Package ‘simITS’

October 14, 2022

Type Package

Title Analysis via Simulation of Interrupted Time Series (ITS) Data

Version 0.1.1

Description Uses simulation to create prediction intervals for post-policy outcomes in interrupted time series (ITS) designs, following Miratrix (2020) <arXiv:2002.05746>. This package provides methods for fitting ITS models with lagged outcomes and variables to account for temporal dependencies. It then conducts inference via simulation, simulating a set of plausible counterfactual post-policy series to compare to the observed post-policy series. This package also provides methods to visualize such data, and also to incorporate seasonality models and smoothing and aggregation/summarization. This work partially funded by Arnold Ventures in collaboration with MDRC.

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Depends dplyr, R (>= 2.10), rlang

Suggests arm, ggplot2, knitr, plyr, purrr, rmarkdown, stats, testthat (>= 2.1.0), tidyr

VignetteBuilder knitr

Encoding UTF-8

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RoxygenNote 7.1.0

NeedsCompilation no

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Repository CRAN

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add_lagged_covariates

Augment dataframe with lagged covariates

Description

Take outcome and a list of covariates and add new columns with lagged versions. Assumes rows of dataframe are in time ascending order. Lagged outcome canonically called 'lag.outcome'. Covariates 'lag.XXX'.

Usage

add_lagged_covariates(dat, outcomename, covariates = NULL)

Arguments

dat The dataframe
outcomename The outcome of interest (string)
covariates The covariates to lag along with the outcome. This can be either of two things. First, it can be a list of string names. Covariates can also be a function with a "lags" attribute with the listed covariates (as returned by, e.g., make_fit_season_model) (which is a list of string names). NULL if no covariates other than outcome should be lagged.
**Value**

Augmented dataframe with lagged covariates as new columns. Will clobber old columns if the names (of form "lag.XXXX") conflict.

**Examples**

```r
data("newjersey")
newjersey = add_lagged_covariates(newjersey, "n.warrant", c("sin.m","cos.m" ) )
head( newjersey[ c( "n.warrant", "sin.m", "lag.outcome", "lag.sin.m" ) ] )
```

---

**adjust_data**

*Adjust an outcome time series based on the group weights.*

**Description**

Reweight the components of a series to match target weights for several categories. This is a good preprocessing step to adjust for time-varying covariates such as changing mix of case types.

**Usage**

```r
adjust_data( 
  dat, 
  outcomename, 
  groupname, 
  Nname, 
  pi_star, 
  is_count = FALSE, 
  include_aggregate = FALSE, 
  covariates = NULL 
)
```

**Arguments**

- **dat**: Dataframe of data. Requires an N column of total cases represented in each row.
- **outcomename**: Name of column that has the outcome to calculated adjusted values for.
- **groupname**: Name of categorical covariate that determines the groups.
- **Nname**: Name of column in dat that contains total cases (this is the name of the variable used to generate the weights in pi_star).
- **pi_star**: The target weights. Each month will have its groups re-weighted to match these target weights.
- **is_count**: Indicator of whether outcome is count data or a continuous measure (this impacts how aggregation is done).
- **include_aggregate**: Include aggregated (unadjusted) totals in the output as well.
- **covariates**: Covariates to be passed to aggregation (list of string variable names).
aggregate_data

Value

Dataframe of adjusted data.

Examples

data("meck_subgroup")
head(meck_subgroup)
pis = calculate_group_weights("category", Nname="n.cases", meck_subgroup, t_min=0, t_max=max(meck_subgroup$month))
pis

agg = aggregate_data(meck_subgroup, outcomename="pbail", groupname="category", Nname="n.cases", is_count=FALSE, rich = TRUE, covariates = NULL)
head(agg)

adjdat = adjust_data(meck_subgroup, "pbail", "category", "n.cases", pis, include_aggregate=TRUE)
head(adjdat)

---

aggregate_data Aggregate grouped data

Description

This will take a dataframe with each row being the outcomes, etc., for a given group for a given month and aggregate those groups for each month.

Usage

aggregate_data(
  dat, 
  outcomename, 
  groupname, 
  Nname, 
  is_count = FALSE, 
  rich = TRUE, 
  covariates = NULL 
)

Arguments

dat Dataframe with one row for each time point and group that we are going to post stratify on. This dataframe should also have an column with passed name "Nname" indicating the number of cases that make up each given row. It should have a ‘month’ column for the time.

outcomename String name of the outcome variable in dat.
aggregate_simulation_results

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>groupname</td>
<td>Name of the column that has the grouping categorical variable</td>
</tr>
<tr>
<td>Nname</td>
<td>Name of variable holding the counts (weight) in each group.</td>
</tr>
<tr>
<td>is_count</td>
<td>If TRUE the data are counts, and should be aggregated by sum rather than by mean.</td>
</tr>
<tr>
<td>rich</td>
<td>If TRUE, add a bunch of extra columns with proportions of the month that are each group and so forth.</td>
</tr>
<tr>
<td>covariates</td>
<td>Group-invariant covariates to preserve in the augmented rich dataframe. These are not used in this method for any calculations. Pass as list of column names of dat</td>
</tr>
</tbody>
</table>

**Value**

Dataframe of aggregated data, one row per month. If rich=TRUE many extra columns with further information.

**Examples**

```r
data( "meck_subgroup" )
head( meck_subgroup )
pis = calculate_group_weights( "category", Nname="n.cases", 
  meck_subgroup, t_min=0, t_max= max( meck_subgroup$month ) )
pis

agg = aggregate_data( meck_subgroup, 
  outcomename="pbail", groupname="category", Nname="n.cases", 
  is_count=FALSE, 
  rich = TRUE, covariates = NULL )
head( agg )

adjdat = adjust_data( meck_subgroup, "pbail", "category", "n.cases", pis, include_aggregate=TRUE )
head( adjdat )
```

---

**aggregate_simulation_results**

*Test a passed test statistic on the simulated data*

**Description**

This method is used to look at summary statistics such as average impact post-policy, and see how the predictive distribution compares to the observed.

**Usage**

```r
aggregate_simulation_results( 
  orig.data, 
  predictions,
```
calculate_average_outcome

outcomename,
summarizer = calculate_average_outcome,
...
)

Arguments

orig.data The raw data (dataframe)
predictions The results from process_outcome_model.
outcomename Outcome to use.
summarizer A function to calculate some summary quantity, Default: calculate_average_outcome
... Extra arguments passed to the summarizer function.

Value

List of length two, with first item being the observed value of the test statistic and the second being a numeric vector representing the empirical reference distribution.

Examples

predictions = process_outcome_model( "pbail", mecklenberg,
t0=0, R = 5,
summarize = FALSE, smooth=FALSE )
sstat = aggregate_simulation_results( orig.data = mecklenberg, outcomename = "pbail",
predictions = predictions, months = 1:18 )
sstat$t
tsstat$t.obs

calculate_average_outcome

Summary function for summarize.simulation.results

Description

Given a set of simulation runs, estimate average impact over range of months.

Usage

calculate_average_outcome(res, outcomename, months = 1:54, ...)

Arguments

res Dataframe of a single series (simulated or otherwise)
outcomename Name of outcome in res
months Which months to average over, Default: 1:18
... Other parameters (ignored)
calculate_group_weights

Value

Single number (in this case mean of given months)

See Also

See aggregate_simulation_results for how this function would be used.

Examples

data( mecklenberg )
calculate_average_outcome( mecklenberg, "pbail", months=1:24 )
calculate_average_outcome( mecklenberg, "pbail", months = 1:18 )

calculate_group_weights

Calculate proportion of subgroups across time

Description

Calculate overall proportion of cases in each group that lie within a given interval of time defined by t_min and t_max.

Usage

calculate_group_weights(
  groupname,
  dat,
  t_min,
  t_max = max(dat$month),
  Nname = "N"
)

Arguments

<table>
<thead>
<tr>
<th>Argument</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>groupname</td>
<td>Name of the column that has the grouping categorical variable</td>
</tr>
<tr>
<td>dat</td>
<td>Dataframe with one row for each time point and group that we are going to post-stratify on. This dataframe should also have an column with passed name &quot;Nname&quot; indicating the number of cases that make up each given row. It should have a 'month' column for the time.</td>
</tr>
<tr>
<td>t_min</td>
<td>The start month to aggregate cases over.</td>
</tr>
<tr>
<td>t_max</td>
<td>The final month (default is last month).</td>
</tr>
<tr>
<td>Nname</td>
<td>Name of variable holding the counts (weight) in each group.</td>
</tr>
</tbody>
</table>

Value

Dataframe of each group along with overall average group weight in the specified timespan.
extrapolate_model

Examples

data( "meck_subgroup" )
head( meck_subgroup )
pis = calculate_group_weights( "category", Nname="n.cases", meck_subgroup, t_min=0, t_max= max( meck_subgroup$month ) )
pis

agg = aggregate_data( meck_subgroup, outcomename="pbail", groupname="category", Nname="n.cases", is_count=FALSE, rich = TRUE, covariates = NULL )
head( agg )

adjdat = adjust_data( meck_subgroup, "pbail", "category", "n.cases", pis, include_aggregate=TRUE )
head( adjdat )

description

This function takes a fitted model and uses it to make the post-policy predictions by simulating data.

Usage

extrapolate_model( M0, outcomename, dat, t0, R = 400, summarize = FALSE, smooth = FALSE, smoother = smooth_series, full_output = FALSE, fix_parameters = FALSE, ...

Arguments

M0 The fit model
outcomename Outcome of interest (name of column)
dat Dataframe with data being analyzed.
t0 Last pre-policy timepoint
R Number of replications
**fit_model_default**

**Default ITS model**

**Description**

This fits the model 'outcome ~ lag.outcome + month', with no covariates.

**Usage**

```r
fit_model_default(dat, outcome_name, lagless = FALSE, ...)
```

**Arguments**

- **dat**
  - Dataframe of pre-policy data to fit model to. Needs a "month" column
- **outcome_name**
  - Outcome of interest
- **lagless**
  - Boolean, include the lagged outcome, or not?
- **...**
  - Extra arguments passed to the lm() call.

**Value**

Dataframe with columns corresponding to the simulations. If summarize=TRUE, one row per month in original data. If FALSE, all the details of all the runs are returned.

**See Also**

- `process_outcome_model` for wrapper function for this method that is easier to use.

**Examples**

```r
data("mecklenberg")
mecklenberg = add_lagged_covariates( mecklenberg, "pbail" )
mecklenberg.pre = dplyr::filter( mecklenberg, month <= 0 )
M0 = fit_model_default( mecklenberg.pre, "pbail" )
res = extrapolate_model( M0, "pbail", mecklenberg, 0, 1,
                      smooth=TRUE)
tail( res )
```
generate_fake_data

Value
A fit model (a 'lm' object from a 'lm()' call) from fitting a simple regression of outcome onto month and lagged month.

Examples
mecklenberg = add_lagged_covariates(mecklenberg, "pbail")
meck.pre = filter( mecklenberg, month <= 0 )
mod = fit_model_default( meck.pre, "pbail", lagless = TRUE )
summary( mod )
mod = fit_model_default( meck.pre, "pbail", lagless = FALSE )
summary( mod )

Description
Make fake data for testing purposes.

Defaults have heavy seasonality, and an extra bump in impact kicks in at 12 months post-policy.

Usage
generate_fake_data(
  t_min = -40,
  t_max = 9,
  t0 = 0,
  rho = 0.5,
  sd.omega = 1,
  coef_line = c(20, 0.05),
  coef_q = c(1, 0, -1, 0),
  coef_temp = 0.1,
  coef_sin = c(0, 0),
  coef_tx = c(0, 0.25, 5)
)

Arguments
  t_min           Index of first month
  t_max           Index of last month
  t0              Last pre-policy time point
  rho             Autocorrelation
  sd.omega        Standard deviation of the true residual
  coef_line       Intercept and slope of the main trendline (list of 2).
  coef_q          Coefficients for the four quarters (list of 4).
  coef_temp       Coefficient for temperature.
generate_fake_grouped_data

coef_sin Coefficients for sin and cos features (list of 2)
coef_tx Coefficient for treatment post-policy (list of 3, initial offset, initial slope, additional slope past 12 months). Treatment is a piecewise linear function.

Value
A data.frame having month, temperature, sin.m, cos.m, Q1, Q2, Q3, Q4, post, Ystr0, Ystr, Y

Examples
fdat = generate_fake_data(-100,100, rho = 0.95, coef_q=c(0,0,0,0), coef_temp = 0)
plot( fdat$month, fdat$Y, type="l" )
fdat2 = generate_fake_data(-100, 100, rho = 0.0, coef_q=c(0,0,0,0), coef_temp = 0)
plot( fdat$month, fdat2$Y, type="l" )

generate_fake_grouped_data
A fake DGP with time varying categorical covariate for illustrating the code.

Description
This code makes synthetic grouped data that can be used to illustrate benefits of post stratification.

Usage
generate_fake_grouped_data(
  t_min,
  t0,
  t_max,
  method = c("complex", "linear", "jersey")
)

Arguments
  t_min Index of first month
  t0 last pre-policy timepoint
  t_max Index of last month
  method Type of post-stratification structure to generate (three designs of 'complex', 'linear' and 'jersey' were originally conceived of when designing simulation studies with different types of structure).

Value
Dataframe of fake data, with one row per group per time period.
**Examples**

```r
dat = generate_fake_grouped_data(t_min=-5, t_max=10, t0 = 0)
table( dat$month )
table( dat$type )
```

**make_envelope_graph**  
*Make envelope style graph with associated smoothed trendlines*

**Description**

This method builds a ggplot object with the trendline and prediction envelope. It can be customized after the fact by adding more ggplot layers via normal ggplot "+" syntax.

**Usage**

```r
make_envelope_graph(envelope, t0, ylab = "Y", xlab = "month")
```

**Arguments**

- `envelope`: The result of a ‘process_outcome_model()’ call, i.e. dataframe with columns of original data, imputed data and, potentially, smoothed data.
- `t0`: Last pre-policy timepoint. Will draw vertical line here.
- `ylab`: Y label of plot
- `xlab`: X label of plot

**Value**

Returns (does not yet display) a ggplot plot object containing the time series along with extrapolation and prediction envelope. This plot can be augmented and changed via standard ggplot commands.

**See Also**

The ggplot2 package.

**Examples**

```r
data( "mecklenberg" )
t0 = 0
envelope = process_outcome_model( "pbail", mecklenberg,
    t0=t0, R = 10,
    summarize = TRUE, smooth=FALSE )
make_envelope_graph(envelope, t0=t0, ylab = "Proportion given bail") +
ggplot2::labs( title="Sample ITS plot")
data( "mecklenberg" )
t0 = 0
envelope = process_outcome_model( "pbail", mecklenberg,
```
**make_fit_season_model**

This method returns a function that will fit a model both with and without lagged outcomes.

**Usage**

```
make_fit_season_model(formula, no_lag = NULL)
```

**Arguments**

- `formula`: Formula specifying seasonality. No outcome or month needed.
- `no_lag`: Formula specifying additional variables to not lag (usually used due to collinearity of lagged outcomes, such as with a sin and cos component).

**Details**

You hand it a formula object specifying the seasonality, e.g., `" ~ Q2 + Q3 + Q4"`, if you have quarterly season effects. This method assumes you want models with a linear month component as well, and will add that and an intercept in automatically.

**Value**

A callable function that takes the arguments of `dat`, `outcomename`, and a lagless flag (see, e.g., the parameters listed in `fit_model_default()`).

**See Also**

- `fit_model_default` for the type of function this method will generate.

**Examples**

```
data( "newjersey")
modF = make_fit_season_model( ~ temperature )
newjersey = add_lagged_covariates( newjersey, "n.warrant", covariates = c("temperature") )
modF( newjersey, "n.warrant" )
```
make_many_predictions  Generate a collection of raw counterfactual trajectories

Description

Given a fit linear model 'fit0', generate R prediction series starting at t0. This takes model uncertainty into account by pulling from the pseudo-posterior of the model parameters (from Gelman and Hill arm package).

Usage

make_many_predictions(fit0, dat, R, outcomename, t0)

make_many_predictions_plug(fit0, dat, R, outcomename, t0)

Arguments

- fit0: The fit linear model to simulate from.
- dat: A dataframe with the covariates needed by the model fit0 for both pre and post-policy months.
- R: Number of series to generate.
- outcomename: The name of the column in dat which is our outcome.
- t0: Last month of pre-policy. Will start predicting at t0+1.

Value

A data.frame with the collection of predicted series, one row per month per replicate (so will have R*ntrow(dat) rows).

Functions

- make_many_predictions_plug: This version makes multiple predictions using estimated parameters without additional uncertainty. This takes point estimates from the fit model as fixed parameters. WARNING: This method will not capture true uncertainty as it is not taking parameter uncertainty into account.

References

The ‘arm’ package, see https://cran.r-project.org/package=arm

Examples

```r
data("mecklenberg"
mecklenberg = add_lagged_covariates( mecklenberg, "pbail" )
mecklenberg.pre = dplyr::filter( mecklenberg, month <= 0 )
M0 = fit_model_default( mecklenberg.pre, "pbail" )
res = make_many_predictions( M0, dat=mecklenberg, outcome="pbail", t0=0, R=2 )
tail( res )
```

Description

This helper function gives back a function that takes the resulting simulation data from a single iteration of the simulation, and fits 'fit_model' to it, smoothes the residuals, and puts the predictions from 'fit_model' back.

Usage

`make_model_smoother(fit_model, covariates)`

Arguments

- `fit_model`: A function that takes data, fits a linear model, and returns the fit model. This function needs an option to include (or not) lagged covariates.
- `covariates`: A dataframe with all covariates needed in the model fitting defined by fit_model.

Details

This can be used to build smoothers that smooth using models other than the model being used for extrapolation (e.g., a model without temperature).

Resulting functions have the following parameters: ‘res’ (the data), ‘t0’ (start time), ‘outcome-name’, ‘post.only’ flag (for smoothing only post data or not), and ‘smooth_k’, a tuning parameter for degree of smoothing.

Value

A smoother function that can be passed to the smoothing routines. This function is of the form listed above.

Examples

```r
data( "newjersey"
modA = make_fit_season_model( ~ temperature )
modB = make_fit_season_model( ~ sin.m + cos.m )
newjersey = add_lagged_covariates( newjersey, "n.warrant",
covariates = c("sin.m", "cos.m", "temperature") )
smoother = make_model_smoother( fit_model = modA, covariates = newjersey )
```
class(smooth)

# Pass made function to process_outcome_model()
envelope = process_outcome_model( "n.warrant", newjersey, t0=-8, R = 1,
summarize = TRUE, smooth=TRUE,
smoother = smoother, smooth_k = 11,
fit.model = modB )

mecklenberg  Mecklenberg PSA Reform Data

Description

Monthly aggregate outcomes of various measures of interest from Mecklenberg. See MDRC Report.

Usage

mecklenberg

Format

A data frame with 54 rows and 10 variables:

month  integer Month, with 0 being month of policy implementation.
karr  integer Total count of arrests.
pbail  double Proportion of cases in a given month assigned bail (or outright detention).
pprel  double Proportion of cases assigned to pretrial supervised release.
pror  double Proportion of cases released on own recognizance.
pb4c  double Proportion of cases assigned to money bail (alternate coding from pbail, above).
avg_days_initial  double Average number of days spent detained before release due to bail, case resolution, etc.
avg_t2d  double Average time to case resolution (in days).
pstint7  double Proportion detained longer than 7 days.
pstint30  double Proportion detained longer than 30 days.
meck_subgroup

Mecklenberg data by subgroup of charge type

Description

Mecklenberg data that gives proportion of different charge categories of cases given bail (by month).

Usage

meck_subgroup

Format

A data frame with 144 rows and 5 variables:

- `month` integer Month, with 0 being month of policy implementation.
- `n.cases` integer Number of cases of that subgroup for that month
- `n.bail` integer Total number of cases given bail for that subgroup for that month
- `pbail` double Proportion of new cases in given subgroup in that month assigned bail
- `category` character Category of group (charge type).

newjersey

New Jersey PSA Reform aggregate data

Description

Montly aggregate counts of arrests of different types in New Jersey.

Usage

newjersey

Format

A data frame with 106 rows and 11 variables:

- `month` integer Index of month.
- `sin.m` double cos of month number
- `cos.m` double sin of month number
- `M12` integer Month number
- `Q1` integer Indicator of 1st quarter.
- `Q2` integer Indicator of 2nd quarter.
- `Q3` integer Indicator of 3rd quarter.
Q4  integer Indicator of 4th quarter.
n.warrant  double Number of warrant arrests
n.summons  double Number of summons arrests
n  double Total number of arrests
temperature  double Average temperature in New Jersey that month.

---

process_outcome_model  Generate an ITS extrapolation simulation.

Description

This is the primary function to use to use this approach on a given dataset.

Usage

```r
process_outcome_model(
  outcomeName, 
  dat, 
  t0, 
  R = 400, 
  summarize = FALSE, 
  smooth = FALSE, 
  smoother = NULL, 
  fit_model = fit_model_default, 
  covariates = NULL, 
  plug_in = FALSE, 
  ...
)
```

Arguments

- `outcomeName`: Name of column in `dat` containing the time series.
- `dat`: Dataframe with a ’month’ column for time. ‘month’ is assumed to be a sequence of integer values.
- `t0`: Last pre-policy timepoint
- `R`: Number of simulated pre-policy extrapolations to generate.
- `summarize`: Summarise the series? (TRUE/FALSE)
- `smooth`: Smooth the series? (TRUE/FALSE)
- `smoother`: Function to smooth residuals, if smoothing set to TRUE. If NULL, will dynamically make a model smoother based on the fit_model method if covariates are passed. Otherwise it will use the simple smoother on the outcomes.
- `fit_model`: The function used to fit the model to simulate from. (This model could be a seasonality model. Default is simple linear model with no covariates.)
**process_outcome_model**

- **covariates**: Vector of covariate names of all covariates used in the passed model function `fit_model`. If null, will attempt to get list of covariates form the "lags" attribute of the passed 'fit_model'.

- **plug_in**: Use the estimated parameters as fixed and do not include extra uncertainty of parameter estimation in the simulation. (Not recommended as it destroys inference.)

- **...**: Extra arguments to be passed to `extrapolate_model()`

**Details**

Take a given outcome variable, fit an ITS model, use it to extrapolate R plausible trajectories, and then using these trajectories, generate final impact results by averaging (if summarize is set to TRUE).

This function is basically a wrapper for `extrapolate_model()` with some extra calls to `make_model_smoother()` to prepare, in the case of smoothing, and adding on a summary trend via `generate_Ybars()` in the case of summarizing.

**Value**

If summarize=TRUE, A dataframe with several columns of interest and one row per month of data. The columns are Ymin and Ymax, the limits of the envelope, 'range', the range of the envelope, 'SE', the standard deviation of the trajectories at that time point, 'Ysmooth' the median smoothed value at that time point (if smoothing), 'Ystar' the median unsmoothed value at that time point (regardless of smooth flag), 'Y', the observed outcome, 'Ysmooth1', the smoothed observed outcomes, and 'Ybar' the predicted outcome given the model with no autoregressive aspect.

If summarize=FALSE, a dataframe of all the raw series generated.

**See Also**

The core internal function that this method is a wrapper for is `extrapolate_model`.

**Examples**

```r
data( "mecklenberg" )
t0 = 0
envelope = process_outcome_model( "pbail", mecklenberg, 
t0=t0, R = 10, 
summarize = TRUE, smooth=FALSE )
make_envelope_graph(envelope, t0=t0, ylab = "Proportion given bail") +
ggplot2::labs( title="Sample ITS plot")
```
Description

Analysis via Simulation of Interrupted Time Series

Details

This package is based on the backbone analytic code for the analyses in, e.g., Redcross et al. (2019) or Golub et al. (2019). See companion paper Miratrix (2020) for technical discussion of the overall approach.

Broadly, this package provides methods for fitting Interrupted Time Series models with lagged outcomes and variables to account for temporal dependencies. It then conducts inference via simulation, simulating a set of plausible counterfactual post-policy series to compare to the observed post-policy series. This package provides methods to visualize such data, and also to incorporate seasonality models and smoothing and aggregation/summarization. See the vignette for a guide of how to conduct such analyses.

References


Description

Smooth residuals after model fit

Usage

smooth_residuals(  
  res,  
  t0,  
  outcomename,  
  post.only = TRUE,  
)
smooth_residuals

```r
smooth_k = SMOOTH_K,
fit_model = fit_model_default,
covariates = res,
full_output = FALSE
```

**Arguments**

- `res` A dataframe with a month column and an `outcomename` column (which is the column that will be smoothed).
- `t0` last pre-policy timepoint
- `outcomename` String name of the outcome variable in dat.
- `post.only` If TRUE fit model and smooth post-policy only. WHY fit model on post-policy data only? Because this will make sure the fixed pre-policy does not dominate too much? We are focusing on post-policy so we want a good fitting model for that so we can get our residuals as "white noise" as possible before smoothing.
- `smooth_k` A rough proxy for the number of observations to primarily consider to kernel weight in the neighborhood of each timepoint (this is a bandwidth, and the loess smoother gets `smooth_k / n` as a span value). We want to smooth with an absolute bandwidth, not one as function of how long the time series is.
- `fit_model` A function that takes data, fits a linear model, and returns the fit model. This function needs an option to include (or not) lagged covariates.
- `covariates` A dataframe with all covariates needed in the model fitting defined by `fit_model`.
- `full_output` If TRUE give back pieces for diagnostics of smoothing process.

**Details**

Use loess smoother on complete series of residuals including original data pre-policy and synthetic data post policy (i.e., smooth the entire plausible series).

**Value**

A numeric vector of the smoothed residuals. If `full_output`=TRUE return a dataframe with several other columns: `resid`, the residuals based on Ystar and the model, `residStar` the smoothed residuals, `Ybar.sm` the structural predictions of the model used for smoothing. Here the smoothed values will be `Ysmooth`.

**See Also**

See `smooth_series` for a more vanilla version that smooths without the model fitting step.

**Examples**

```r
data( "newjersey" )
smooth = smooth_series( newjersey, outcomename = "n.warrant", t0= -8,
  smooth_k = 30,
  post.only = FALSE)
```
smooth_series

Smooth a series using a static loess smoother

Description

Use loess smoother on complete series of residuals including original data pre-policy and synthetic
data post policy (i.e., smooth the entire plausible series).

Usage

smooth_series(res, outcome_name, t0, smooth_k = SMOOTH_K, post_only = TRUE, ...)

Arguments

res A dataframe with a month column and an 'outcome_name' column (which is the
column that will be smoothed).
outcome_name String name of the outcome variable in dat.
t0 last pre-policy timepoint
smooth_k A rough proxy for the number of observations to primarily consider to kernal
weight in the neighborhood of each timepoint (this is a bandwidth, and the loess
smoother gets smooth_k / n as a span value). We want to smooth with an abso-
lute bandwidth, not one as function of how long the time series is.
post_only If TRUE fit model and smooth post-policy only. WHY fit model on post-policy
data only? Because this will make sure the fixed pre-policy does not dominate
too much? We are focusing on post-policy so we want a good fitting model for
that so we can get our residuals as "white noise" as possible before smoothing.
... Extra arguments (not used in this function).

Details

This method takes several parameters it does not use, to maintain compatability with smooth_residuals.
smooth_series

Value

An updated version of the ‘res’ dataframe with ‘Ysmooth’, the smoothed predictions of the original Ystar outcome. Also includes ‘Ystar’ the original sequence to be smoothed.

Examples

data( "newjersey" )
smooth = smooth_series( newjersey, outcomename = "n.warrant", t0= -8,
  smooth_k = 30,
  post.only = FALSE)
plot( newjersey$month, newjersey$n.warrant )
lines( newjersey$month, smooth, col="red" )
mod = make_fit_season_model( ~ temperature )
newjersey = add_lagged_covariates( newjersey, outcomename = "n.warrant",
  covariates = c("temperature") )
smooth = smooth_residuals( newjersey, outcomename = "n.warrant", t0=-8,
  smooth_k = 30,
  post.only = FALSE,
  fit_model = mod )
plot( newjersey$month, newjersey$n.warrant )
lines( newjersey$month, smooth, col="red" )
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