconomic Status; FSRP = Framingham Stroke Risk Profile; AIP = Attention Information Processing. * $p \leq 0.05$; ** $p \leq 0.01$.

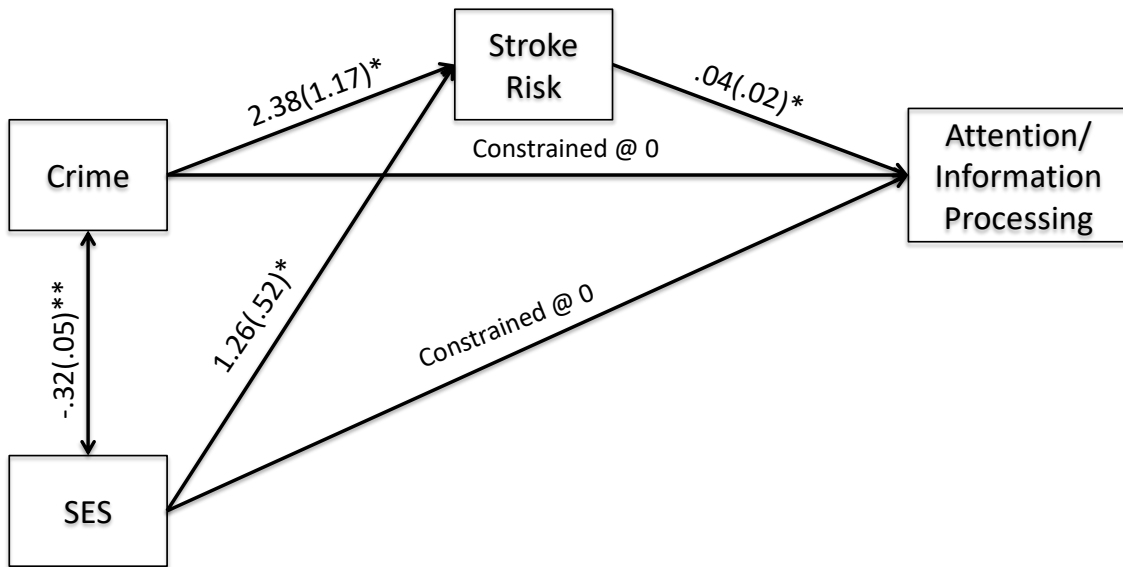


Figure 1. Final model involving neighborhood variables (SES and crime), stroke risk (Framingham Stroke Risk Profile scores – FSRP) , and cognitive variable (attention/information processing). Path coefficient: B (SE). Significance: $*p \leq 0.05$; $**p \leq 0.01$