

GPS Mobility as a Digital Biomarker for Posttraumatic Dysfunction: The Moderating Role of Neighborhood Context

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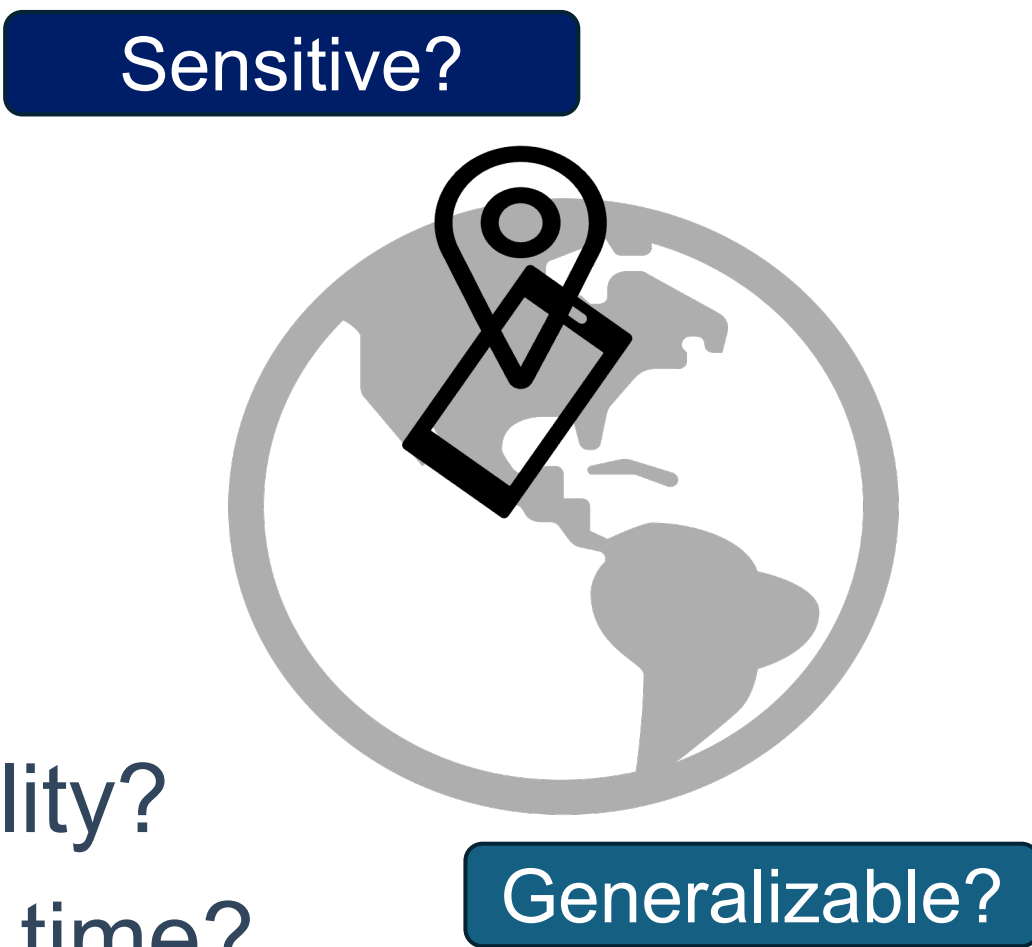
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Introduction

- Of the 47 million trauma survivors evaluated in U.S. Emergency Departments each year, ~30% with develop an adverse posttraumatic outcome (eg. PTSD, depression, pain).¹
- More accurate predictors of posttraumatic dysfunction are needed to identify patients requiring early intervention.
- GPS-derived mobility metrics are ideal predictors because they are objective and cost-effective.²
- Average home time is associated with PTSD and depression, but the predictive utility is unclear.³⁻⁴
- Neighborhood factors shape daily mobility patterns and may impact predictive models.⁵
 - Predictive model for depression had low prediction accuracy in a sociodemographically diverse nationwide sample.⁶

Research Questions:

- Does average home time predict posttraumatic outcomes?
- How do neighborhood-level factors influence the predictive utility?
- What variables explain day-to-day variability in average home time?



Methods

- Trauma-exposed adults were recruited from 29 urban emergency departments across the United States as part of the AURORA study.¹
- Passive GPS sensing from participant’s smartphone was used to derive average home time.
- Depression, Anxiety, and Pain (PROMIS surveys) as well as PTSD (PCL-5) and Dissociation (DES-B) symptoms were evaluated at 2 weeks, 8 weeks, 3 months, and 6 months post-trauma.
- Participant’s home addresses were geocoded to derive neighborhood factors.

Statistical analysis:

- First, linear mixed-effects models tested whether average home time predicted symptoms of PTSD after controlling for individual and geocoded factors.
- Next models tested ADI x Home Time and NDVI x Home Time interactions.

Participants were predominantly female (69%), non-Hispanic Black (60%), younger/middle age (35±12 years).

Neighborhood Disadvantage



Area Deprivation Index

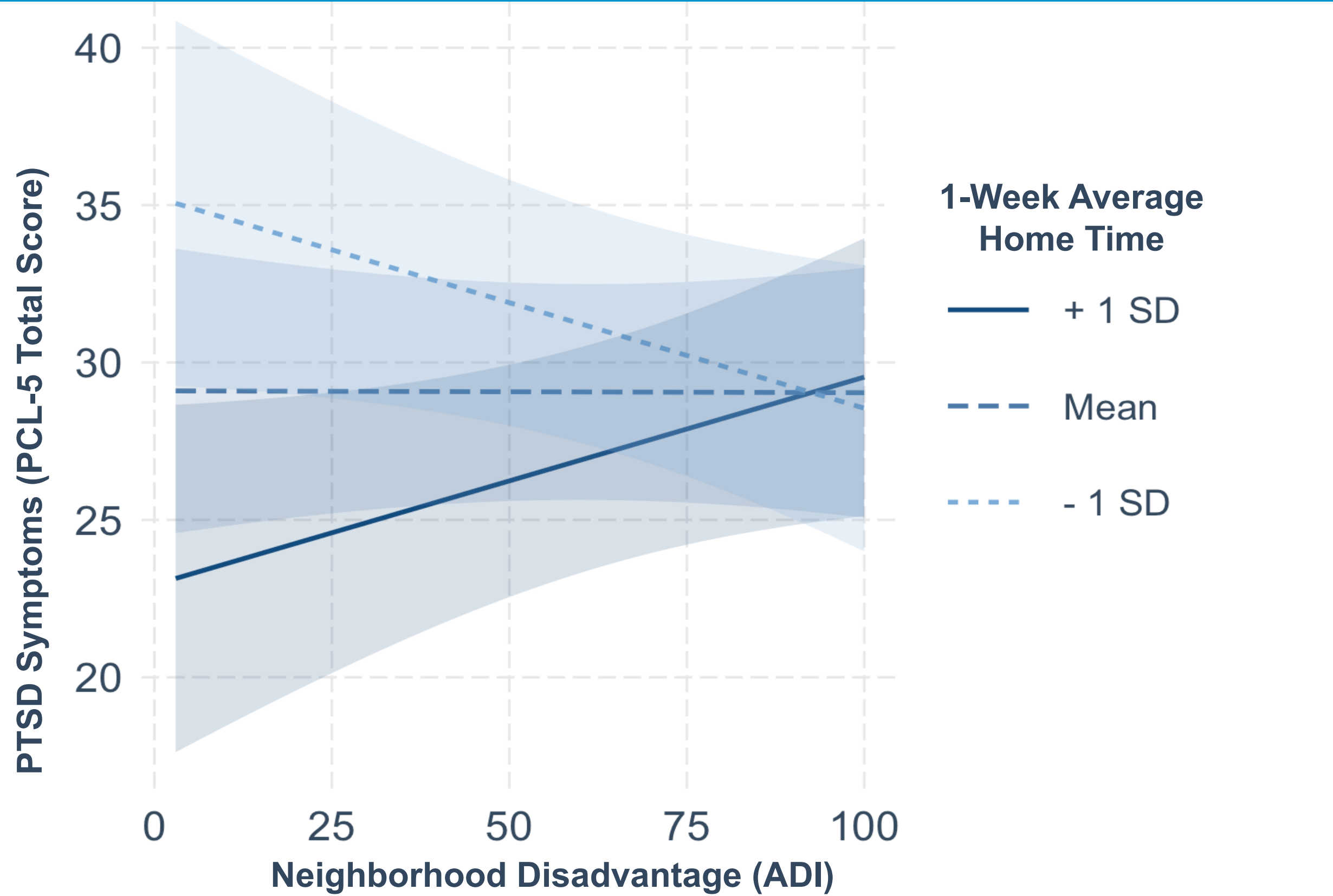
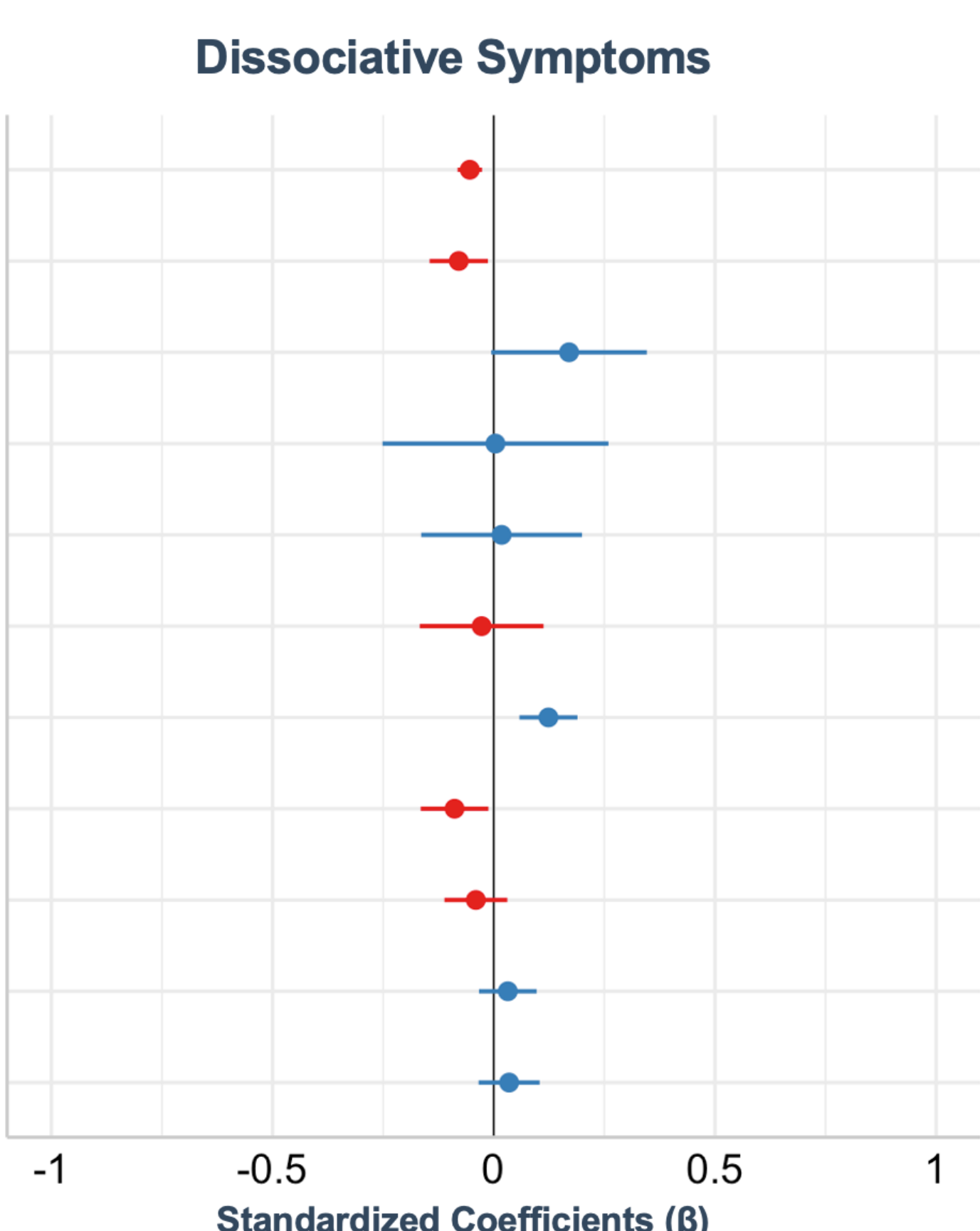
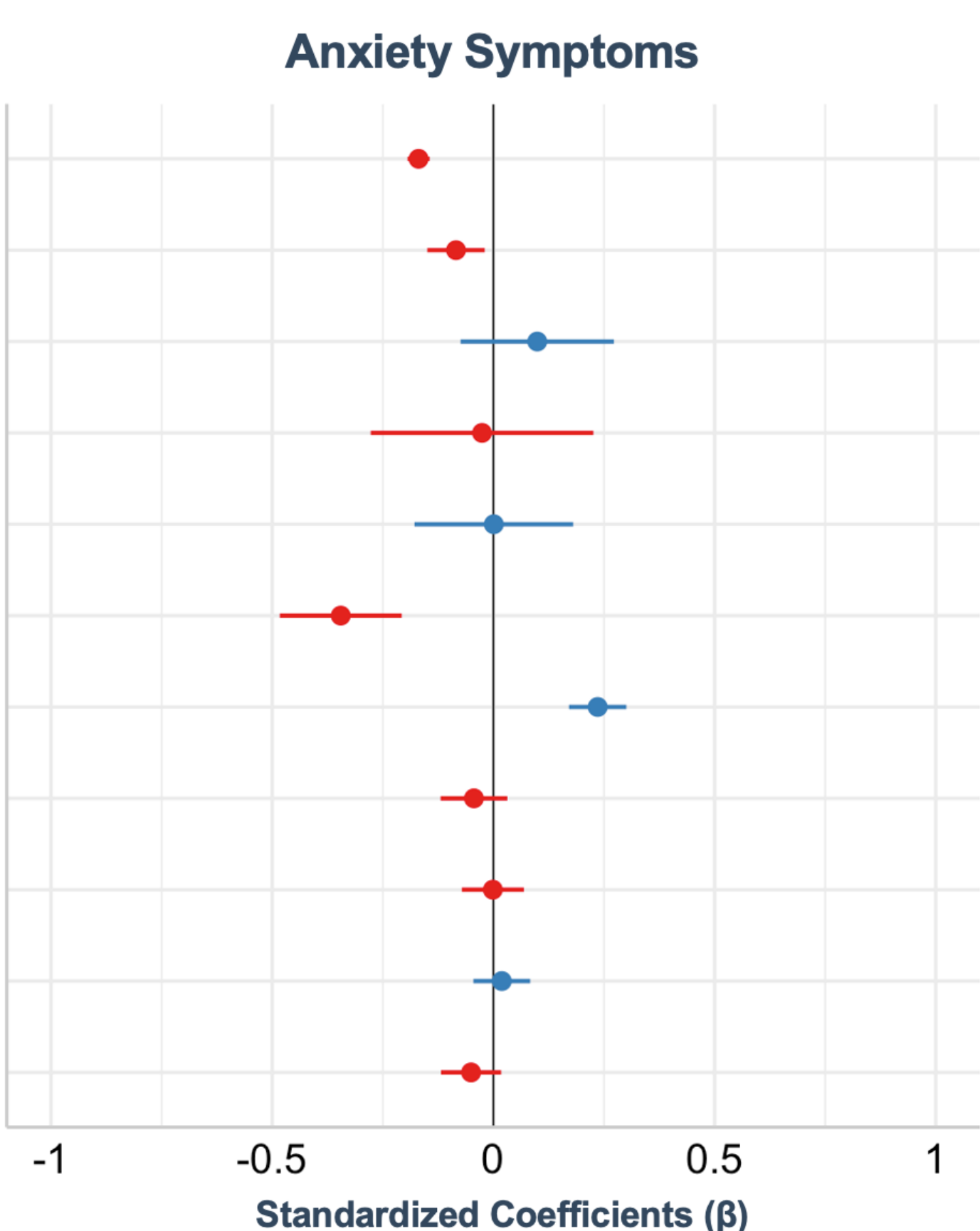
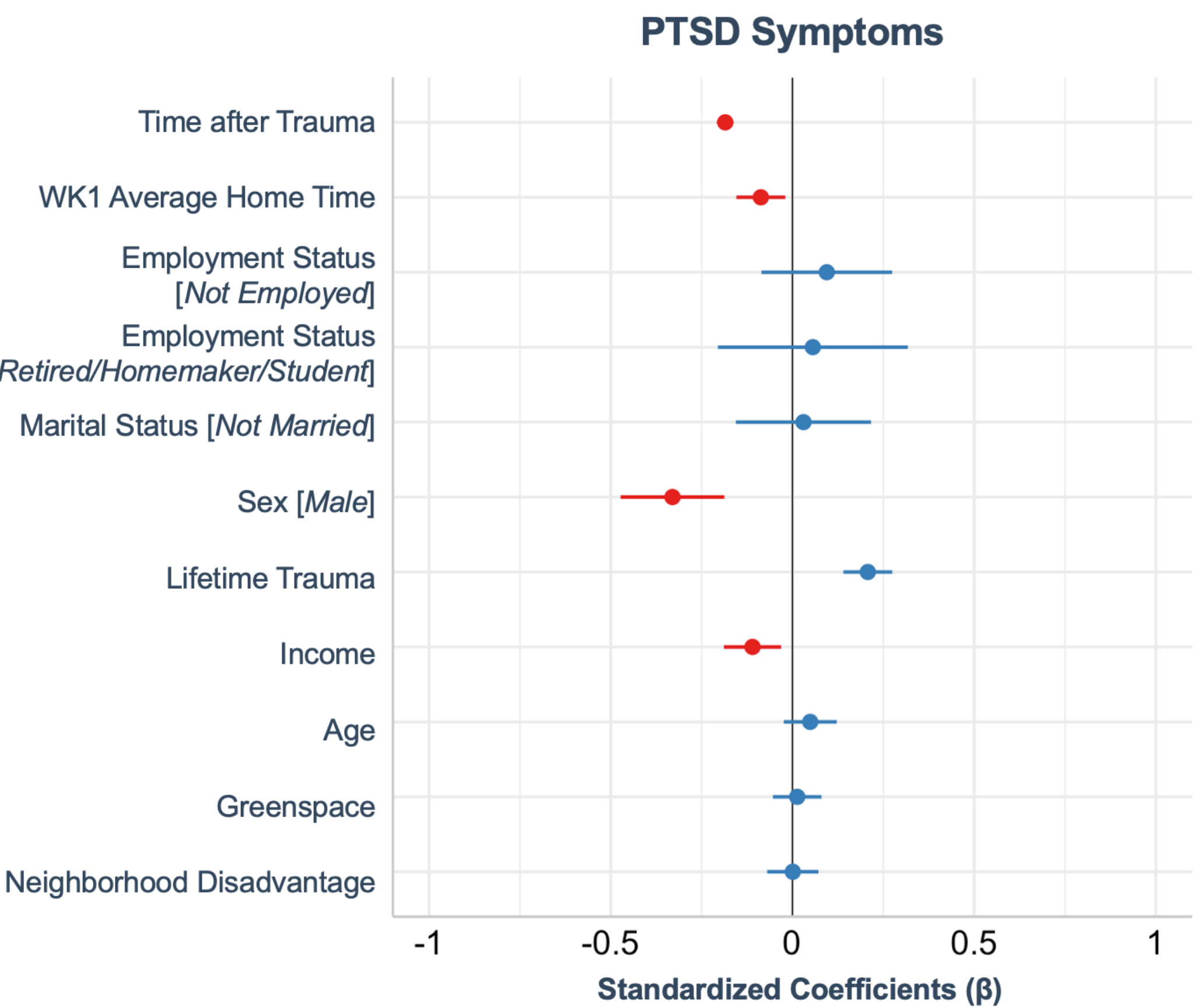
Greenspace



Normalized Difference Vegetation Index

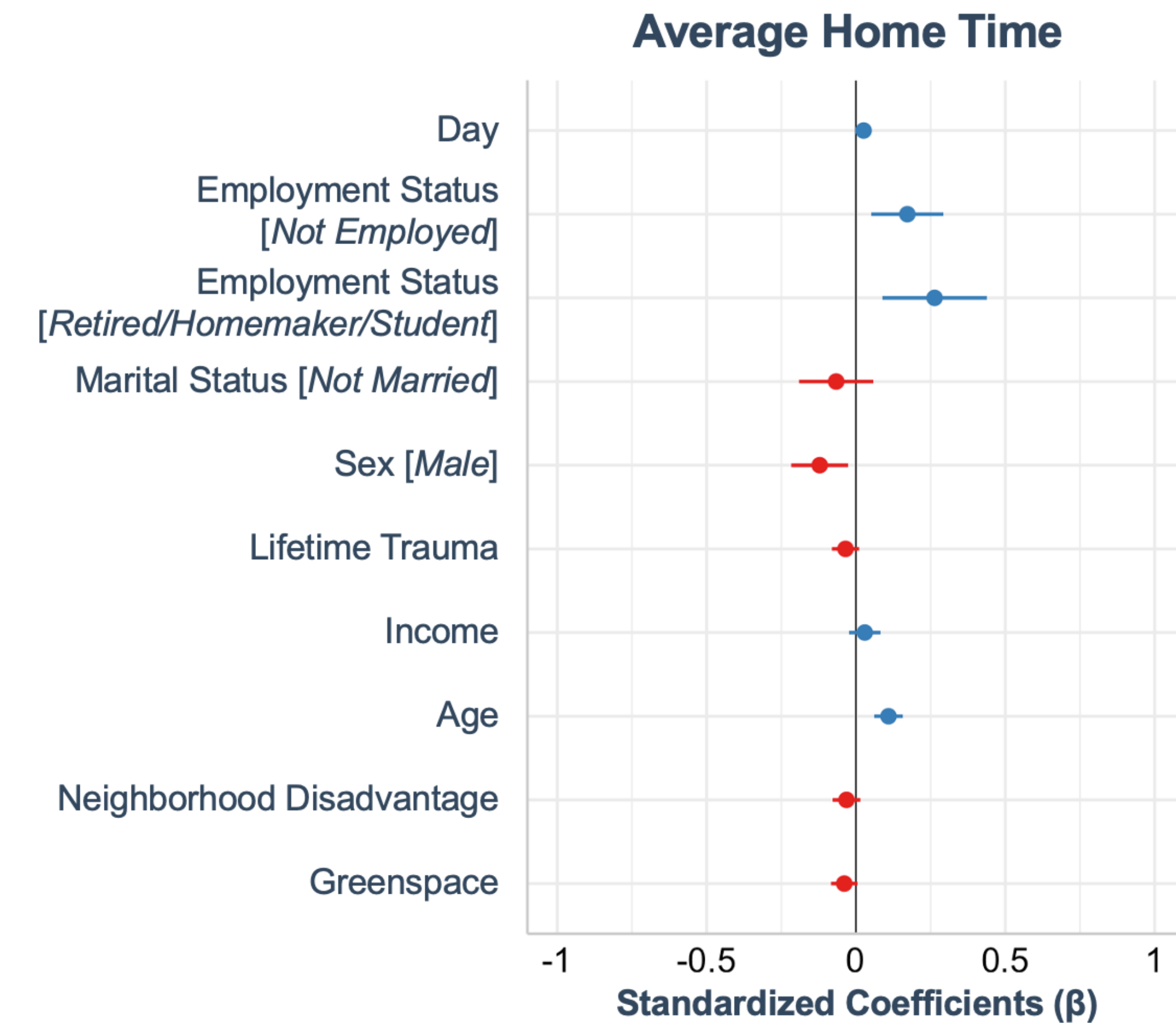
Results

Individuals who spent more time at home had fewer PTSD, anxiety, and dissociation symptoms on average.



However, for PTSD symptoms, more time at home was only beneficial among trauma survivors living in more advantaged neighborhoods.

There was no effect of average home time on pain or depression symptoms.



Neighborhood factors did not explain day-to-day variability in Week-1 home time.

Effect of 1-week average home time: PTSD $t(2150)=-2.53$, $p_{unc}=.012$; Anxiety: $t(2150)=-2.55$, $p_{unc}=.011$; Dissociation: $t(2150)=-2.35$, $p_{unc}=.019$; PTSD Interaction effect: $t(2150)=2.65$, $p_{unc}=.008$

Discussion

- GPS-derived mobility metrics can help identify trauma survivors at-risk for adverse posttraumatic outcomes.
- Spending more time at home in the first week following a trauma may aid psychological recovery by promoting greater access to social support, facilitating physical recovery, and promoting sleep.^{7,8}
- For some trauma survivors, neighborhoods may serve as trauma-reminders (eg., physical site of collision, hearing sirens, etc.) and time at home may exacerbate PTSD symptoms.⁹
- Further research is needed to assess how both neighborhood factors and posttraumatic symptoms shape mobility over time.
- Ambulatory self-report assessments paired with GPS capture may reveal mechanisms underlying the observed associations.
- Despite the prospective advantages of passive GPS-sensing, the use of mobility metrics for the detection of at-risk trauma survivors requires careful consideration of the socioenvironmental context.

References

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