# DK responses in surveys on inflation expectations

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# Plan

Motivation

Regression model with DK responses

Robust Heckit estimator

Reexamination of Sheen and Wang (2023, EER)

Results

Conclusion

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# Missing response in surveys

Survey questions with many missing responses:

- wage
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- quantitative inflation expectation

Types of missing responses:

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   a) unit nonresponse
   b) item nonresponse
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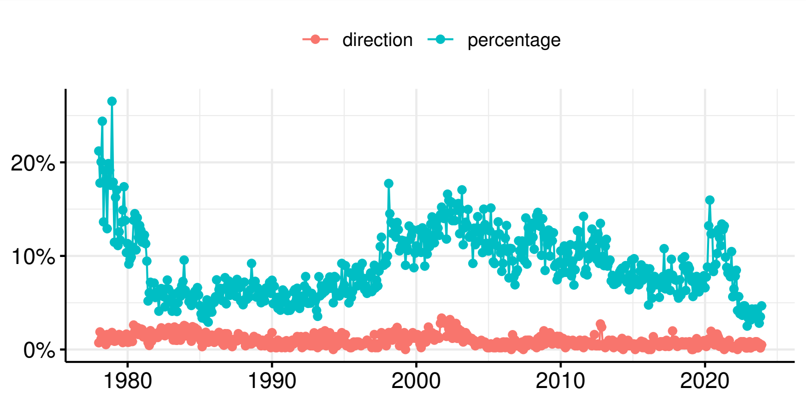
# Missing response rates for inflation expectations (Michigan Survey of Consumers)

Proportion of DK responses + item nonresponses



# Dealing with DK responses

Recent works (on inflation expectations) discard DK responses in regression analysis:

- Sheen and Wang (2023, Eur. Econ. Rev.)
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- Wang, Sheen, Trück, Chao, and Härdle (2020, Macroecon. Dyn.)
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Possible excuse for discarding DK responses:

1. They are ignorable $\implies$ need justification
2. Heckman-type bias correction requires strong assumptions
   - normality
   - homoskedasticity
   - exclusion restriction

   $\implies$ use a robust estimator

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# Aim of this paper

1. Use a robust Heckit estimator to handle DK responses
    - developed by Zhelonkin, Genton, and Ronchetti (2016)
    - available as an R package `ssmrob`
2. Reexamine an analysis in Sheen and Wang (2023, EER)
    - Study the influence of monetary condition news on household inflation expectations
    - Use data from the MSC during 2008M12–2015M12 ('zero lower bound' period)
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# Plan

# Sample selection model

Let

- $y^*$ be the latent numerical response
- $d$ be the (numerical) response dummy

Sample selection model

$$y = \begin{cases} y^* & \text{if } d = 1 \\ \text{NA} & \text{if } d = 0 \end{cases}$$

$$d = [\mathbf{x}'\boldsymbol{\alpha} + z > 0]$$

$$y^* = \mathbf{x}'\boldsymbol{\beta} + u$$

$$\begin{pmatrix} z \\ u \end{pmatrix} | \mathbf{x} \sim \mathrm{N}\left(\mathbf{0}, \begin{bmatrix} 1 & \sigma_{zu} \\ \sigma_{uz} & \sigma_u^2 \end{bmatrix}\right)$$

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# Sample selection bias

Outcome equation for the selected sample

$$\mathrm{E}(y|d = 1, x) = x'\beta + \mathrm{E}(u|z > -x'\boldsymbol{\alpha}, x)$$

Consider estimation of $\beta$

- OLS estimator is inconsistent
- ML and Heckit estimators are consistent, but not widely used in the context of DK responses

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# Heckit estimator

Moment restrictions:

- Selection equation (probit):

$$E(s\mathbf{x}h(s\mathbf{x}'\boldsymbol{\alpha})) = \mathbf{0}$$

  where $s := 2d - 1$ gives the sign, and $h(.) := \phi(.)/\Phi(.)$ gives the inverse Mill's ratio
- Outcome equation (for the selected sample):

$$E(\mathbf{x}(y - \mathbf{x}'\boldsymbol{\beta} - \sigma_{uz}h(\mathbf{x}'\boldsymbol{\alpha}))d) = \mathbf{0}$$
$$E(h(\mathbf{x}'\boldsymbol{\alpha})(y - \mathbf{x}'\boldsymbol{\beta} - \sigma_{uz}h(\mathbf{x}'\boldsymbol{\alpha}))d) = 0$$

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# M-estimator

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$$\psi_1(z;\boldsymbol{\theta}) := sxh(sx'\boldsymbol{\alpha})$$

$$\psi_2(z;\boldsymbol{\theta}) := \begin{pmatrix} x \\ h(x'\boldsymbol{\alpha}) \end{pmatrix} (y - x'\boldsymbol{\beta} - \sigma_{uz}h(x'\boldsymbol{\alpha}))d$$

where $\boldsymbol{z} := (d, s, y, x')'$ and $\boldsymbol{\theta} := (\boldsymbol{\alpha}', \boldsymbol{\beta}', \sigma_{uz})'$

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$$\psi(z;\boldsymbol{\theta}) := \begin{pmatrix} \psi_1(z;\boldsymbol{\theta}) \\ \psi_2(z;\boldsymbol{\theta}) \end{pmatrix}$$

M-estimator of $\boldsymbol{\theta}$ solves

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# Robustness

- An estimator is robust if its influence function is bounded
- Influence function of an $M$-estimator:

$$\mathrm{IF}(z) \propto \psi(z; \theta)$$

- For the Heckit estimator, $\mathrm{IF}(.)$ is unbounded

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# Bounded-influence estimator

- Bound $\psi(.;\boldsymbol{\theta})$ to obtain a robust estimator
- Huber function:

$$\Psi(z) := \begin{cases} z & \text{for } |z| \leq K \\ \operatorname{sgn}(z)K & \text{for } |z| > K \end{cases}$$

- Apply a Huber function to the standardized prediction error
- Bound covariates if necessary
- Implementation is easy using `ssmrob` package for R

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# Plan

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- Study the influence of monetary condition news on SR and LR household inflation expectations
- Use data from the MSC during 2008M12–2015M12 (‘zero lower bound’ period)
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# Inflation expectations in the MSC

Q1: Direction

- `px1q1` prices up/down next year
- `px5q1` prices up/down next 5 years

Q2: Size (only if up/down to Q1)

- `px1q2` prices % up/down next year
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Percentage

- `px1` price expectations 1yr recoded
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# Covariates

Micro

| | |
|---|---|
| `MPN` | news: monetary condition |
| `IN` | news: inflation |
| `ytl` | income quartiles |
| `age` | age of respondent |
| `female` | female dummy |
| `hsize` | household size |
| `edu` | education of respondent |

Macro

| | |
|---|---|
| `IP` | industrial production (growth rate at $t-1$) |
| `UR` | unemployment rate (at $t-1$) |
| `CPI` | consumer price index (growth rate at $t-1$) |

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# Covariates

Micro

| | |
|---|---|
| `MPN` | news: monetary condition |
| `IN` | news: inflation |
| `ytl` | income quartiles |
| `age` | age of respondent |
| `female` | female dummy |
| `hsize` | household size |
| `edu` | education of respondent |

Macro

| | |
|---|---|
| `IP` | industrial production (growth rate at $t-1$) |
| `UR` | unemployment rate (at $t-1$) |
| `CPI` | consumer price index (growth rate at $t-1$) |

# Sample selection

We follow Sheen and Wang (2023):

- Use only wave 2 data to include lagged `px1`/`px5`
- Exclude respondents with missing news or demographic variables

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# Sample size

| | | wave 1 | |
|---|---|---|---|
| horizon | wave 2 | observed | missing |
| 1 year | observed | 13426 | 960 |
| | missing | 734 | 417 |
| 5 year | observed | 13234 | 997 |
| | missing | 789 | 517 |

# Exclusion restriction

- Higher inflation uncertainty may increase the likelihood of DK responses, but not the level of inflation expectations
- Include the absolute change of the CPI inflation rate in the previous month in the selection equation
- Correct sign, but insignificant
- Still better to include

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# Plan

Motivation

Regression model with DK responses

Robust Heckit estimator

Reexamination of Sheen and Wang (2023, EER)

Results

Conclusion

# Classical estimation

Classical estimation:

- Compare OLS, ML, and Heckit estimates
- Use `sampleSelection` package for R

Parameters of interest:

1. Coefficient on MPN
2. Coefficient on the bias correction term (IMR)

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# Classical estimation (SR)

Outcome equation for px1

| | OLS | ML | Heckit |
|---|---|---|---|
| MPN | 0.17 (0.20) | 0.17 (0.20) | 0.22 (0.21) |
| IN | 0.65 (0.18)*** | 0.65 (0.18)*** | 0.64 (0.19)*** |
| Lpx1 | 0.24 (0.01)*** | 0.24 (0.01)*** | 0.25 (0.01)*** |
| MPN:Lpx1 | 0.04 (0.04) | 0.04 (0.04) | 0.04 (0.04) |
| IN:Lpx1 | 0.08 (0.03)* | 0.08 (0.03)* | 0.09 (0.03)** |
| | ⋮ | | |
| rho | | −0.01 (0.05) | −0.72 |
| invMillsRatio | | | −2.77 (2.00) |
| Num. obs. | 13426 | 14160 | 14160 |
| Censored | | 734 | 734 |

# Classical estimation (LR)

Outcome equation for px5

| | OLS | ML | Heckit |
|---|---|---|---|
| MPN | −0.13 (0.19) | −0.13 (0.19) | −0.03 (0.22) |
| IN | 0.53 (0.15)*** | 0.53 (0.15)*** | 0.58 (0.18)** |
| Lpx5 | 0.29 (0.01)*** | 0.29 (0.01)*** | 0.32 (0.01)*** |
| MPN:Lpx5 | 0.06 (0.05) | 0.06 (0.05) | 0.05 (0.05) |
| IN:Lpx5 | −0.07 (0.03) | −0.07 (0.03) | −0.06 (0.04) |
| ⋮ | | | |
| rho | | −0.01 (0.05) | −1.30 |
| invMillsRatio | | | −4.13 (1.42)** |
| Num. obs. | 13234 | 14023 | 14023 |
| Censored | | 789 | 789 |

# Robust estimation

Why are the ML and Heckit estimates different?

$\Longrightarrow$ Model misspecification

Possible cases:

1. Only Heckit is consistent
2. Both ML and Heckit are inconsistent

Robustness check:

- Compare classical and robust Heckit estimates
- Use `ssmrob` package for R
- Set $K = 100$ (classical) or $K = 1.345$ (robust)

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# Robust estimation (SR)

Outcome equation for px1

| | classical ($K = 100$) | robust ($K = 1.345$) |
|---|---|---|
| MPN | 0.22 (0.25) | 0.12 (0.19) |
| IN | 0.64 (0.19)*** | 0.60 (0.14)*** |
| Lpx1 | 0.25 (0.01)*** | 0.24 (0.02)*** |
| MPN:Lpx1 | 0.04 (0.06) | 0.04 (0.06) |
| IN:Lpx1 | 0.09 (0.05) | 0.04 (0.05) |
| | ⋮ | |
| IMR1 | −2.78 (2.49) | 0.61 (6.23) |
| Num. obs. | 14160 | 14160 |
| Censored | 734 | 734 |

# Robust estimation (LR)

Outcome equation for px5

| | classical ($K = 100$) | robust ($K = 1.345$) |
|---|---|---|
| MPN | $-0.03$ (0.30) | 0.15 (0.22) |
| IN | 0.58 $(0.21)^{**}$ | 0.43 $(0.19)^{*}$ |
| Lpx5 | 0.32 $(0.02)^{***}$ | 0.31 $(0.02)^{***}$ |
| MPN:Lpx5 | 0.05 (0.10) | $-0.01$ (0.06) |
| IN:Lpx5 | $-0.06$ (0.06) | $-0.04$ (0.06) |
| | $\vdots$ | |
| IMR1 | $-4.13$ $(1.92)^{*}$ | $-3.90$ (3.54) |
| Num. obs. | 14023 | 14023 |
| Censored | 789 | 789 |

# Plan

# Findings

1. For both SR and LR inflation expectations, OLS and ML estimates are almost identical
   $\Longrightarrow$ No sample selection bias (?)
2. ML and Heckit estimates somewhat differ. For LR expectations, the bias correction term is significant
   $\Longrightarrow$ Sample selection bias
3. Classical and robust Heckit estimates somewhat differ
   $\Longrightarrow$ Robust estimate is more reliable
4. Monetary condition news remains insignificant
   $\Longrightarrow$ Support the conclusion of Sheen and Wang (2023)

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# Summary

- One cannot assume *a priori* that DK responses are ignorable. Use a sample selection model.
- ML and Heckit estimates may be quite different, perhaps because of model misspecification.
- Use a robust Heckit estimator for robustness checks.

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# Limitations

1. Global misspecification
   - Our model may not be even approximately correct
   - Need a robust semi/non-parametric estimator
2. DK responses in explanatory variables
   - Can include them using DK dummies $\Longrightarrow$ conditional heteroskedasticity
   - Need a robust generalized Heckit estimator
3. Unit nonresponses
   - Need additional information, e.g., regional nonresponse rates
4. Qualitative information in DK responses
   - Combine data on the direction and percentage of inflation expectations

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