Dartmouth GEISEL SCHOOL OF MEDICINE

DEPARTMENT OF BIOMEDICAL DATA SCIENCE
GEISEL SCHOOL OF MEDICINE

Center for Technology and Behavioral Health
Innovate · Evaluate · Disseminate

It's Time to Ask When: Investigating the Timing of Dynamics in Intensive Longitudinal Data

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SAA
Society for Ambulatory Assessment 2020

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Popular Methods of Analyzing Longitudinal Data

- Examples of Models Used in Analyzing Longitudinal Data:
  - Linear and non-linear time series models (including variations of vector autoregressive moving average (VARMA) models)
  - state-space models
  - dynamical systems models
  - multilevel modeling
  - and many other examples.[1]

- Useful when researchers have preconceived notions about the number of lagged occasions to include in models

1. (Boker & Graham, 1998; Box, Jenkins, & Reinsel, 2013; Browne & Nesselroade, 2005; Durbin & Koopman, 2012; Goldstein, Healy, & Rasbash, 1994)

Few Psychological Theories Specifically Mention the Timing of Effects

- Psychological theories often are completely inadequate in dictating "when" variables are thought to take effect
- This is problematic on MANY fronts:

- Leads to *arbitrary* timing of collecting data (timing of prompts in study)
- Leads to *arbitrary* measurement of analysis
- Does not allow us to fully test our theories

Introducing the lag

- A lagged is a shift in the time of the response at time *t*
- For example, if a study were assessed every hour on the hour
  - A lag of 1 (i.e. *t-1*) would correspond to 1 hour

Choosing Lags due to convenience

- The vast majority of EMA studies that utilize dynamic relationships only analyze at lower-order lags
  - Typically lags of 1

- This strategy assumes that higher order lags are negligible
  - This NOT an innocuous assumption

- Failing to account for higher-order lags leads (when higher-order lags exists) leads to:
  - Misleading inferential results (i.e. biased parameter estimates, with underestimated standard errors)

Choose Time Lags

- Methods to choose lag times
  - Traditionally chosen in an exploratory fashion using diagnostics such as auto- and partial correlation plots
  - In a confirmatory way as guided by theories
  - Comparing results from model fitting at different lags[1]

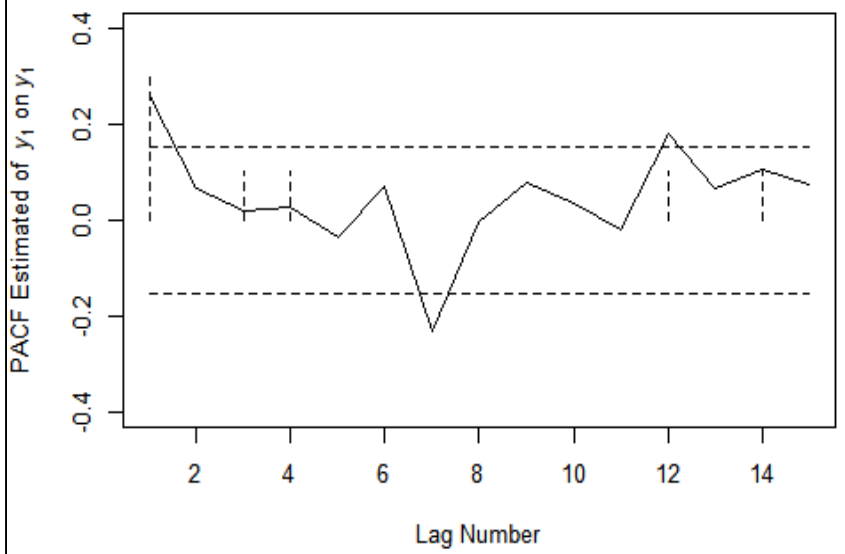
1. (e.g., Chow, Nesselroade, Shifren, & McArdle, 2004)

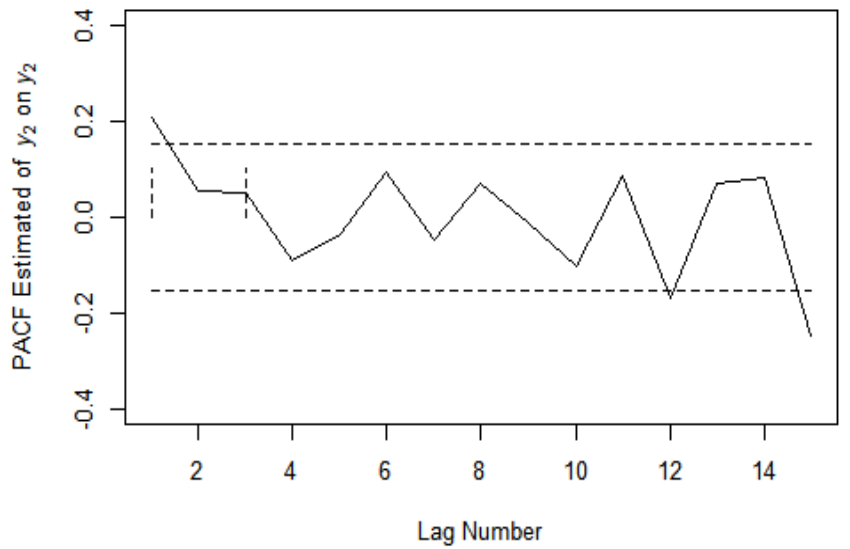
Inadequacies of Previous Methods for Behavioral Science Data

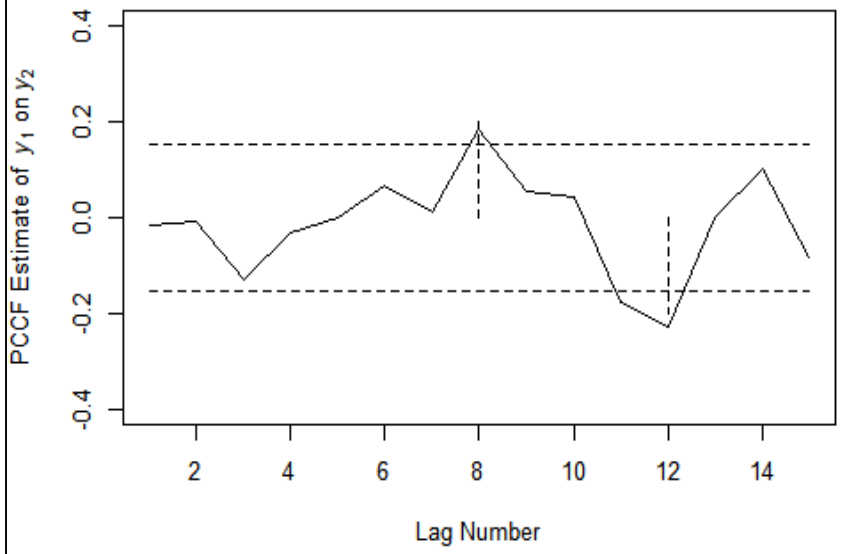
1. Exploratory methods have been designed for:
   - Single-subject time series data of more substantial lengths
     - (e.g. with more than 100 time points and no missingness)
2. Confirmatory methods:
   - Computationally inefficient with large amount of lags

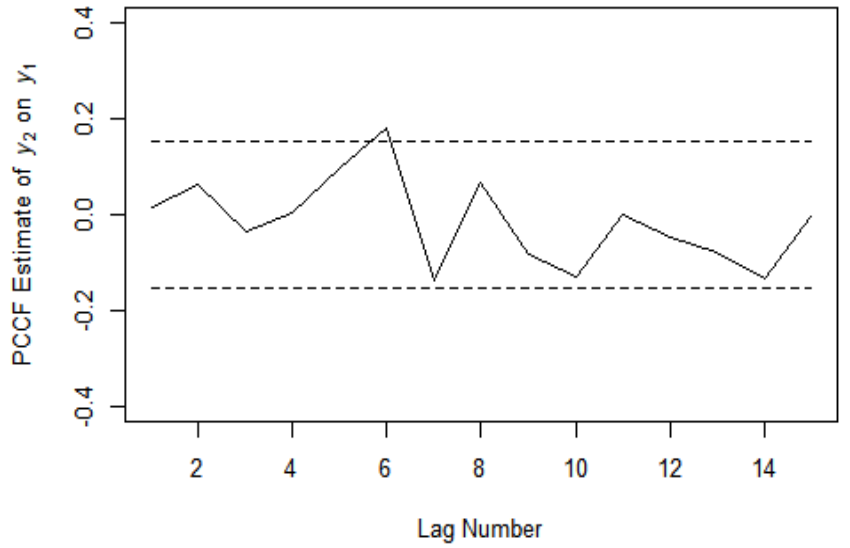
1. (e.g. Bottan & Perez Truglia, 2011; Buckner, Crosby, Wonderlich, & Schmidt, 2012; Buysse et al., 2007; Carels et al., 2004; Starr & Davila, 2012)

1b: Illustration 2 $N = 1$ $T = 170$, No Missing Data

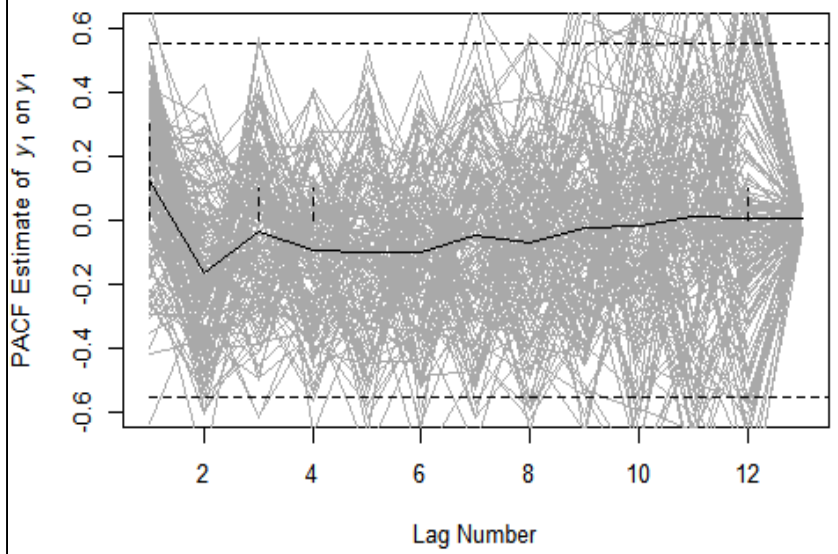


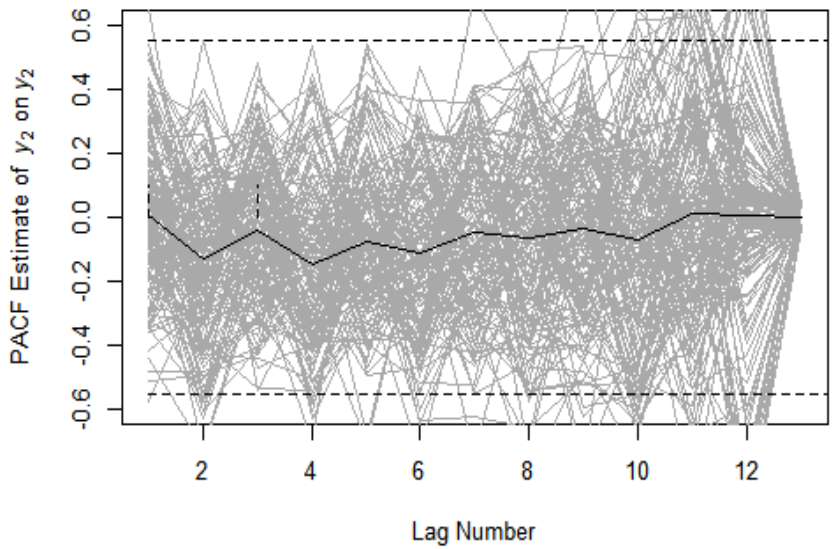


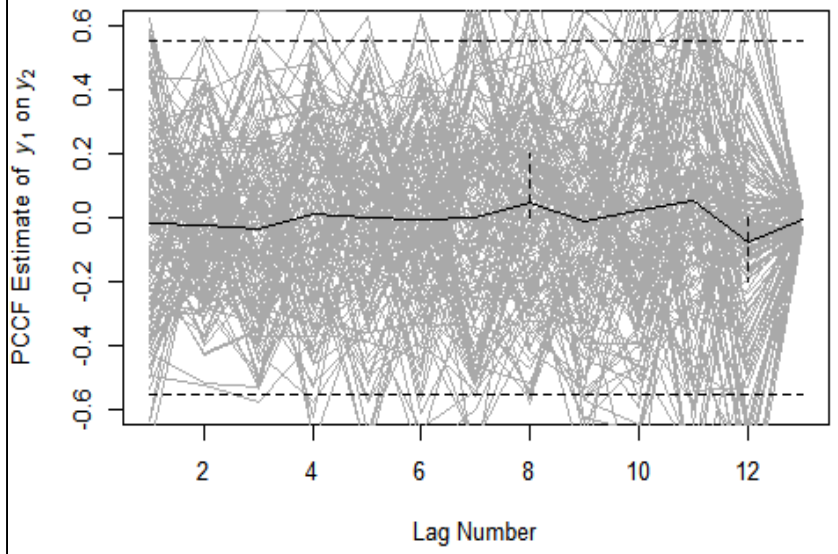


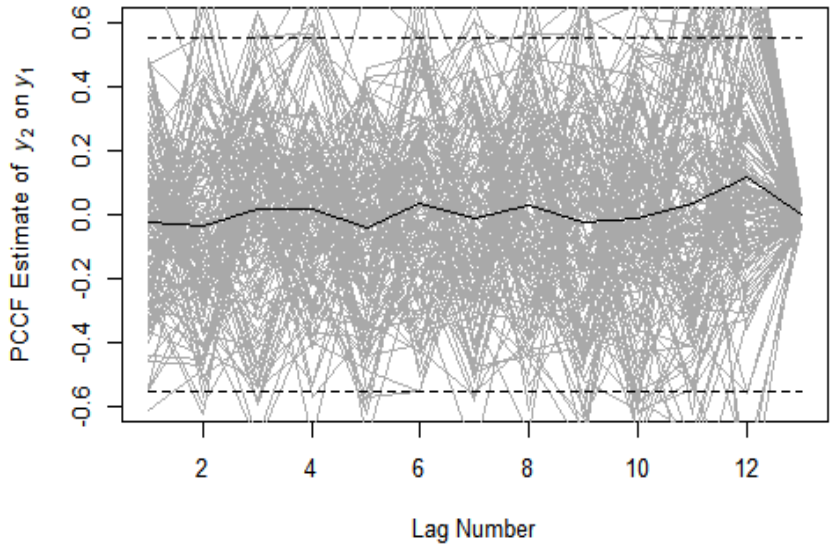


1c: Illustration 3 $N = 159$ $T = 14$, No Missing Data

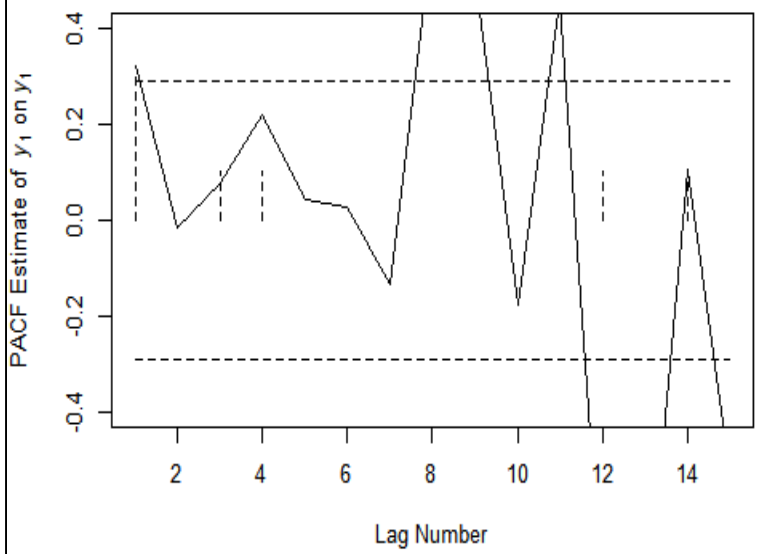


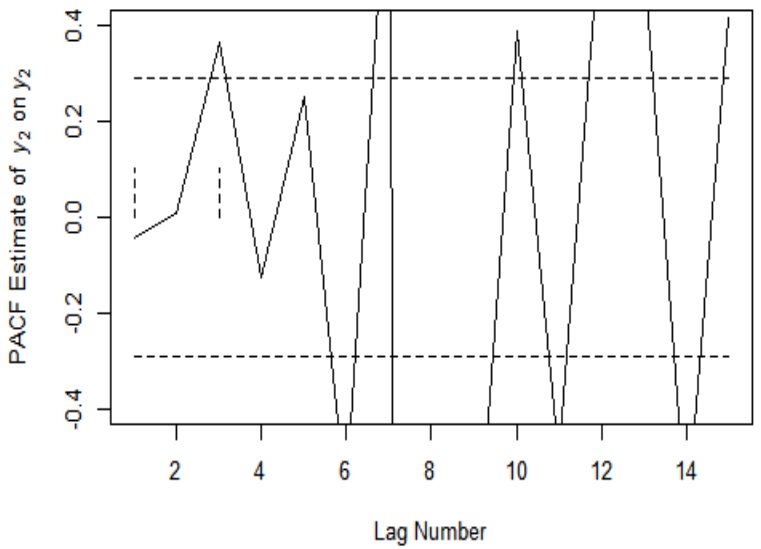


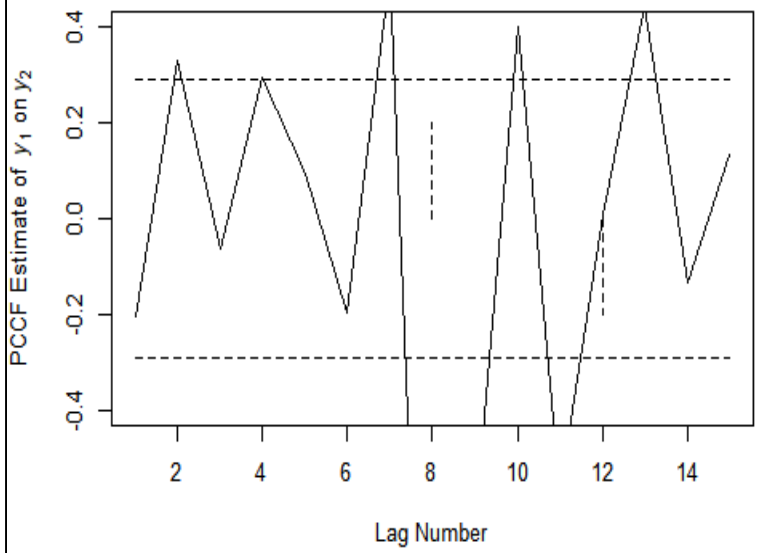


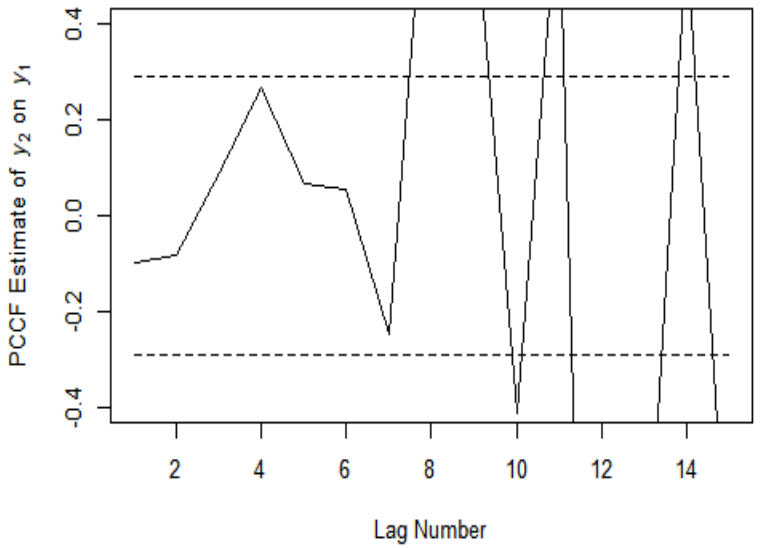


1d: Illustration 4 $N = 1$ $T = 170$, 72% Missing Data

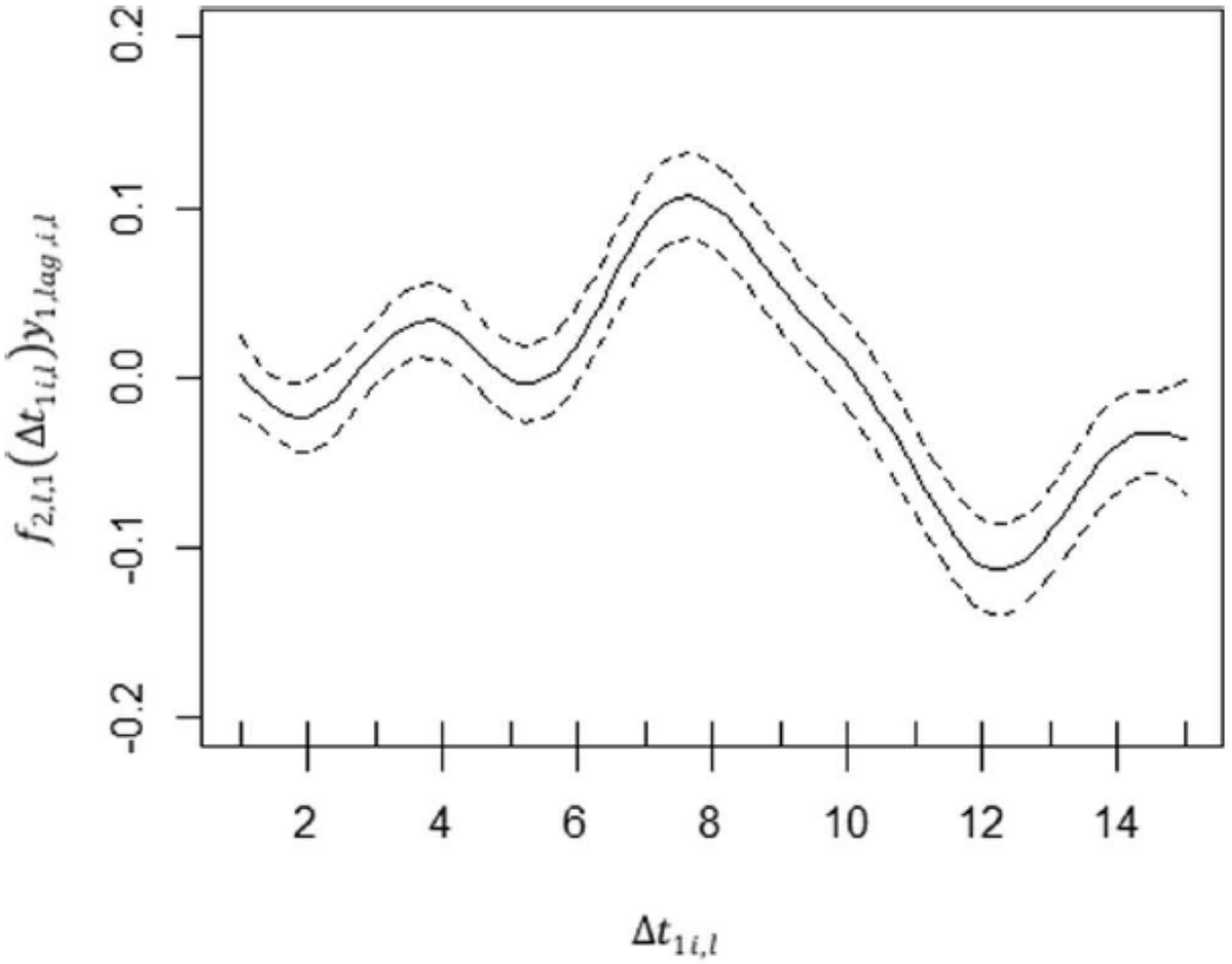




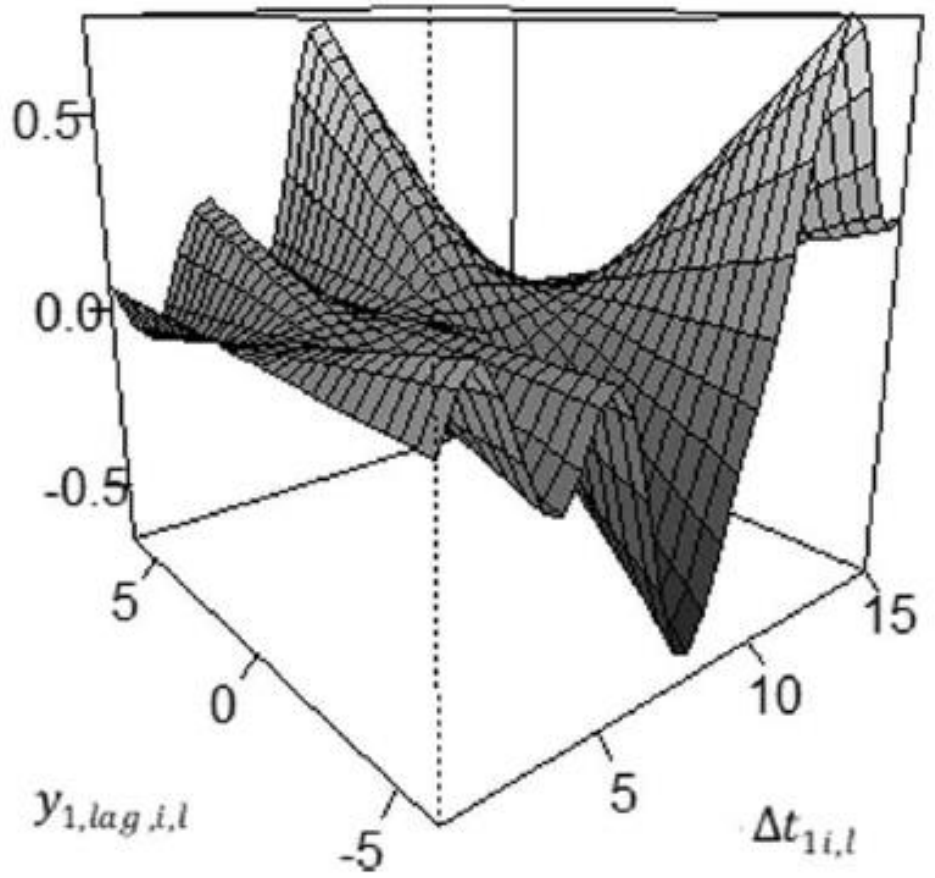




Introducing DTVEM

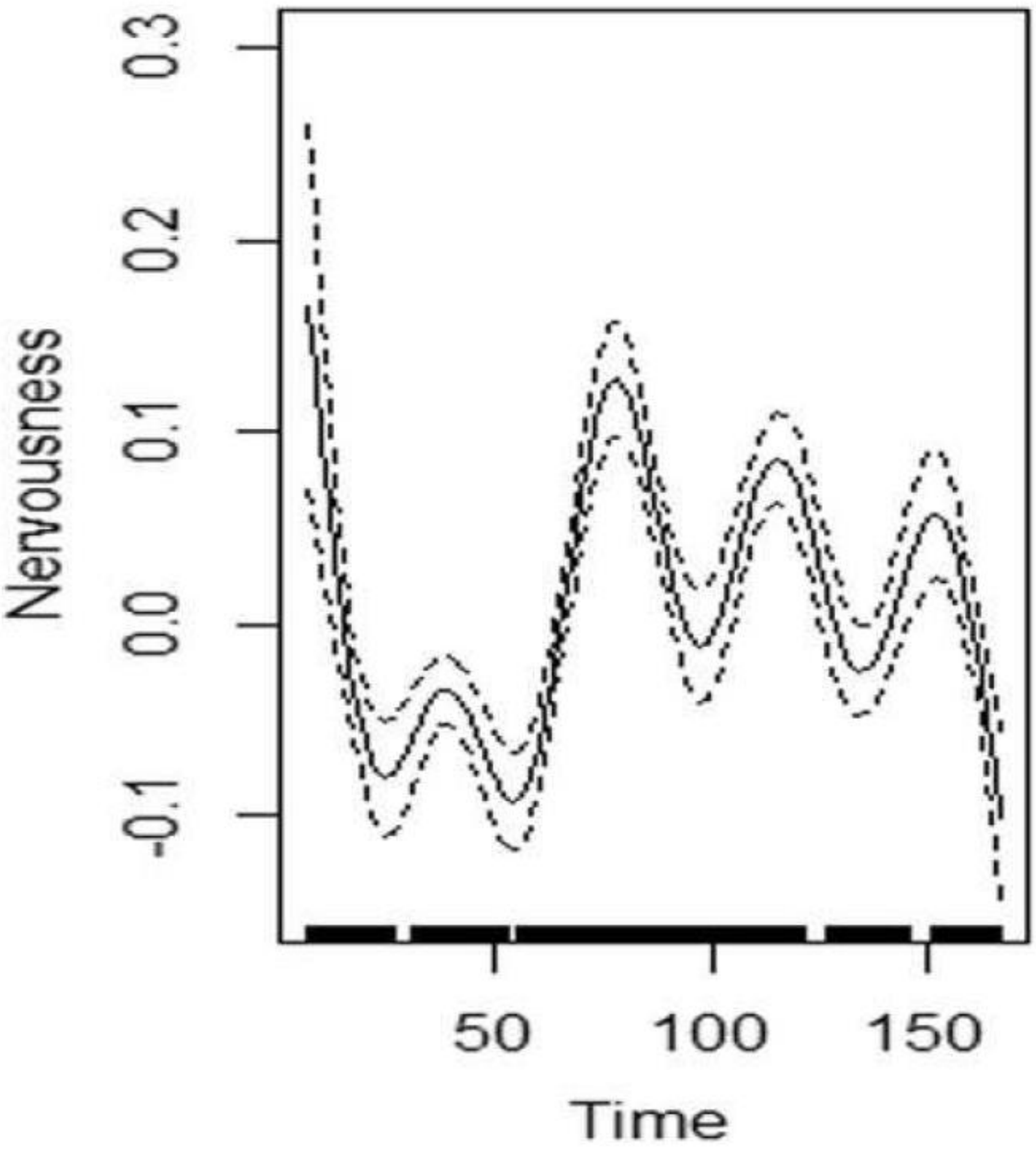


Predicted y_2



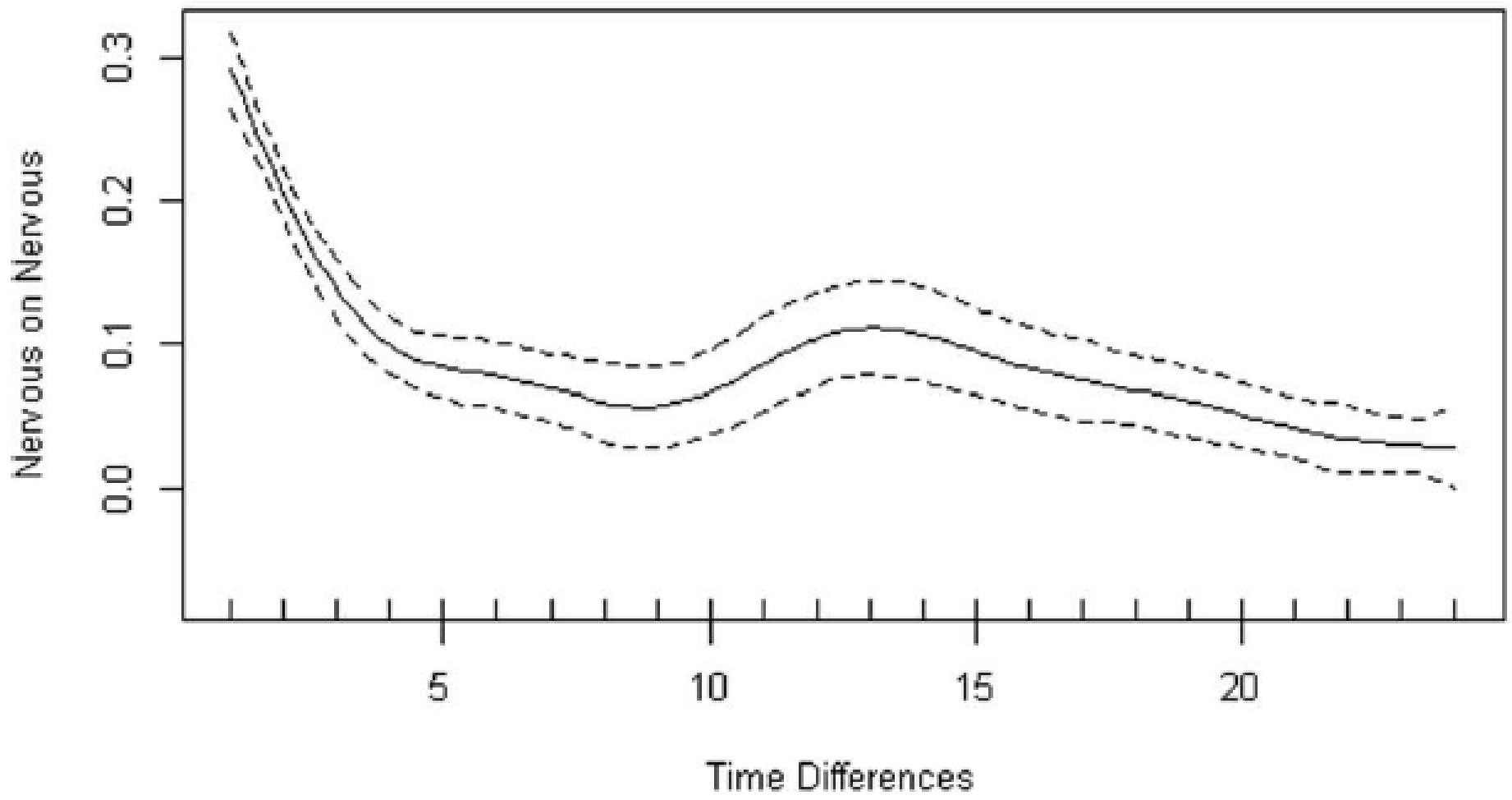
Automated Routine

- Exploratory Stage:
- Fits smooth curves to study optimal time periods in which one construct predicts another
  - Used to discover the optimal time lags in which constructs predict one another
- Confirmatory Stage:
- Fit the optimal lags found in the exploratory stage in a confirmatory vector autoregressive model using a state-space routine

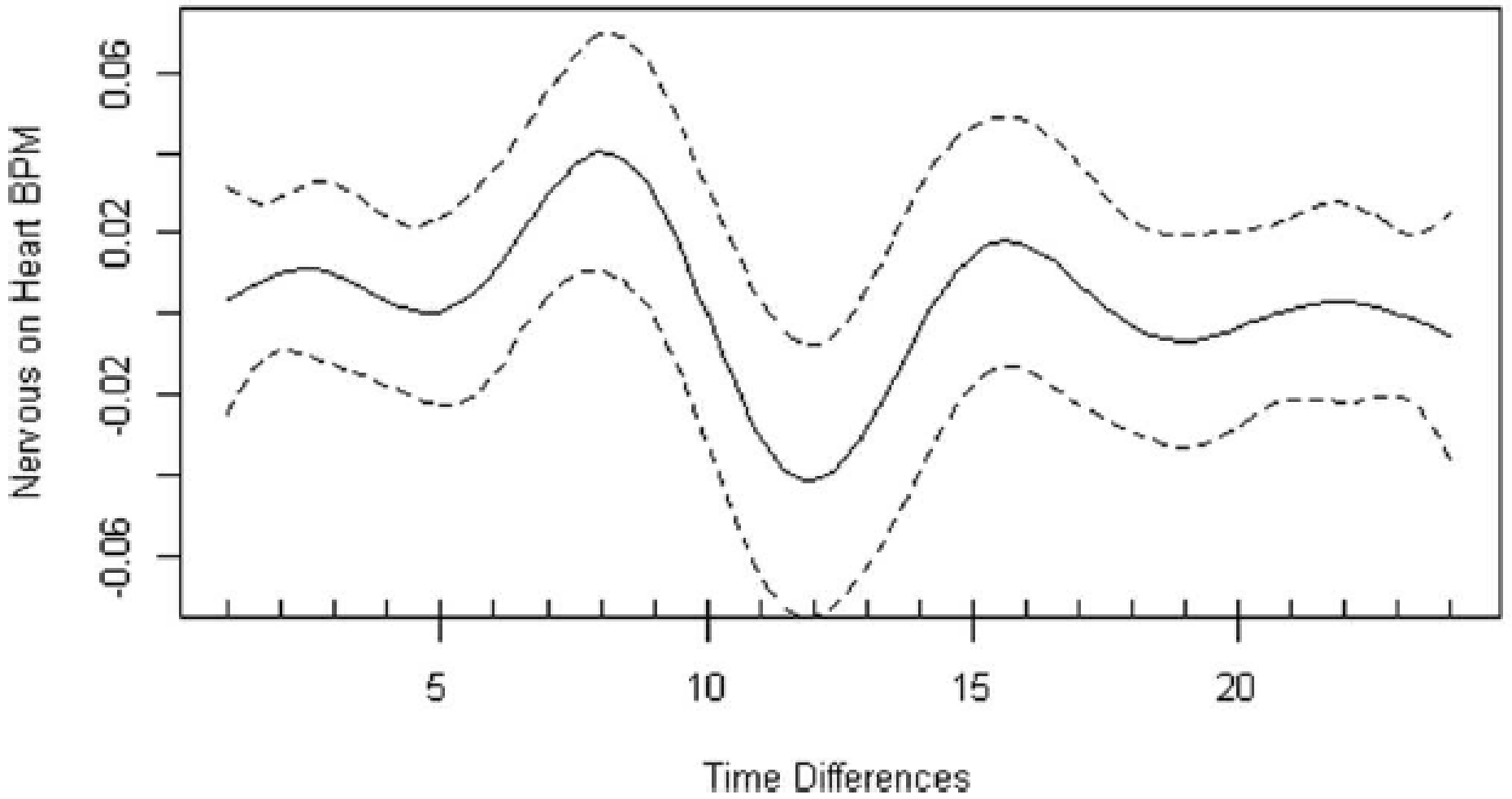


Nervousness
0.3
0.2
0.1
0.0
-0.1
50
100
150
Time

Effects of Nervousness on Itself



Effects of Nervousness on Heart Rate



Simulation Studies

- Accurately able to detect higher-order lags
- High exploratory power and low type-I error rates
- Accurate point estimates

- More details available in the study

Behavior Research Methods
https://doi.org/10.3758/s13428-018-1101-0

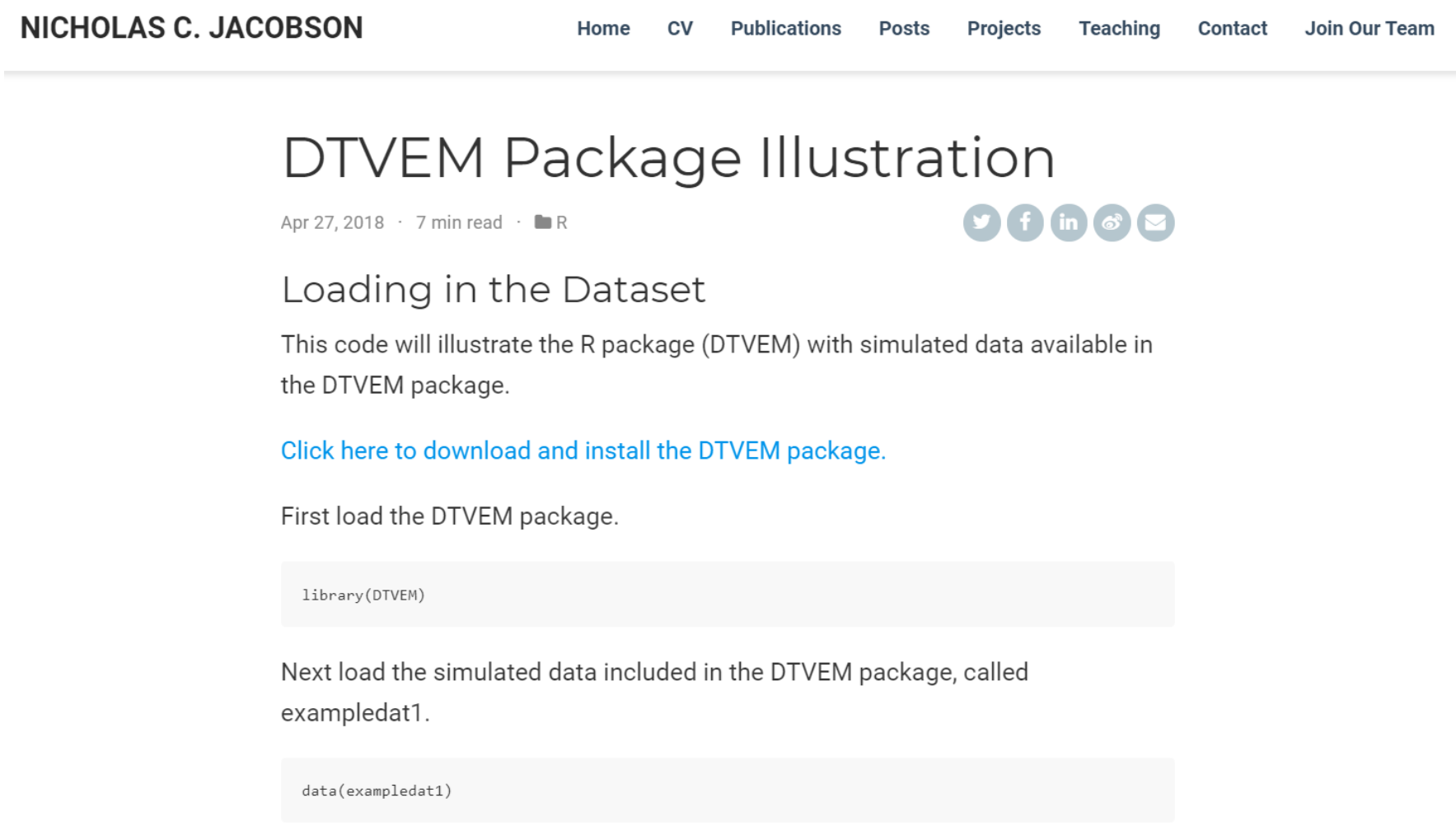
The Differential Time-Varying Effect Model (DTVEM): A tool for diagnosing and modeling time lags in intensive longitudinal data

Nicholas C. Jacobson [1] · Sy-Miin Chow [1] · Michelle G. Newman [1]

http://www.nicholasjacobson.com/project/dtvem/

Easy Tutorial Available

nicholasjacobson.com/post/illustration_of_dtvem/



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DTVEM Package Illustration

Apr 27, 2018 · 7 min read · R

Loading in the Dataset

This code will illustrate the R package (DTVEM) with simulated data available in the DTVEM package.

Click here to download and install the DTVEM package.

First load the DTVEM package.

```
library(DTVEM)
```

Next load the simulated data included in the DTVEM package, called exampledat1.

```
data(exampledat1)
```

A *single* line of code to run

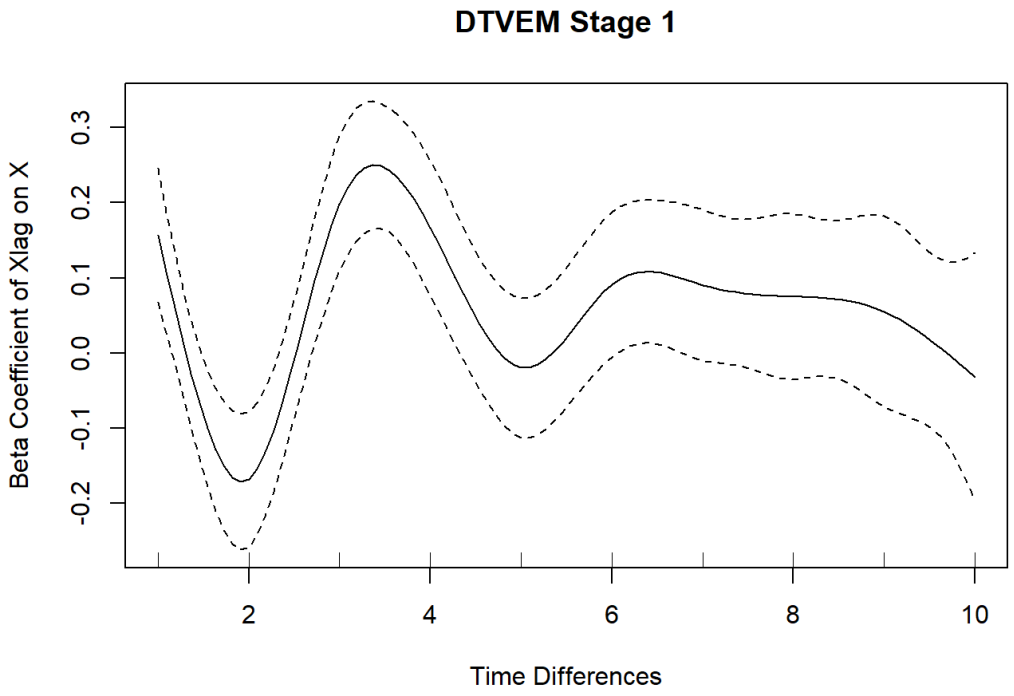
- out=LAG("X",differntialtimevaryingpredictors=c("X"),outcome=c("X"), data=exampledat1,ID="ID",Time="Time",k=9,standardized=FALSE,prediction start = 1,predictionsend = 10,predictionsinterval = 1)

Output

Confirmatory

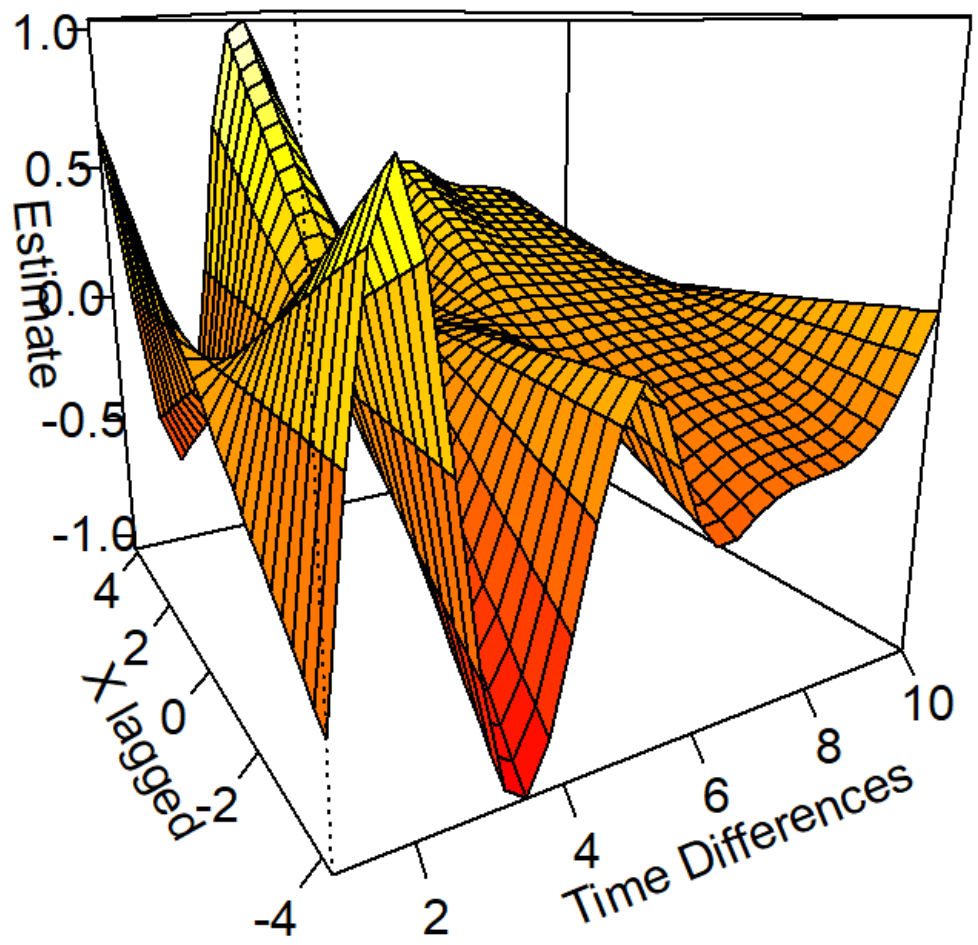
```
##          name matrix row col   Estimate  Std.Error lbound ubound lboundMet
## 1 XlagonXlag1   s1.A   1   1  0.2360088 0.04461888     NA     NA      FALSE
## 2 XlagonXlag2   s1.A   1   2 -0.2485319 0.04220480     NA     NA      FALSE
## 3 XlagonXlag3   s1.A   1   3  0.2835748 0.04300307     NA     NA      FALSE
##   uboundMet     tstat       pvalue  sig
## 1     FALSE  5.289438 1.226928e-07 TRUE
## 2     FALSE -5.888712 3.892167e-09 TRUE
## 3     FALSE  6.594293 4.272871e-11 TRUE
```

Exploratory



A second line of code to visualize

- vis.gam(out$stage1out$mod,xlab="Time Differences",ylab="X lagged",zlab="Estimate",theta=-30,ticktype="detailed")



Thank You to My Lab!

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- Rapael Huang
- Vernoica Abreu
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