Package 'didimputation'

December 17, 2025

Type Package
Title Imputation Estimator from Borusyak, Jaravel, and Spiess (2021)
Version 0.5.0
Description Estimates Two-way Fixed Effects difference-in-differences/event-study models using the imputation-based approach proposed by Borusyak, Jaravel, and Spiess (2021).
Encoding UTF-8
LazyData true
RoxygenNote 7.3.2
Depends R ($>= 4.1.0$), fixest ($>= 0.13.2$), data.table ($>= 1.10.0$)
Imports Matrix
Suggests haven, testthat (>= 3.0.0)
Config/testthat/edition 3
<pre>URL https://github.com/kylebutts/didimputation</pre>
License MIT + file LICENSE
NeedsCompilation no
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Repository CRAN
Date/Publication 2025-12-17 06:40:41 UTC
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2 df_hom

df_het

Simulated data with two treatment groups and heterogenous effects

Description

```
Generated using the following call: did2s::gen_data(panel = c(1990, 2020), g1 = 2000, g2 = 2010, g3 = 0, te1 = 2, te2 = 1, te3 = 0, te_m1 = 0.05, te_m2 = 0.15, te_m3 = 0)
```

Usage

df_het

Format

```
A data frame with 31000 rows and 15 variables:
```

```
unit individual in panel data
```

year time in panel data

g the year that treatment starts

dep var outcome variable

treat T/F variable for when treatment is on

rel_year year relative to treatment start. Inf = never treated.

rel_year_binned year relative to treatment start, but <=-6 and >=6 are binned.

unit_fe Unit FE

year_fe Year FE

error Random error component

te Static treatment effect = te

te_dynamic Dynamic treatmet effect = te_m

state State that unit is in

group String name for group

df_hom

Simulated data with two treatment groups and homogenous effects

Description

```
Generated using the following call: did2s::gen_data(panel = c(1990, 2020), g1 = 2000, g2 = 2010, g3 = 0, te1 = 2, te2 = 2, te3 = 0, te_m1 = 0, te_m2 = 0, te_m3 = 0)
```

Usage

df_hom

Format

```
unit individual in panel data
year time in panel data
g the year that treatment starts
dep_var outcome variable
treat T/F variable for when treatment is on
rel_year year relative to treatment start. Inf = never treated.
rel_year_binned year relative to treatment start, but <=-6 and >=6 are binned.
unit_fe Unit FE
year_fe Year FE
error Random error component
te Static treatment effect = te
te_dynamic Dynamic treatmet effect = te_m
group String name for group
state State that unit is in
weight Weight from runif()
```

A data frame with 31000 rows and 15 variables:

did_imputation

Borusyak, Jaravel, and Spiess (2021) Estimator

Description

Treatment effect estimation and pre-trend testing in staggered adoption diff-in-diff designs with an imputation approach of Borusyak, Jaravel, and Spiess (2021)

Usage

```
did_imputation(
  data,
  yname,
  gname,
  tname,
  idname,
  first_stage = NULL,
  wname = NULL,
  wtr = NULL,
  horizon = NULL,
  pretrends = NULL,
  cluster_var = NULL
)
```

Arguments

data A data.frame

yname String. Variable name for outcome. Use fixest c() syntax for multiple lhs, e.g.

"c(y1, y2)".

gname String. Variable name for unit-specific date of treatment (never-treated should

be zero or NA).

tname String. Variable name for calendar period.
idname String. Variable name for unique unit id.

first_stage Formula for Y(0). Formula following fixest::feols. Fixed effects specified

after "|". If not specified, then just unit and time fixed effects will be used.

wname String. Variable name for estimation weights of observations. This is used in

estimating Y(0) and also augments treatment effect weights.

wtr Character vector of treatment weight names (see horizon for standard static and

event-study weights)

horizon Integer vector of event_time or TRUE. This only applies if wtr is left as NULL.

if specified, weighted averages/sums of treatment effects will be reported for each of these horizons separately (i.e. tau0 for the treatment period, tau1 for one period after treatment, etc.). If TRUE, all horizons are used. If wtr and horizon

are null, then the static treatment effect is calculated.

pretrends Integer vector or TRUE. Which pretrends to estimate. If TRUE, all pretrends are

used.

cluster_var String. Variable name for clustering groups. If not supplied, then idname is used

as default.

Details

The imputation-based estimator is a method of calculating treatment effects in a difference-indifferences framework. The method estimates a model for Y(0) using untreated/not-yet-treated observations and predicts Y(0) for the treated observations $hat(Y_it(0))$. The difference between treated and predicted untreated outcomes $Y_it(1) - hat(Y_it(0))$ serves as an estimate for the treatment effect for unit i in period t. These are then averaged to form average treatment effects for groups of (i, t).

Value

A data.frame containing treatment effect term, estimate, standard error and confidence interval. This is in tidy format.

Examples

Load example dataset which has two treatment groups and homogeneous treatment effects

```
# Load Example Dataset
data("df_hom", package="didimputation")
```

Static TWFE:

You can run a static TWFE fixed effect model for a simple treatment indicator

Event Study:

Or you can use relative-treatment indicators to estimate an event study estimate

```
did_imputation(data = df_hom, yname = "dep_var", gname = "g",
               tname = "year", idname = "unit", horizon=TRUE)
#>
         term estimate std.error conf.low conf.high
#>
       <char>
                 <num>
                            <num>
                                     <num>
                                               <num>
#>
   1:
            0 2.117232 0.07368419 1.972811
                                            2.261653
#>
   2:
            1 1.856536 0.07672104 1.706163
                                            2.006909
#>
    3:
            2 1.986357 0.07137180 1.846468
                                            2.126246
#>
   4:
            3 2.004843 0.07653409 1.854836
                                            2.154850
#>
   5:
            4 1.950228 0.07543636 1.802372 2.098083
#> 6:
            5 2.038302 0.07580288 1.889728
                                            2.186875
#> 7:
            6 2.031571 0.07223098 1.889999
                                           2.173144
#> 8:
            7 2.025286 0.07541719 1.877468 2.173104
#> 9:
            8 1.976081 0.07493409 1.829210
                                            2.122951
#> 10:
            9 2.121434 0.07268404 1.978974
                                            2.263895
#> 11:
           10 2.087984 0.08271442 1.925864
                                            2.250105
#> 12:
           11 1.942825 0.11421421 1.718965
                                            2.166685
           12 1.940532 0.11200348 1.721005
#> 13:
                                            2.160059
#> 14:
           13 1.964569 0.11361969 1.741875
                                            2.187264
#> 15:
           14 2.023456 0.11753255 1.793092
                                           2.253820
#> 16:
           15 2.235051 0.12110086 1.997693
                                            2.472409
#> 17:
           16 2.178438 0.11552325 1.952013
                                            2.404864
#> 18:
           17 1.935576 0.11278311 1.714521
                                            2.156631
           18 2.134953 0.10993120 1.919488
#> 19:
                                           2.350418
#> 20:
           19 2.111984 0.11146282 1.893517
                                           2.330451
           20 1.925168 0.11214206 1.705370 2.144967
#> 21:
#>
         term estimate std.error conf.low conf.high
```

Example from Cheng and Hoekstra (2013):

Here's an example using data from Cheng and Hoekstra (2013)

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