Package 'GMMSensitivity'

July 29, 2020

Title Optimal Sensitivity Analysis in Generalized Method of Moments Models

Version 0.1.2

Description Construct confidence intervals in generalized method of moments models that are valid and optimal under local misspecification.

Depends R (>= 4.0.0)

License GPL-3

Encoding UTF-8

Suggests spelling,
testthat,
knitr,
CVXR,
rmarkdown

Imports stats

RoxygenNote 7.1.1

VignetteBuilder knitr

LazyData true

Language en-US

URL https://github.com/kolesarm/GMMSensitivity/

BugReports https://github.com/kolesarm/GMMSensitivity/issues

R topics documented:

blp *Estimates from Berry, Levinsohn, and Pakes (1995)*

Description

This dataset contains estimates of the model in Berry, Levinsohn, and Pakes (1995), as implemented by Andrews, Gentzkow, and Shapiro (2017). It is used to illustrate the confidence intervals implemented in this package.

Usage

```
blp
```

Format

A list, consisting 11 objects:

G Matrix with 31 rows and 17 columns, estimate of derivative of the moment condition evaluated at initial estimate of θ from Berry, Levinsohn, and Pakes (1995), $\hat{\theta}_{initial}$.

H Vector of length 17, estimate of derivative of average markup $h(\theta)$ with respect to model parameters θ, evaluated at $\hat{\theta}_{initial}$.

W Weight matrix used to obtain the estimate $\hat{\theta}_{initial}$, preliminary estimate of variance of moment conditions.

g_init Average moment condition, evaluated at $\hat{\theta}_{initial}$.

h_init Estimate of the average markup, $h(\hat{\theta}_{initial})$.

names Two lists, one for names of the moment conditions, and one for elements of θ.

ZZ Gram matrix $Z'Z$ of the instruments, used to specify the misspecification set $\mathcal{C}$.

Sig Estimate of variance of moment condition.

sdZ Vector of standard deviations of the instruments.

perturb scaling parameters to give interpretable meaning to violations of supply-side conditions. See vignette `vignette("GMMSensitivity")` for details.

n Sample size, number of car models.

See Armstrong and Kolesár (2020) for a detailed description of these objects.

Source

Replication files for Andrews, Gentzkow, and Shapiro (2017), available at https://doi.org/10.7910/DVN/LLARSN

References

Andrews, I., M. Gentzkow, and J. M. Shapiro (2017): Measuring the Sensitivity of Parameter Estimates to Sample Statistics, Quarterly Journal of Economics, 132, 1553–1592.

Armstrong, T. B., and M. Kolesár (2020): Sensitivity Analysis Using Approximate Moment Condition Models, https://arxiv.org/abs/1808.07387

Berry, S. T., J. Levinsohn, and A. Pakes (1995): Automobile Prices in Market Equilibrium, Econometrica, 63, 841–890.

`EffBounds` *Efficiency bounds under ℓ_p constraints*

Description

Computes the asymptotic efficiency of two-sided fixed-length confidence intervals at $c = 0$, as well as the efficiency of one-sided confidence intervals that optimize a given `beta` quantile of excess length, when the set $\mathcal{C}$ is characterized by ℓ_p constraints.

Usage

```
EffBounds(eo, B, M, p = 2, beta = 0.5, alpha = 0.05)
```

Arguments

`eo`	List containing initial estimates with the following components: **Sig** Estimate of variance of the moment condition, matrix with dimension d_g by d_g, where d_g is the number of moments **G** Estimate of derivative of the moment condition, matrix with dimension d_g by d_θ, where d_θ is the dimension of θ **H** Estimate of derivative of $h(\theta)$. A vector of length d_θ **n** sample size **g_init** Moment condition evaluated at initial estimate
`B`	matrix B with full rank and dimension d_g by d_γ that determines the set $\mathcal{C}$, where d_γ is the number of invalid moments, and d_g is the number of moments
`M`	Bound on the norm of γ
`p`	Parameter determining which ℓ_p norm to use, must equal `1`, `2`, or `Inf`.
`beta`	Quantile of excess length that a one-sided confidence interval is optimizing.
`alpha`	determines confidence level, `1-alpha`, for constructing/optimizing confidence intervals.

Details

The set $\mathcal{C}$ takes the form $B\gamma$ where the ℓ_p norm of γ is bounded by M.

Value

A list with two elements, "onesided" for efficiency of one-sided CIs and "twosided" for efficiency of two-sided CIs

References

Armstrong, T. B., and M. Kolesár (2020): Sensitivity Analysis Using Approximate Moment Condition Models, https://arxiv.org/abs/1808.07387

Examples

```
## Replicates first line of Table 2 in Armstrong and Kolesár (2020)
## First compute matrix B
I <- vector(mode="logical", length=nrow(blp$G))
I[6] <- TRUE
B <- (blp$ZZ %*% diag(sqrt(blp$n)*abs(blp$perturb)/blp$sdZ))[, I, drop=FALSE]
eo <- list(H=blp$H, G=blp$G, Sig=solve(blp$W), n=blp$n, g_init=blp$g_init)
EffBounds(eo, B, M=1, p=Inf, beta=0.5, alpha=0.05)
```

Jtest — *J-test of overidentifying restrictions under local misspecification*

Description

Computes J-test of overidentifying restrictions with critical value adjusted to allow for local misspecification, when the parameter c takes the form $c = B\gamma$ with the ℓ_p norm of γ bounded by M.

Usage

```
Jtest(eo, B, M = 1, p = 2, alpha = 0.05)
```

Arguments

`eo` List containing initial estimates with the following components:

- **Sig** Estimate of variance of the moment condition, matrix with dimension d_g by d_g, where d_g is the number of moments
- **G** Estimate of derivative of the moment condition, matrix with dimension d_g by d_θ, where d_θ is the dimension of θ
- **n** sample size
- **g_init** Moment condition evaluated at initial estimate

`B` matrix B with full rank and dimension d_g by d_γ that determines the set $\mathcal{C}$, where d_γ is the number of invalid moments, and d_g is the number of moments

`M` Bound on the norm of γ

`p` Parameter determining which ℓ_p norm to use, must equal `1`, `2`, or `Inf`.

`alpha` determines confidence level, `1-alpha`, for constructing/optimizing confidence intervals.

Details

The test assumes initial estimator in `eo` is optimal under correct specification, computed using `eo$Sig` as the weight matrix. The test is based on a J statistic using critical values that account for local misspecification; see appendix B in Armstrong and Kolesár (2020) for details.

Value

List with three elements:

J Value of J statistic

p0 P-value of usual J test

pC P-value for J-test that allows for local misspecification

Mmin Minimum value of M for which the J-test does not reject

References

Armstrong, T. B., and M. Kolesár (2020): Sensitivity Analysis Using Approximate Moment Condition Models, https://arxiv.org/abs/1808.07387

Examples

```
## Replicates first line of Table 1 in Armstrong and Kolesár (2020)
## 1. Compute matrix B when instrument D/F # cars is invalid
I <- vector(mode="logical", length=nrow(blp$G))
I[6] <- TRUE
B <- (blp$ZZ %*% diag(sqrt(blp$n)*abs(blp$perturb)/blp$sdZ))[, I, drop=FALSE]
## 2. Make sure Sig corresponds to inverse of weight matrix
eo <- list(G=blp$G, Sig=solve(blp$W), n=blp$n, g_init=blp$g_init)
Jtest(eo, B, M=1, p=2, alpha=0.05)
Jtest(eo, B, M=1, p=Inf, alpha=0.05)
```

`lph` *Compute solution path for ℓ_∞ or ℓ_1 constraints*

Description

Computes the optimal sensitivity vector at each knot of the solution path that traces out the optimal bias-variance frontier when the set C takes the form $c = B\gamma$ with the ℓ_p norm of γ is bounded by a constant, for $p = 1$, or $p = \infty$. This path is used as an input to `OptEstimator`.

Usage

```
lph(eo, B, p = Inf)
```

Arguments

`eo` List containing initial estimates with the following components:

- **Sig** Estimate of variance of the moment condition, matrix with dimension d_g by d_g, where d_g is the number of moments
- **G** Estimate of derivative of the moment condition, matrix with dimension d_g by d_θ, where d_θ is the dimension of θ
- **H** Estimate of derivative of $h(\theta)$. A vector of length d_θ
- **n** sample size
- **h_init** Initial estimate of $h(\theta)$
- **k_init** Initial sensitivity
- **g_init** Moment condition evaluated at initial estimate

`B` matrix B with full rank and dimension d_g by d_γ that determines the set $\mathcal{C}$, where d_γ is the number of invalid moments, and d_g is the number of moments

`p` Parameter determining which ℓ_p norm to use, one of `1`, or `Inf`.

Details

The algorithm is described in Appendix A of Armstrong and Kolesár (2020)

Value

Optimal sensitivity matrix. Each row corresponds optimal sensitivity vector at each step in the solution path.

References

Armstrong, T. B., and M. Kolesár (2020): Sensitivity Analysis Using Approximate Moment Condition Models, https://arxiv.org/abs/1808.07387v4

`OptEstimator` *One-step estimator based on optimal sensitivity under ℓ_p constraints*

Description

Computes the optimal sensitivity and the optimal estimator when the set $\mathcal{C}$ takes the form $c = B\gamma$ with the ℓ_p norm of γ bounded by M.

Usage

```
OptEstimator(
  eo,
  B,
  M,
  p = 2,
  spath = NULL,
```

```
  alpha = 0.05,
  opt.criterion = "FLCI"
)
```

Arguments

`eo` List containing initial estimates with the following components:

- **Sig** Estimate of variance of the moment condition, matrix with dimension d_g by d_g, where d_g is the number of moments
- **G** Estimate of derivative of the moment condition, matrix with dimension d_g by d_θ, where d_θ is the dimension of θ
- **H** Estimate of derivative of $h(\theta)$. A vector of length d_θ
- **n** sample size
- **h_init** Initial estimate of $h(\theta)$
- **k_init** Initial sensitivity
- **g_init** Moment condition evaluated at initial estimate

`B` matrix B with full rank and dimension d_g by d_γ that determines the set $\mathcal{C}$, where d_γ is the number of invalid moments, and d_g is the number of moments

`M` Bound on the norm of γ

`p` Parameter determining which ℓ_p norm to use, must equal `1`, `2`, or `Inf`.

`spath` Optionally, the solution path, output of `lph` to speed up computation. For `p==1` and `p==Inf` only.

`alpha` determines confidence level, `1-alpha`, for constructing/optimizing confidence intervals.

`opt.criterion` Optimality criterion for choosing optimal bias-variance tradeoff. The options are:

- `"MSE"` Minimize worst-case mean squared error of the estimator.
- `"FLCI"` Length of (fixed-length) two-sided confidence intervals.
- `"Valid"` Optimal estimator under valid moments. This returns the original estimator, with confidence intervals adjusted for possible misspecification

Value

Object of class `"GMMEstimate"`, which is a list with at least the following components:

- **h** Point estimate
- **bias** Worst-case bias of estimator
- **se** Standard error of estimator
- **hl** Half-length of confidence interval, so that the confidence interval takes the form $h + -hl$

References

Armstrong, T. B., and M. Kolesár (2020): Sensitivity Analysis Using Approximate Moment Condition Models, https://arxiv.org/abs/1808.07387

Examples

```
## Replicates estimates in first line of Figure 1 in Armstrong and Kolesár
## (2020)
## 1. Compute matrix B when all instruments are invalid
I <- vector(mode="logical", length=nrow(blp$G))
I[c(6:13, 20:31)] <- TRUE
B <- blp$ZZ %*% diag(sqrt(blp$n)*abs(blp$perturb)/blp$sdZ)[, I, drop=FALSE]
## 2. Collect initial estimates
blp$k_init <- -drop(blp$H %*% solve(crossprod(blp$G, blp$W %*% blp$G),
                                    crossprod(blp$G, blp$W)))
eo <- list(H=blp$H, G=blp$G, Sig=blp$Sig, n=blp$n, g_init=blp$g_init,
           k_init=blp$k_init, h_init= blp$h_init)
OptEstimator(eo, B, M=sqrt(sum(I)), p=2, alpha=0.05, opt.criterion="Valid")
OptEstimator(eo, B, M=sqrt(sum(I)), p=2, alpha=0.05, opt.criterion="FLCI")
```

Index