Estimation Systems for Rolling Samples

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Outline

- Introduction
  - background
  - operational considerations
  - estimation system
- Weighting alternatives
  - *ad hoc* moving average
  - time series model: exponential smoothing, local linear trend
  - nonparametric regression model: local polynomial regression
- Summary
  - assessing quality of estimation systems

Notation

- Finite population of plots: $U = \{1, \ldots, i, \ldots, N\}$
- Draw sample $s \subset U$ (sample size n) via $p(\cdot)$ with probabilities π_i
- Partition s into T panels as $s = \cup_{h=1}^{T} s_{t-T+h}$:

Element	Most Recent Observation
$i \in s_{t-T+1}$	$y_{i,t-T+1}$
$\vdots$	$\vdots$
$i \in s_{t-T+h}$	$y_{i,t-T+h}$
$\vdots$	$\vdots$
$i \in s_{t-T+T}$	$y_{i,t}$

- Suppose $\Pr[i \in s_{t-T+h} \mid s] = 1/T$
- Population mean at time t:

$$\theta_t = N^{-1} \sum_{i \in U} y_{i,t}$$

Operational Considerations

- Not interested in *single* study variable
  - many study variables on survey instrument
  - thousands of point estimates in core tables
  - unlimited number of possible derived variables (transformations, subdomains, lagged differences, cross-products, etc.)
- Want internal consistency
  - additivity of hierarchical subpopulations; tables should "add up"
- Want to avoid detailed modeling operations
  - too many variables
  - too few resources: time, money, personnel
  - potential for controversy among end users

Estimation System

- Want straightforward estimates of
  - status
  - one-year change, two-year change, ..., five-year change, ...
  - standard errors
- Estimation system: data structure plus estimation routines
- Should almost run by itself
  - simple data structure
  - simple routines to get estimates from data

Unbiased Estimation

- Could estimate θ_t using direct estimate

$$\hat{\theta}_t = N^{-1} \sum_{i \in s_t} \frac{y_{i,t}}{\pi_i (1/T)}$$

- Design unbiased: think two-phase sample $s_t \subset s \subset U$

$$\begin{aligned} \mathrm{E}_p\left[\hat{\theta}_t\right] &= \mathrm{E}_p\left[\mathrm{E}\left[N^{-1} \sum_{i \in s_t} \frac{y_{i,t}}{\pi_i (1/T)} \,\middle|\, s\right]\right] \\ &= \mathrm{E}_p\left[N^{-1} \sum_{i \in s} \frac{y_{i,t}}{\pi_i}\right] \\ &= \theta_t \end{aligned}$$

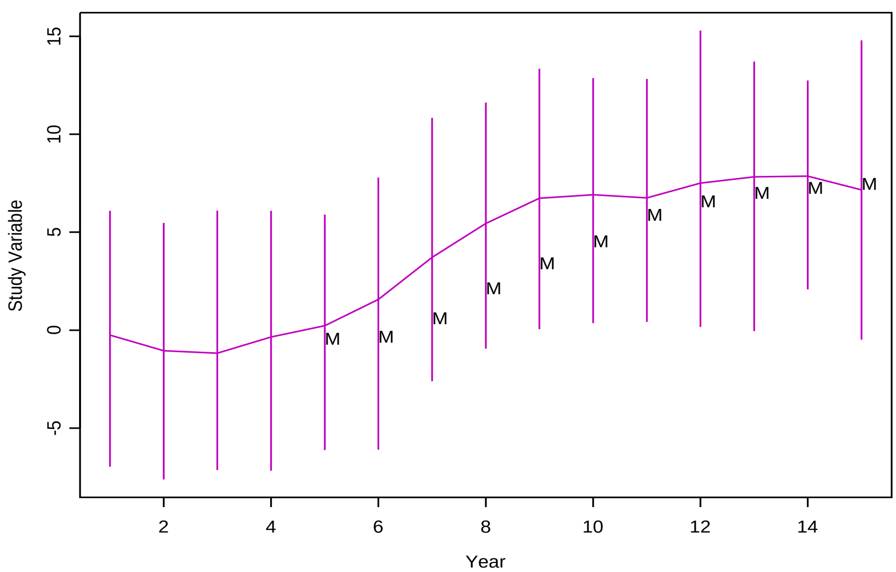
- Variance may be large due to small sample size

Trading Bias Against Variance

- Small area estimation problem
- Use observations from past years
  - borrows strength across time
  - increases sample size
  - reduces variance
- Increases bias unless population is unchanged over time
  - time delay bias

Time Delay Bias

- Example: simple moving average of design-based estimates
  - two-year delay



A Class of Estimation Systems

- Questions: *importance of operational considerations? simplicity? internal consistency? statistical efficiency? reliance on models? how much past data? credibility? status versus change? revisions?*
- Start with candidate class of estimation systems
- Candidate class: build weighted data set of n records
  - one record for each plot
  - includes one or more weights for each record
  - includes most recent observation of each study variable
- Weighted data set summarizes most recent T years of data
  - may depend on past by defining new study variables:

$$y^*_{i,t-T+h} = y_{i,t-2T+h}$$

Weighting

- Construct n weights $\{\omega_{i,t-T+h}\}$ for $i \in s_{t-T+h}$, $h = 1, \ldots, T$
  - reflect design properties
  - incorporate auxiliary information
  - apply to any study variable
- For any study variable y, estimate $\theta_t = N^{-1} \sum_{i \in U} y_{i,t}$ via

$$\hat{\theta}_t = \sum_{h=1}^{T} \sum_{i \in s_{t-T+h}} \omega_{i,t-T+h} y_{i,t-T+h}$$

- Internally consistent:

$$\begin{aligned}
\hat{\theta}_{y+z,t} &= \sum_{h=1}^{T} \sum_{i \in s_{t-T+h}} \omega_{i,s_{t-T+h}} (y_{i,t-T+h} + z_{i,t-T+h}) \\
&= \sum_{h=1}^{T} \sum_{i \in s_{t-T+h}} \omega_{i,s_{t-T+h}} y_{i,t-T+h} + \sum_{h=1}^{T} \sum_{i \in s_{t-T+h}} \omega_{i,s_{t-T+h}} z_{i,t-T+h} \\
&= \hat{\theta}_{y,t} + \hat{\theta}_{z,t}
\end{aligned}$$

Data Structure

- Tabulation data set: n records with one weight per record

$$\left[\begin{array}{cccc} [\omega_{i,s_{t-T+1}} & y_{i,t-T+1}^{(1)} & \cdots & y_{i,t-T+1}^{(J)}]_{i\in s_{t-T+1}} \\ \vdots & \vdots & & \vdots \\ [\omega_{i,s_{t-1}} & y_{i,t-1}^{(1)} & \cdots & y_{i,t-1}^{(J)}]_{i\in s_{t-1}} \\ [\omega_{i,s_t} & y_{i,t}^{(1)} & \cdots & y_{i,t}^{(J)}]_{i\in s_t} \end{array}\right]$$

- Sum of weight times study variable is status estimate

Weight Generation?

- Unmotivated, *ad hoc*
  - simple moving average
- Motivated by time series model
  - exponentially weighted moving average
  - local linear trend
  - simple moving average
- Motivated by nonparametric regression model
  - local polynomial regression
  - simple moving average

A Simple Time Series Model

- Time series: sequence of design-based estimates, $\hat{\theta}_t$
- Model: random walk plus noise (ARIMA(0,1,1))

$$\begin{aligned}\hat{\theta}_t &= \theta_t + \epsilon_t, \quad \{\epsilon_t\} \text{ iid N}(0, \sigma^2) \\ \theta_t &= \theta_{t-1} + \eta_t, \quad \{\eta_t\} \text{ iid N}(0, \sigma_\eta^2)\end{aligned}$$

- σ_η^2 is "signal" variance; σ^2 is sampling error variance

$$\text{signal-to-noise ratio} = \text{SNR} = \frac{\sigma_\eta^2}{\sigma^2}$$

Exponential Smoothing

- Define first difference matrix

$$\boldsymbol{\Delta}_1 = \begin{bmatrix} -1 & 1 & & & \\ & -1 & 1 & & \\ & & \ddots & \ddots & \\ & & & -1 & 1 \end{bmatrix}$$

- Best mean square predictor of $(\theta_{t-T+1}, \ldots, \theta_t)'$ is

$$\left\{ \mathbf{I} - \boldsymbol{\Delta}_1' \left(\frac{\sigma_\eta^2}{\sigma^2} \mathbf{I} + \boldsymbol{\Delta}_1 \boldsymbol{\Delta}_1' \right)^{-1} \boldsymbol{\Delta}_1 \right\} \begin{bmatrix} \hat{\theta}_{t-T+1} \\ \vdots \\ \hat{\theta}_t \end{bmatrix}$$

Exponential Smoothing Weights

- Last row of matrix

$$\mathbf{I} - \mathbf{\Delta}_1' \left(\frac{\sigma_\eta^2}{\sigma^2} \mathbf{I} + \mathbf{\Delta}_1 \mathbf{\Delta}_1' \right)^{-1} \mathbf{\Delta}_1$$

gives weights for estimating θ_t:

	Time				
SNR	$t-4$	$t-3$	$t-2$	$t-1$	t
0.0	0.20	0.20	0.20	0.20	0.20
0.1	0.04	0.08	0.12	0.26	0.50
1.0	0.02	0.04	0.10	0.24	0.62
2.0	0.00	0.02	0.06	0.20	0.74
10.0	0.00	0.00	0.00	0.08	0.92
∞	0.00	0.00	0.00	0.00	1.00

– as SNR$\to 0$, signal $\to$ constant

– as SNR$\to \infty$, sampling error $\to 0$

– need to choose SNR to get estimation system

Concerns about Exponential Smoothing

- Restrictiveness of model?
- Need to specify one SNR for all variables
- Implicit first difference method
  - may have trouble with curvature
- Estimation of change:
  - model implies study variable follows ARIMA(0,1,1)
  - five-year change in variable follows ARIMA(0,1,6)
- Variance estimation?
  - correlation induced by averaging
- Incorporation of auxiliary information?

Local Linear Trend Model

- Time series: sequence of design-based estimates, $\hat{\theta}_t$
- Model: local linear trend plus noise (ARIMA(0,2,2))

$$\begin{aligned}
\hat{\theta}_t &= \theta_t + \epsilon_t, \quad \{\epsilon_t\} \text{ iid N}(0, \sigma^2) \\
\theta_t &= \theta_{t-1} + \beta_{t-1} + \eta_t, \quad \{\eta_t\} \text{ iid N}(0, \sigma_\eta^2) \\
\beta_t &= \beta_{t-1} + \xi_t, \quad \{\xi_t\} \text{ iid N}(0, \sigma_\xi^2)
\end{aligned}$$

- Define the second difference matrix

$$\mathbf{\Delta}_2 = \begin{bmatrix} 1 & -2 & 1 & & & \\ & 1 & -2 & 1 & & \\ & & \ddots & \ddots & \ddots & \\ & & & 1 & -2 & 1 \end{bmatrix}$$

- Weights for current status given by last row of

$$\mathbf{I} - \mathbf{\Delta}_2' \left(\frac{\sigma_\xi^2}{\sigma^2} \mathbf{I} + \frac{\sigma_\eta^2}{\sigma^2} \mathbf{\Delta}_1 \mathbf{\Delta}_1' + \mathbf{\Delta}_2 \mathbf{\Delta}_2' \right)^{-1} \mathbf{\Delta}_2$$

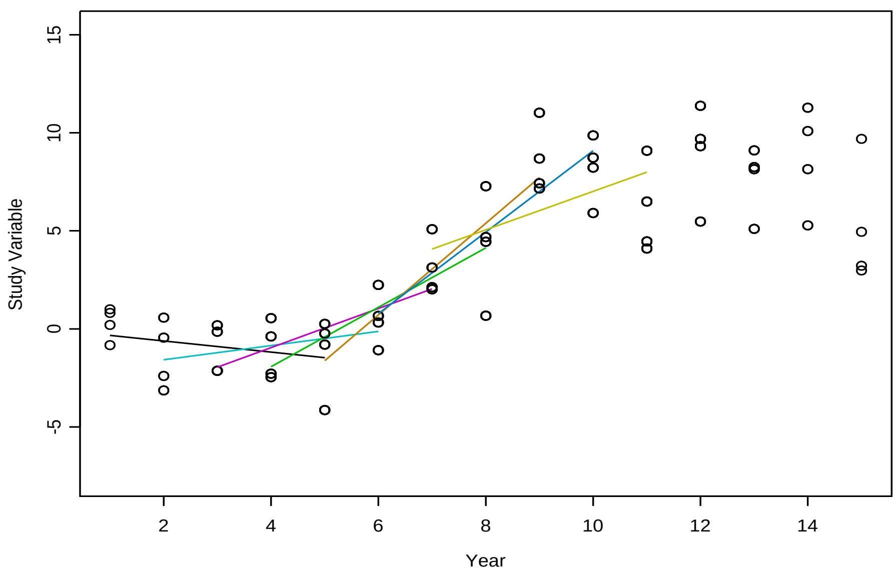
  - need to choose two variance ratios to get estimation system

Concerns

- Restrictiveness of model?
- Need to specify one pair of variance ratios for all variables
- Possibility of negative weights
- Estimation of change:
  - model implies study variable follows ARIMA(0,2,2)
  - five-year change in variable follows ARIMA(0,2,7)
- Variance estimation?
  - correlation induced by averaging
- Incorporation of auxiliary information?

Nonparametric Regression

- Signal can be modeled as:
  - positively autocorrelated stochastic process: time series
  - smooth deterministic function of time: nonparametric regression
- Local linear regression:



Local Polynomial Regression

- Define the $n \times (q+1)$ matrix

$$\mathbf{X}_t = \left[\left[\begin{array}{cccc} 1 & h & \cdots & h^q \end{array}\right]_{i \in s_{t-T+h}}\right]_{h=1}^{T},$$

  the $n \times n$ matrix

$$\mathbf{W}_t = \text{blockdiag}\left\{\text{diag}\left\{\frac{1}{\pi_i}\right\}_{i \in s_{t-T+h}}\right\}_{h=1}^{T},$$

  and the $n \times 1$ vector

$$\mathbf{y}_t = \left[\left[y_{i,t-T+h}\right]_{i \in s_{t-T+h}}\right]_{h=1}^{T}.$$

- Obtain local qth order polynomial fit via weighted least squares:

$$\begin{aligned}\hat{m}(t-T+k) &= \left[\begin{array}{cccc} 1 & k & \cdots & k^q \end{array}\right] \left(\mathbf{X}_t'\mathbf{W}_t\mathbf{X}_t\right)^{-1} \mathbf{X}_t'\mathbf{W}_t\mathbf{y}_t \\ &= \left[\begin{array}{cccc} 1 & k & \cdots & k^q \end{array}\right] \left(\mathbf{X}_t'\mathbf{W}_t\mathbf{X}_t\right)^{-1} \sum_{h=1}^{T} \sum_{i \in s_{t-T+h}} \left[\begin{array}{c} 1 \\ h \\ \vdots \\ h^q \end{array}\right] \frac{1}{\pi_i} y_{i,t-T+h}\end{aligned}$$

Two-Phase Regression Estimator

- Two-phase sampling with $s_t \subset s \subset U$:
  - predict $y_{i,t}$ by $\hat{y}_{i,t}^{(U)}$ for $i \in U$
  - predict $y_{i,t}$ by $\hat{y}_{i,t}^{(s)}$ for $i \in s$
  - predict $y_{i,t}$ by $y_{i,t}$ for $i \in s_t$
- Two-phase regression estimator (Särndal, Swensson, and Wretman, 1992, Ch. 9):

$$\sum_{i \in U} \frac{\hat{y}_{i,t}^{(U)}}{N} + \sum_{h=1}^{T} \sum_{i \in s_{t-T+h}} \frac{\hat{y}_{i,t}^{(s)} - \hat{y}_{i,t}^{(U)}}{N\pi_i} + \sum_{i \in s_t} \frac{y_{i,t} - \hat{y}_{i,t}^{(s)}}{N\pi_i(1/T)}$$

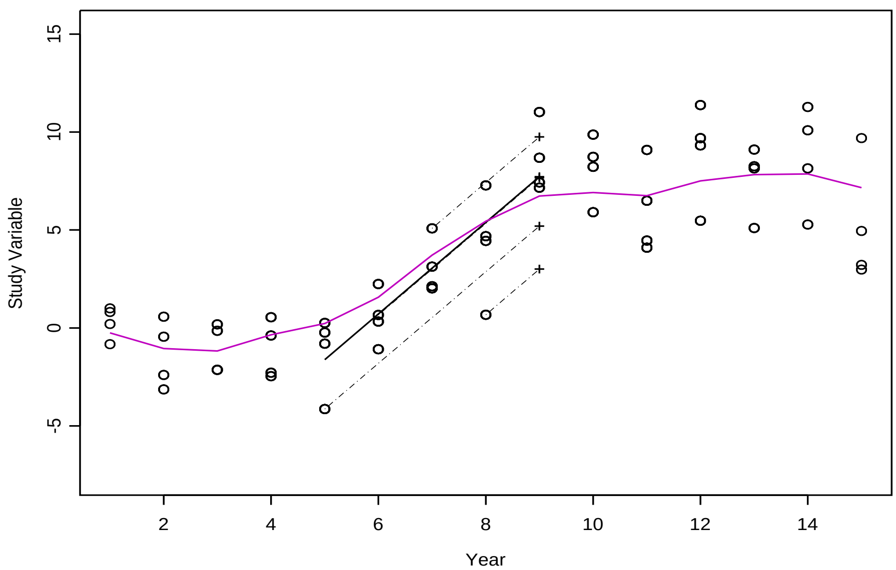
  - approximately design-unbiased
  - good MSE properties if predictions are good

Local Polynomial Regression Predictions

- Plot-level model:
$$y_{i,t} = m(t) + \delta_i + \epsilon_{it}$$
  - $m(t)$ is a smooth function of time
  - $\{\delta_i\}$ iid $(0, \sigma_\delta^2)$
  - $\{\epsilon_{it}\}$ zero-mean stochastic processes, independent across i
- Predictions:
  - predict $y_{i,t}$ by $\hat{y}_{i,t}^{(U)} = \hat{m}(t)$ for $i \in U$
  - predict $y_{i,t}$ by $\hat{y}_{i,t}^{(s)} = \hat{m}(t) + y_{i,t-T+h} - \hat{m}(t-T+h)$ for $i \in s_{t-T+h}$
  - predict $y_{i,t}$ by $y_{i,t}$ for $i \in s_t$
- Note:
$$\sum_{h=1}^{T} \sum_{i \in s_{t-T+h}} \frac{\hat{y}_{i,t}^{(s)} - \hat{y}_{i,t}^{(U)}}{N\pi_i} = 0$$
  and
$$\sum_{i \in s_t} \frac{y_{i,t} - \hat{y}_{i,t}^{(s)}}{N\pi_i(1/T)} = 0$$

Graphical Interpretation

- Predictions: $\hat{y}_{i,t}^{(s)} = \hat{m}(t) + y_{i,t-T+h} - \hat{m}(t - T + h)$



Local Polynomial Regression Estimator

- Local polynomial regression estimator of θ_t is given by

$$\begin{aligned}\tilde{\theta}_t &= \sum_{i \in U} \frac{\hat{y}_{i,t}^{(U)}}{N} + \sum_{h=1}^{T} \sum_{i \in s_{t-T+h}} \frac{\hat{y}_{i,t}^{(s)} - \hat{y}_{i,t}^{(U)}}{N\pi_i} + \sum_{i \in s_t} \frac{y_{i,t} - \hat{y}_{i,t}^{(s)}}{N\pi_i(1/T)} \\ &= \hat{m}(t)\end{aligned}$$

  - approximately design-unbiased
  - good MSE properties if predictions are good

Plot Weights for Local Linear Regression

- Weighted form of local linear regression estimator:

$$
\begin{aligned}
\tilde{\theta}_t &= \hat{m}(t) = \left[\begin{array}{cc} 1 & T \end{array}\right] \left(\mathbf{X}_t' \mathbf{W}_t \mathbf{X}_t\right)^{-1} \mathbf{X}_t' \mathbf{W}_t \mathbf{y}_t \\
&= \sum_{h=1}^{T} \sum_{i \in s_{t-T+h}} \left[\begin{array}{cc} 1 & T \end{array}\right] \left\{ \left(\mathbf{X}_t' \mathbf{W}_t \mathbf{X}_t\right)^{-1} \left[\begin{array}{c} 1 \\ h \end{array}\right] \frac{1}{\pi_i} \right\} y_{i,t-T+h} \\
&= \sum_{h=1}^{T} \sum_{i \in s_{t-T+h}} \left[\begin{array}{cc} 1 & T \end{array}\right] \boldsymbol{\omega}_{i,t-T+h} y_{i,t-T+h} \\
&= \sum_{h=1}^{T} \sum_{i \in s_{t-T+h}} \omega_{i,t-T+h} y_{i,t-T+h}
\end{aligned}
$$

  – easy to compute
  – can be rearranged to get moving average of design-based estimators

Local Polynomial Regression: Moving Average Weights

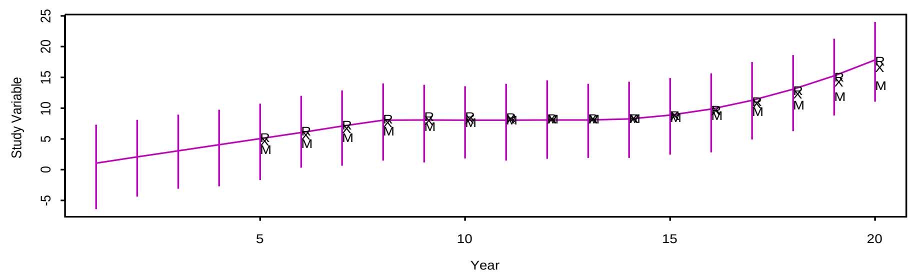
- Moving average weights for $T = 5$

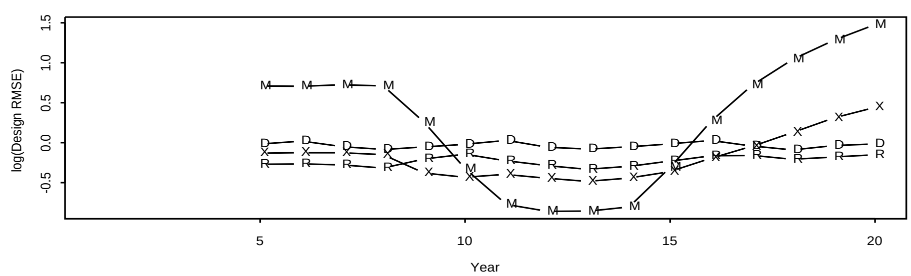
Polynomial Order	Time				
q	$t-4$	$t-3$	$t-2$	$t-1$	t
0	0.200	0.200	0.200	0.200	0.200
1	-0.200	0.000	0.200	0.400	0.600
2	0.086	-0.143	-0.086	0.257	0.886
3	-0.014	0.057	-0.086	0.057	0.986
4	0.000	0.000	0.000	0.000	1.000

  - fitting of local constant equivalent to simple moving average
  - otherwise, more weight on current conditions
  - negative weights imply possibility of negative estimates

Simulation Results

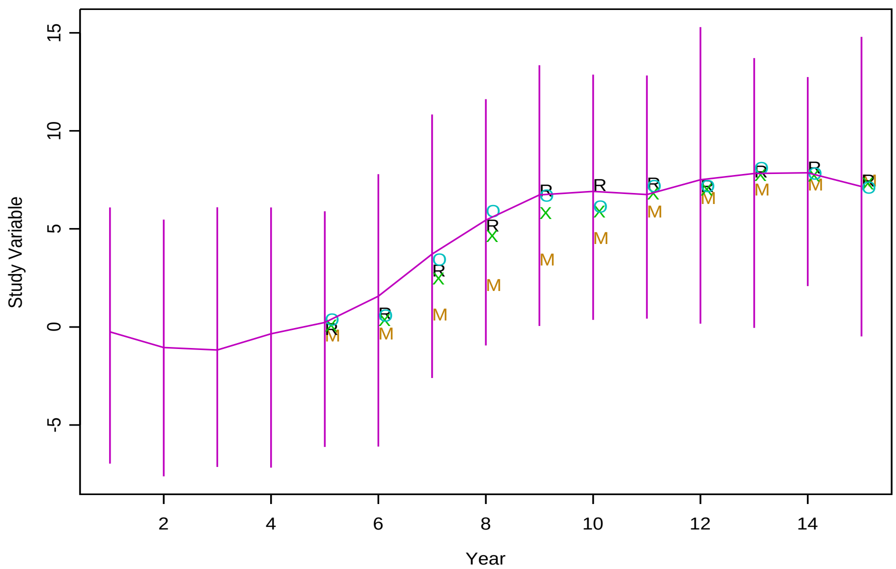
- Estimators in 100 simple random samples:
  - simple moving average (M),
  - local linear regression (R),
  - exponential smoothing with SNR= 1 (X)





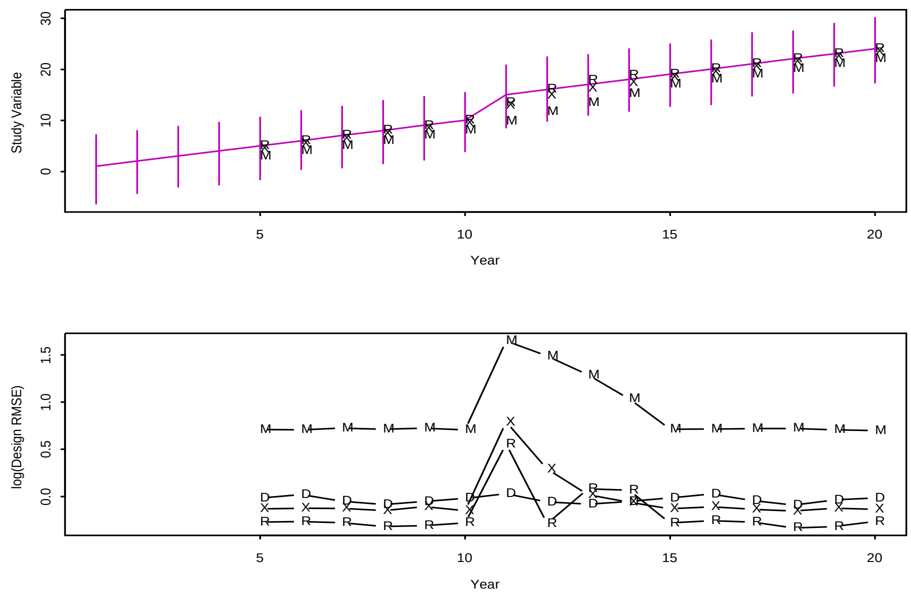
Example: Stochastic Trend

- Stochastic trend generated by local linear trend model
  - optimal mean squared error predictor (O)



Example: Discontinuous Trend

- Line with jump:



Variance Estimation

- Estimator of design variance based on Taylor series linearization:

$$\left[\, 1 \;\; T \,\right] \left(\mathbf{X}_t' \mathbf{W}_t \mathbf{X}_t\right)^{-1} \mathbf{V}_t \left(\mathbf{X}_t' \mathbf{W}_t \mathbf{X}_t\right)^{-1} \left[\begin{array}{c} 1 \\ T \end{array}\right]$$

where

$$\mathbf{V}_t = \left[\sum_{h=1}^{T} \sum_{i \in s_{t-T+h}} \sum_{k=1}^{T} \sum_{j \in s_{t-T+k}} \frac{\pi_{ij} - \pi_i \pi_j}{\pi_{ij}} \frac{h^f e_{i,t-T+h} k^g e_{j,t-T+k}}{\pi_i \pi_j}\right]_{f,g=0}^{1}$$

and

$$e_{i,t-T+h} = y_{i,t-T+h} - \hat{m}(t - T + h)$$

  - simplifies for designs like simple random sampling

Estimators of Lagged Status

- Estimators of lagged status: at time t, two-phase regression estimator of θ_{t-T+k} $(k = 1, \ldots, T)$ is:

$$\begin{aligned}\tilde{\theta}_{t-T+k|t} &= \hat{m}(t-T+k) \\ &= \sum_{h=1}^{T} \sum_{i \in s_{t-T+h}} \left[\begin{array}{cc} 1 & k \end{array}\right] \boldsymbol{\omega}_{i,t-T+h} y_{i,t-T+h}\end{aligned}$$

  – might be interesting to study properties of revisions; for example:

$$\tilde{\theta}_{t-T+k|t} - \tilde{\theta}_{t-T+k|t-1}$$

Estimators of Change

- Estimator of k-year change ($k = 1, \ldots, T-1$):

$$\tilde{\theta}_t - \tilde{\theta}_{t-T+k|t} = \sum_{h=1}^{T} \sum_{i \in s_{t-T+h}} \left[\, 0 \;\; T-k \, \right] \boldsymbol{\omega}_{i,t-T+h} y_{i,t-T+h}$$

  – no direct measurements of k-year change for $k < T$

- Estimator of T-year change:

  – define direct measurements of T-year change

$$y^*_{i,t-T+h} = y_{i,t-T+h} - y_{i,t-2T+h}$$

  – change estimator is

$$\sum_{h=1}^{T} \sum_{i \in s_{t-T+h}} \left[\, 1 \;\; T \, \right] \boldsymbol{\omega}_{i,t-T+h} y^*_{i,t-T+h}$$

  – nonparametric model still holds for T-year difference

$$m^*(t) = m(t) - m(t-T)$$

Data Structure

- Tabulation data set: n records with two weights per record

$$\begin{bmatrix} [\boldsymbol{\omega}'_{i,s_{t-T+1}} & y^{(1)}_{i,t-T+1} & \cdots & y^{(J)}_{i,t-T+1}]_{i\in s_{t-T+1}} \\ \vdots & \vdots & & \vdots \\ [\boldsymbol{\omega}'_{i,s_{t-1}} & y^{(1)}_{i,t-1} & \cdots & y^{(J)}_{i,t-1}]_{i\in s_{t-1}} \\ [\boldsymbol{\omega}'_{i,s_t} & y^{(1)}_{i,t} & \cdots & y^{(J)}_{i,t}]_{i\in s_t} \end{bmatrix}$$

- Sum of study variable times weight vector times
  - $(1, T)'$ is current status estimate
  - $(1, k)'$ is lagged status estimate
  - $(0, T-k)'$ is k-year change estimate

Incorporating Auxiliary Information

- Have r regressors $\mathbf{x}_{i,t-T+h}$ for $i \in s_{t-T+h}$ and know $\sum_{i \in U} \mathbf{x}_{i,t}$
  - GIS coverage
  - imagery
- Plot-level model:

$$y_{i,t} = m(t) + \mathbf{x}'_{it}\boldsymbol{\gamma} + \delta_i + \epsilon_{it}$$

  - $m(t)$ is a smooth function of time
  - $\boldsymbol{\gamma}$ is a vector of constants
  - $\{\delta_i\}$ iid $(0, \sigma_\delta^2)$
  - $\{\epsilon_{it}\}$ zero-mean stochastic processes
- Define the $n \times (2 + r)$ matrix

$$\mathbf{X}_t = \left[\left[\begin{array}{ccc} 1 & h & \mathbf{x}'_{i,t-T+h} \end{array} \right]_{i \in s_{t-T+h}} \right]_{h=1}^{T}$$

- Local regression fit given by:

$$(\mathbf{X}'_t \mathbf{W}_t \mathbf{X}_t)^{-1} \mathbf{X}'_t \mathbf{W}_t \mathbf{y}_t$$

Predictions Using Auxiliary Information

- Model:

$$y_{i,t} = m(t) + \mathbf{x}'_{it}\boldsymbol{\gamma} + \delta_i + \epsilon_{it}$$

- Predictions:
  - predict $y_{i,t}$ by $\hat{y}^{(U)}_{i,t} = \hat{m}(t) + \mathbf{x}'_{it}\hat{\boldsymbol{\gamma}}$ for $i \in U$
  - predict $y_{i,t}$ by $\hat{y}^{(s)}_{i,t} = \hat{m}(t) + \mathbf{x}'_{it}\hat{\boldsymbol{\gamma}} + y_{i,t-T+h} - \hat{m}(t-T+h) - \mathbf{x}'_{it}\hat{\boldsymbol{\gamma}}$ for $i \in s_{t-T+h}$
  - predict $y_{i,t}$ by $y_{i,t}$ for $i \in s_t$

- Note:

$$\sum_{h=1}^{T} \sum_{i \in s_{t-T+h}} \frac{\hat{y}^{(s)}_{i,t} - \hat{y}^{(U)}_{i,t}}{N\pi_i} = 0$$

  and

$$\sum_{i \in s_t} \frac{y_{i,t} - \hat{y}^{(s)}_{i,t}}{N\pi_i(1/T)} = 0$$

Two-Phase Regression Estimator Using Auxiliary Information

- Two-phase regression estimator is then

$$
\begin{aligned}
\tilde{\theta}_t &= \sum_{i \in U} \frac{\hat{m}(t) + \mathbf{x}'_{it}\hat{\boldsymbol{\gamma}}}{N} \\
&= \left[\, 1 \;\; T \;\; N^{-1} \textstyle\sum_{i \in U} \mathbf{x}'_{it} \,\right] (\mathbf{X}'_t \mathbf{W}_t \mathbf{X}_t)^{-1} \mathbf{X}'_t \mathbf{W}_t \mathbf{y}_t \\
&= \sum_{h=1}^{T} \sum_{i \in s_{t-T+h}} \omega_{i,t-T+h} y_{i,t-T+h}
\end{aligned}
$$

  - weights have *calibration* property:

$$
\sum_{h=1}^{T} \sum_{i \in s_{t-T+h}} \omega_{i,t-T+h} \mathbf{x}_{i,t-T+h} = N^{-1} \sum_{i \in U} \mathbf{x}_{i,t}
$$

- May be trouble with timing, availability of auxiliary information
  - literature on “benchmarking” of survey data may be useful

Further Work on Regression Approach

- Negative estimates?
  - negative weight on most distant past observation
  - negative estimate indicates trouble (unusually small subpopulation, unusual trend)
  - *ad hoc* fix via composite estimation:

$$(1-k)\tilde{\theta}_t + k\hat{\theta}_t$$

- More complex panel structure?
  - can always reduce to case considered here
- Start up?
- Benchmarking? (irregularly timed remote sensing data)

Summary

- Estimation system: data structure plus estimation routines
  - must handle huge number of study variables
  - should yield internally consistent estimates
  - should have simple data structure, estimation routines
  - should borrow strength across time
  - should be able to incorporate auxiliary information
  - should not be overly dependent on modeling assumptions
  - should have reasonable efficiency for status and change estimates
  - (in particular, should be better than direct estimates)