“Don’t know” responses in surveys on inflation expectations: Are they ignorable?

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First draft: November 2024
This version: May 22, 2025

Abstract

Although consumer survey data on quantitative inflation expectations often include many “don’t know” (DK) responses, most empirical studies discard them and apply OLS, which may cause sample selection bias. One can use a sample selection model to test and correct for the bias, but the ML and Heckit methods may give conflicting results if the model is not exactly correct. This paper proposes using a *robust* Heckit method in such cases as a robustness check in the true statistical sense. A reexamination of a recent study on the influence of monetary condition news on household inflation expectations illustrates the approach.

JEL classification: C24, D84, E31

Keywords: missing data, nonresponse bias, sample selection, robust Heckit

Highlights

- “Don’t know” (DK) responses are common in surveys on inflation expectations
- To check if DK responses are ignorable, we must estimate a sample selection model
- However, the ML and Heckit methods may give conflicting results
- We propose using a robust Heckit method for a robustness check
- We reexamine a recent empirical study on household inflation expectations

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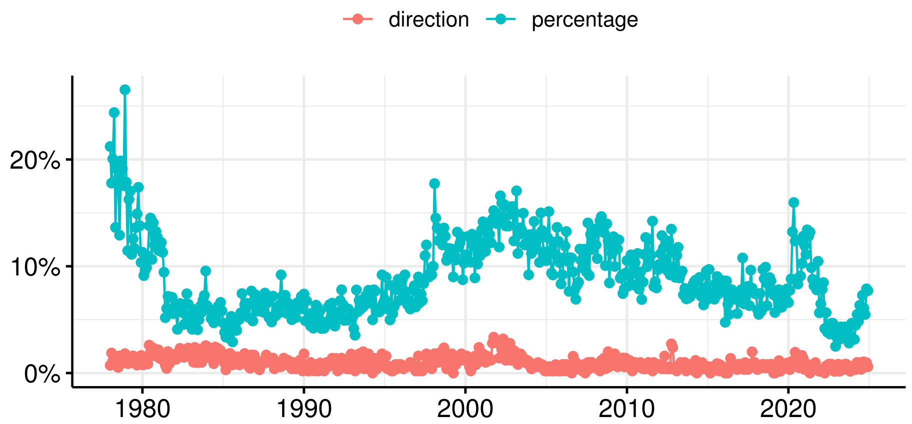

Figure 1: Missing response rates for the direction and percentage of inflation during the next 12 months in the MSC, 1978M01–2024M12

1 Introduction

Many, if not all, economists nowadays seem to believe that subjective inflation expectations matter for economic decisions and inflation.[1] Weber, D'Acunto, Gorodnichenko, and Coibion (2022, p. 158) explain,

> ...the key reason why subjective inflation expectations matter is that they affect the prices and wages firms set as well as the consumption–saving decisions of households.

As a consequence, the literature on the formation of subjective inflation expectations is growing. See D'Acunto, Malmendier, and Weber (2023) for a recent survey, which focuses on household inflation expectations.

Many empirical studies on household inflation expectations rely on surveys. Since not all consumers can always articulate their inflation expectations quantitatively, surveys that allow for "don't know" (DK) answers often have many missing responses (DK responses and item nonresponses). Figure 1 plots the missing response rates for the direction and percentage of inflation during the next 12 months in the Michigan Survey of Consumers (MSC).[2] The missing response rates are much higher for percentage (around 10%) than for direction (often less than 1%).[3]

In practice, most empirical studies using consumer survey data on quantitative inflation expectations discard DK responses from the analysis; e.g., Sheen and Wang (2023), Wang, Sheen, Trück, Chao, and Härdle (2020), and Ehrmann,

[1] See Rudd (2022) for a criticism against the belief that subjective inflation expectations matter.

[2] See Curtin (1996) for the exact question wording and the actual questionnaire form of the MSC.

[3] The missing response rates are much lower for point and density forecasts in the New York Fed's Survey of Consumer Expectations (SCE), as the SCE does not allow for DK answers; see Armantier, Topa, van der Klaauw, and Zafar (2017) for an overview of the SCE. However, Comerford (2024) criticizes that density forecasts collected by the SCE suffer from selective nonresponse and biased response.

Pfajfar, and Santoro (2017), who use the MSC, and Tsiaplias (2020, 2021), who uses the Consumer Attitudes, Sentiments and Expectations in Australia Survey (CASiE), among many others.[4] Ignoring DK responses may cause severe sample selection bias, unless they occur at random conditional on the observables, or the missingness mechanism is *ignorable* in the sense of Little and Rubin (2019, p. 133), which may not hold in practice.[5]

A possible excuse for ignoring DK responses is that the standard sample selection model involves strong assumptions (e.g., normality, homoscedasticity, and an exclusion restriction) and the classical ML and Heckit estimators are not robust to model misspecification. This paper addresses such a concern by applying a robust statistical method as a robustness check in the true statistical sense.[6] Specifically, we use a robust Heckit estimator proposed by Zhelonkin, Genton, and Ronchetti (2016) to check if (i) DK responses are ignorable and (ii) the classical ML and Heckit estimates are reliable. The `ssmrob` package for R developed by Zhelonkin and Ronchetti (2021) helps to apply a robust Heckit estimator.

To illustrate the approach, this paper reexamines an analysis in Sheen and Wang (2023, sec. 5), who study the influence of monetary condition news on short- and medium-run household inflation expectations during the zero lower bound period using data from the MSC between 2008M12–2015M12.[7] They estimate regression equations for the percentage of inflation by OLS, ignoring nonresponses. Hence their results may suffer from sample selection bias.[8] We assume a sample selection model instead, and compare the OLS, ML, Heckit, and robust Heckit estimates of the outcome equation. Interesting findings are as follows:

1. For both short- and medium-run expectations, the ML estimates are almost identical to the OLS estimates, with almost no correlation between the errors in the selection and outcome equations. Hence DK responses are ignorable and the OLS estimates have no sample selection bias.

2. The ML and Heckit estimates somewhat differ. In particular, for medium-run expectations, the Heckit estimate of the coefficient on the bias correction term significantly differs from 0. Hence for medium-run expectations,

[4] One exception is Pfajfar and Santoro (2013), who use rotating panel data from the MSC to study the effect of news on updating of inflation expectations using a binary probit model with Heckman correction to control for attrition bias; see Pfajfar and Santoro (2013, p. 1060).

[5] To be precise, the missingness mechanism is ignorable for likelihood inference if (i) the missing data are missing at random (MAR) at the observed values and (ii) the parameters in the selection and outcome equations are distinct; cf. Little and Rubin (2019, Corollary 6.1A). Hence when we say "ignorable", we implicitly assume that the second condition holds, though it is unnecessary for consistency of the OLS estimator.

[6] Existing empirical studies in economics rarely use robust statistical methods for robustness checks.

[7] The focus of Sheen and Wang (2023) is not inflation expectations per se, but how monetary condition news affected households' readiness to spend on durables via their interest rate and inflation expectations during the zero lower bound period. We focus only on one analysis in their work for our purpose of illustration.

[8] In fact, nonresponses in their samples are not DK responses but correspond to respondents who skipped the question on the percentage of inflation because they answered in the previous question that prices "stay the same". Hence we must treat these nonresponses as "0 percent" instead of missing. This error explains the extremely high missing response rates (26.3% for 1 year ahead expectations) in their samples. We fix this error and construct our own samples with DK responses in Section 4.

DK responses are not ignorable and the OLS estimate suffers from sample selection bias.

3. The classical and robust Heckit estimates somewhat differ, suggesting that even the classical Heckit estimates may not be reliable.

The standard sample selection model assumes a bivariate normal distribution with homoscedastic errors, and the ML estimator is consistent under these assumptions. However, the Heckit estimator is consistent under weaker assumptions; see Olsen (1980). Hence the difference between the two estimates may invalidate the assumption of bivariate normality or homoscedasticity, implying that the Heckit estimate is more reliable.[9] Moreover, even the weaker assumptions for consistency of the Heckit estimator may not hold in practice.[10] Hence the difference between the classical and robust Heckit estimates suggests that the robust estimate is more reliable.

As an empirical contribution, this paper shows that addressing the issues of sample selection bias, (non)robustness, and mistreatment of skipped responses (discussed in Section 4) does not change the conclusion of Sheen and Wang (2023, p. 12) that "households do not adjust their inflation expectations upon hearing monetary condition news, neither in the short-term (1 year) nor long-term (5–10 years)", since the estimates of the corresponding regression coefficients remain insignificant. Though acceptance of the null hypothesis is not a strong evidence, our results strengthen their conclusion and contribute to the literature on the formation of subjective inflation expectations.

The paper proceeds as follows. Section 2 specifies a regression model with DK responses as a sample selection model. Section 3 reviews robust estimation of a sample selection model. Section 4 illustrates the approach by reexamining an analysis in Sheen and Wang (2023). Section 5 discusses implications of this research. Section 6 concludes.

2 Regression model with DK responses

Let $(y, \boldsymbol{x}')'$ be a $(1+k)$-variate random vector, where y is either a numerical or DK response. Let y^* be the latent numerical response underlying y, and d be the numerical response dummy so that $y = y^*$ if and only if $d = 1$. Assume a sample selection model for y given $\boldsymbol{x}$ such that

$$
\begin{aligned}
y &= \begin{cases} y^* & \text{if } d = 1 \\ \mathrm{NA} & \text{if } d = 0 \end{cases} \\
d &= [U > 0] \\
U &= \boldsymbol{x}'\boldsymbol{\alpha} + z \\
y^* &= \boldsymbol{x}'\boldsymbol{\beta} + u \\
\begin{pmatrix} z \\ u \end{pmatrix} |\boldsymbol{x} &\sim \mathrm{N}\left(\boldsymbol{0}, \begin{bmatrix} 1 & \sigma_{zu} \\ \sigma_{uz} & \sigma_u^2 \end{bmatrix}\right)
\end{aligned}
$$

[9]One source of nonnormality of the percentage of inflation is that some respondents round the percentage to multiples of 5 while others do not, resulting in a multi-modal distribution.

[10]The Heckit estimator is consistent under a certain form of conditional heteroscedasticity, but not in general; see Carlson and Zhao (2025).

where U is a latent variable determining d, and $(z,u)'$ is an error vector with $\mathrm{var}(z)=1$ by rescaling U. Consider estimation of $\boldsymbol{\beta}$ given a random sample of $(d,y,\boldsymbol{x}')'$.

By simple algebra, the outcome equation for the selected sample is

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

If z and u are independent, then the second term is zero, so one can ignore DK responses and apply OLS to obtain a consistent estimator of $\boldsymbol{\beta}$. Otherwise the second term remains, and the OLS estimator is inconsistent (sample selection bias). One can avoid the bias using the ML or Heckit estimator, but they are not widely used in the context of DK responses, perhaps because they are not robust to model misspecification.

3 Robust Heckit estimator

3.1 Heckit estimator

Let $\Phi(.)$ be the cdf of $\mathrm{N}(0,1)$, $\phi(.):=\Phi'(.)$ be the pdf, and $h(.):=\phi(.)/\Phi(.)$ be the inverse Mills ratio. One can write the outcome equation (1) as

$$\mathrm{E}(y|d=1,\boldsymbol{x})=\boldsymbol{x}'\boldsymbol{\beta}+\sigma_{uz}h(\boldsymbol{x}'\boldsymbol{\alpha})$$

See, e.g., Hansen (2022, p. 883). One obtains the Heckit estimator of $\boldsymbol{\beta}$ in two steps.

The selection equation for d is a binary probit model, so we apply the ML method to estimate $\boldsymbol{\alpha}$. Let $s:=2d-1$. The moment restriction that defines $\boldsymbol{\alpha}$ is

$$\mathrm{E}(s\boldsymbol{x}h(s\boldsymbol{x}'\boldsymbol{\alpha}))=\boldsymbol{0} \tag{2}$$

See, e.g., Hansen (2022, p. 834).

Given the bias correction term $h(\boldsymbol{x}'\boldsymbol{\alpha})$, one can estimate $(\boldsymbol{\beta}',\sigma_{uz})'$ by OLS using the selected sample. The moment restriction that defines $(\boldsymbol{\beta}',\sigma_{uz})'$ is

$$\begin{aligned}\mathrm{E}(\boldsymbol{x}(y-\boldsymbol{x}'\boldsymbol{\beta}-\sigma_{uz}h(\boldsymbol{x}'\boldsymbol{\alpha}))|d=1)&=\boldsymbol{0}\\ \mathrm{E}(h(\boldsymbol{x}'\boldsymbol{\alpha})(y-\boldsymbol{x}'\boldsymbol{\beta}-\sigma_{uz}h(\boldsymbol{x}'\boldsymbol{\alpha}))|d=1)&=0\end{aligned}$$

which implies

$$\mathrm{E}(\boldsymbol{x}(y-\boldsymbol{x}'\boldsymbol{\beta}-\sigma_{uz}h(\boldsymbol{x}'\boldsymbol{\alpha}))d)=\boldsymbol{0} \tag{3}$$

$$\mathrm{E}(h(\boldsymbol{x}'\boldsymbol{\alpha})(y-\boldsymbol{x}'\boldsymbol{\beta}-\sigma_{uz}h(\boldsymbol{x}'\boldsymbol{\alpha}))d)=0 \tag{4}$$

3.2 M-estimator

The sample analogs of the moment restrictions (2)–(4) give the estimating equation that defines the Heckit estimator as an M-estimator. Let $\boldsymbol{z}:=(d,s,y,\boldsymbol{x}')'$. Let $\boldsymbol{\theta}:=(\boldsymbol{\alpha}',\boldsymbol{\beta}',\sigma_{uz})'$. Define the estimating functions as

$$\begin{aligned}\boldsymbol{\psi}_1(\boldsymbol{z};\boldsymbol{\theta})&:=s\boldsymbol{x}h(s\boldsymbol{x}'\boldsymbol{\alpha})\\ \boldsymbol{\psi}_2(\boldsymbol{z};\boldsymbol{\theta})&:=\begin{pmatrix}\boldsymbol{x}\\ h(\boldsymbol{x}'\boldsymbol{\alpha})\end{pmatrix}(y-\boldsymbol{x}'\boldsymbol{\beta}-\sigma_{uz}h(\boldsymbol{x}'\boldsymbol{\alpha}))d\end{aligned}$$

Stack the two estimating functions and define

$$\boldsymbol{\psi}(\boldsymbol{z};\boldsymbol{\theta}) := \begin{pmatrix} \boldsymbol{\psi}_1(\boldsymbol{z};\boldsymbol{\theta}) \\ \boldsymbol{\psi}_2(\boldsymbol{z};\boldsymbol{\theta}) \end{pmatrix}$$

Let $F(.)$ be the joint cdf of $\boldsymbol{z}$. Let $T(.)$ be a statistical functional that defines $\boldsymbol{\theta}$, so that $\boldsymbol{\theta} := T(F(.))$. Then

$$\mathrm{E}(\boldsymbol{\psi}(\boldsymbol{z};\boldsymbol{\theta})) = \mathbf{0}$$

or

$$\int \boldsymbol{\psi}(\boldsymbol{z};T(F(.)))\,\mathrm{d}F(\boldsymbol{z}) = \mathbf{0}$$

Let $\boldsymbol{Z}$ be a random sample of size n from $F(.)$. Let $F_n(.)$ be the empirical cdf of $\boldsymbol{Z}$. The M-estimator of $\boldsymbol{\theta}$ given $\boldsymbol{Z}$ is $\hat{\boldsymbol{\theta}} := T(F_n(.))$ such that

$$\frac{1}{n}\sum_{i=1}^{n} \boldsymbol{\psi}\left(\boldsymbol{z}_i;\hat{\boldsymbol{\theta}}\right) = \mathbf{0}$$

or

$$\int \boldsymbol{\psi}(\boldsymbol{z};T(F_n(.)))\,\mathrm{d}F_n(\boldsymbol{z}) = \mathbf{0}$$

3.3 Robustness

The influence function of $T(.)$ at $F(.)$ is the functional (Gâteaux) derivative of $T(.)$ with respect to the cdf of a point mass (outlier) evaluated at $F(.)$. If the influence function of $T(.)$ is bounded, then any outlier has a bounded influence on $T(.)$, so $T(.)$ is robust; see Wilcox (2022, pp. 29–30). The influence function of an M-estimator is proportional to its estimating function. In our case, the influence function of $T(.)$ at $F(.)$ is $\forall \boldsymbol{z}$,

$$\mathrm{IF}_{T(.),F(.)}(\boldsymbol{z}) = -\left(\int \boldsymbol{\psi}_{\boldsymbol{\theta}}(\boldsymbol{z};T(F(.)))\,\mathrm{d}F(\boldsymbol{z})\right)^{-1} \boldsymbol{\psi}(\boldsymbol{z};T(F(.)))$$

See Hampel, Ronchetti, Rousseeuw, and Stahel (1986, p. 230). One can show by L'Hôspital's rule that $h(z) \to \infty$ as $z \to -\infty$, implying that $\boldsymbol{\psi}(.;T(F(.)))$ is unbounded. Since $\mathrm{IF}_{T(.),F(.)}(.)$ is unbounded, an extreme outlier has a huge influence on $T(.)$, so the Heckit estimator is not robust.

3.4 Bounded-influence estimator

One can obtain a robust Heckit estimator by bounding $\boldsymbol{\psi}(.;\boldsymbol{\theta})$. Consider bounding $\boldsymbol{\psi}_1(.;\boldsymbol{\theta})$ and $\boldsymbol{\psi}_2(.;\boldsymbol{\theta})$ in turn.

Since $\boldsymbol{\psi}_1(.;\boldsymbol{\theta})$ is the estimating function for a binary probit model, we can rewrite $\boldsymbol{\psi}_1(\boldsymbol{z};\boldsymbol{\theta})$ as

$$\boldsymbol{\psi}_1(\boldsymbol{z};\boldsymbol{\theta}) = \frac{\boldsymbol{x}\phi(\boldsymbol{x}'\boldsymbol{\alpha})(d - \Phi(\boldsymbol{x}'\boldsymbol{\alpha}))}{\Phi(\boldsymbol{x}'\boldsymbol{\alpha})\Phi(-\boldsymbol{x}'\boldsymbol{\alpha})}$$

See, e.g., Wooldridge (2010, p. 478). Write the binary probit model for d as a regression model:

$$\begin{aligned} \mathrm{E}(d|\boldsymbol{x}) &= \Phi(\boldsymbol{x}'\boldsymbol{\alpha}) \\ \mathrm{var}(d|\boldsymbol{x}) &= \Phi(\boldsymbol{x}'\boldsymbol{\alpha})\Phi(-\boldsymbol{x}'\boldsymbol{\alpha}) \end{aligned}$$

Let r_1 be the standardized prediction error of d given $\boldsymbol{x}$, i.e.,

$$r_1 := \frac{d - \Phi(\boldsymbol{x}'\boldsymbol{\alpha})}{\sqrt{\Phi(\boldsymbol{x}'\boldsymbol{\alpha})\Phi(-\boldsymbol{x}'\boldsymbol{\alpha})}}$$

which need not be symmetric around 0. We can write

$$\begin{aligned}\boldsymbol{\psi}_1(\boldsymbol{z};\boldsymbol{\theta}) &= \frac{\boldsymbol{x}\phi(\boldsymbol{x}'\boldsymbol{\alpha})r_1}{\sqrt{\Phi(\boldsymbol{x}'\boldsymbol{\alpha})\Phi(-\boldsymbol{x}'\boldsymbol{\alpha})}} \\ &= \boldsymbol{x}\sqrt{h(\boldsymbol{x}'\boldsymbol{\alpha})h(-\boldsymbol{x}'\boldsymbol{\alpha})}r_1\end{aligned}$$

Let $\Psi(.)$ be the Huber function with bound $K > 0$, i.e., $\forall z \in \mathbb{R}$,

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

Let

$$\boldsymbol{\psi}_1^*(\boldsymbol{z};\boldsymbol{\theta}) := w_1(\boldsymbol{x})\boldsymbol{x}\sqrt{h(\boldsymbol{x}'\boldsymbol{\alpha})h(-\boldsymbol{x}'\boldsymbol{\alpha})}(\Psi(r_1) - \mathrm{E}(\Psi(r_1)|\boldsymbol{x})) \tag{5}$$

where $w_1(.)$ is a weight function to downweight extreme $\boldsymbol{x}$. Since r_1 need not be symmetric around 0, $\mathrm{E}(\Psi(r_1)|\boldsymbol{x}) \neq 0$ in general, so we need an adjustment term to guarantee that $\mathrm{E}(\boldsymbol{\psi}_1^*(\boldsymbol{z};\boldsymbol{\theta})) = 0$. One can show by L'Hôspital's rule that $z^2h(z)h(-z) \to 0$ as $z \to \infty$, implying that $\boldsymbol{\psi}_1^*(.;\boldsymbol{\theta})$ is bounded if $w_1(.)$ is bounded, e.g., $w_1(.) := 1$.

For the outcome equation, we have

$$\begin{aligned}\mathrm{E}(y|d = 1, \boldsymbol{x}) &= \boldsymbol{x}'\boldsymbol{\beta} + \sigma_{uz}h(\boldsymbol{x}'\boldsymbol{\alpha}) \\ \operatorname{var}(y|d = 1, \boldsymbol{x}) &= \sigma_w^2\end{aligned}$$

where $\sigma_w^2 := \sigma_u^2 - \sigma_{uz}^2$. Let r_2 be the standardized prediction error of y given $\boldsymbol{x}$, i.e.,

$$r_2 := \frac{y - \boldsymbol{x}'\boldsymbol{\beta} - \sigma_{uz}h(\boldsymbol{x}'\boldsymbol{\alpha})}{\sigma_w}$$

which follows $\mathrm{N}(0, 1)$ given $d = 1$ and $\boldsymbol{x}$. We can write

$$\boldsymbol{\psi}_2(\boldsymbol{z};\boldsymbol{\theta}) = \begin{pmatrix} \boldsymbol{x} \\ h(\boldsymbol{x}'\boldsymbol{\alpha}) \end{pmatrix} \sigma_w r_2 d$$

Let

$$\boldsymbol{\psi}_2^*(\boldsymbol{z};\boldsymbol{\theta}) := w_2\left(\begin{pmatrix} \boldsymbol{x} \\ h(\boldsymbol{x}'\boldsymbol{\alpha}) \end{pmatrix}\right) \begin{pmatrix} \boldsymbol{x} \\ h(\boldsymbol{x}'\boldsymbol{\alpha}) \end{pmatrix} \Psi(r_2)d \tag{6}$$

where $w_2(.)$ is a weight function to downweight extreme $(\boldsymbol{x}', h(\boldsymbol{x}'\boldsymbol{\alpha}))'$. Since r_2 is symmetric around 0, $\mathrm{E}(\Psi(r_1)|\boldsymbol{x}) = 0$, so $\mathrm{E}(\boldsymbol{\psi}_2^*(\boldsymbol{z};\boldsymbol{\theta})) = 0$ with no adjustment term. For $\boldsymbol{\psi}_2^*(.;\boldsymbol{\theta})$ to be bounded, however, $w_2((\boldsymbol{x}', h(\boldsymbol{x}'\boldsymbol{\alpha}))')(\boldsymbol{x}', h(\boldsymbol{x}'\boldsymbol{\alpha}))'$ must be bounded. Let

$$w_2\left(\begin{pmatrix} \boldsymbol{x} \\ h(\boldsymbol{x}'\boldsymbol{\alpha}) \end{pmatrix}\right) := \begin{cases} 1 & \text{for } \|(\boldsymbol{x}', h(\boldsymbol{x}'\boldsymbol{\alpha}))'\| \leq c \\ c/\|(\boldsymbol{x}', h(\boldsymbol{x}'\boldsymbol{\alpha}))'\| & \text{for } \|(\boldsymbol{x}', h(\boldsymbol{x}'\boldsymbol{\alpha}))'\| > c \end{cases}$$

where $c > 0$ and $\|.\|$ is a norm. Then $\boldsymbol{\psi}_2^*(.;\boldsymbol{\theta})$ is bounded. Other specifications for $w_2(.)$ are possible as long as it approaches to 0 sufficiently fast for extreme $\boldsymbol{x}$.

The estimating functions (5) and (6) give the estimating equation that defines a robust M-estimator of $\boldsymbol{\theta}$, hence a robust Heckit estimator of $\boldsymbol{\beta}$.

Table 1: Variables used to replicate Sheen and Wang (2023, p. 12)

Variable	Description
`px1q1`	prices up/down next year
`px5q1`	prices up/down next 5 years
`px1q2`	prices % up/down next year
`px5q2`	prices % up/down next 5 years
`px1`	price expectations 1yr recoded
`px5`	price expectations 5yr recoded
`MPN`	news: monetary condition
`IN`	news: inflation
`ytl`	income quartiles
`age`	age of respondent
`female`	female dummy
`hsize`	household size
`edu`	education of respondent
`IP`	industrial production (growth rate at $t-1$)
`UR`	unemployment rate (at $t-1$)
`CPI`	consumer price index (growth rate at $t-1$)

4 Illustration

4.1 Data

Sheen and Wang (2023, sec. 5) study the influence of monetary condition news on short- and medium-run household inflation expectations using consumer survey data from the MSC and macroeconomic data from FRED (Federal Reserve Economic Data) for 2008M12–2015M12. We use this study for our illustration because it is a recent interesting empirical study on household inflation expectations published in a top journal, and because its replication data and code are available on the journal's website. Table 1 lists the variables used in the their analysis and ours. See Sheen and Wang (2023, sec. 2) for data description.

We replicated their results using R 4.5.0 developed by R Core Team (2025) and found two errors:

1. They mistakenly use `px1q2`/`px5q2` as respondents' numerical inflation expectations. The questions are only for respondents expecting prices to go up/down, asking about the size of the change. Hence these variables are missing if a respondent expects prices to stay the same, and positive even if a respondent expects prices to go down. We must use `px1`/`px5` instead.

2. For medium-run expectations, they mistakenly use `px1q2` instead of `px5q2` to construct a cross term, which makes even the sample size incorrect; see line 114 of their Stata code for variable definitions (`DefineVariable.do`).

Table 2 replicates and corrects the two results in Sheen and Wang (2023, p. 12). The result for `px1q2` is identical to that in Sheen and Wang (2023, p. 12), but incorrect because of the first error. The result for `px1` is free from that error. The result for `px5q2` differs from that in Sheen and Wang (2023, p. 12) because of the second error, and still incorrect because of the first error. The result for `px5` is free from the two errors. Sheen and Wang (2023, p. 12) writes their main findings as follows:

Table 2: Replication and correction of Sheen and Wang (2023, p. 12)

	px1q2	px1	px5q2	px5
MPN	0.13	0.23	0.18	−0.08
IN	0.35	0.45*	0.17	0.45**
Lpx1q2	0.32***			
MPN:Lpx1q2	0.05			
IN:Lpx1q2	0.01			
Lpx1		0.23***		
MPN:Lpx1		0.03		
IN:Lpx1		0.11**		
Lpx5q2			0.34***	
MPN:Lpx5q2			0.01	
IN:Lpx5q2			−0.04	
Lpx5				0.29***
MPN:Lpx5				0.09
IN:Lpx5				−0.07
ytl42	−0.59***	−0.41***	−0.28***	−0.23**
ytl43	−0.80***	−0.67***	−0.37***	−0.19*
ytl44	−1.05***	−0.91***	−0.46***	−0.27**
age	0.01**	0.01***	0.00	0.00
female	0.17*	0.33***	0.15***	0.19***
hsize	0.06*	0.09**	0.04*	0.05*
edu2	−0.29	−0.16	−0.25	−0.29
edu3	−0.31	−0.35	−0.36**	−0.28
edu4	−0.49*	−0.58*	−0.44**	−0.34*
IP	−0.19***	0.47***	−0.06	−0.01
UR	0.15***	−0.06*	0.10***	0.05**
CPI	0.16	1.17***	0.10	0.06
(Intercept)	2.03***	2.74***	1.69***	1.95***
Adj. R^2	0.18	0.11	0.16	0.11
Num. obs.	7785	10566	9956	10566

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$ (based on the usual standard errors)

> The results show households do not adjust their inflation expectations upon hearing monetary condition news, neither in the short-term (1 year) nor long-term (5–10 years).

We see that fixing the two errors does not change their conclusion. However, for short-run expectations, the sign and significance of the effects of IP, UR, and CPI become more intuitive and consistent with their results for the direction of inflation; see Sheen and Wang (2023, p. 12). The corrected results still ignore DK responses, which may cause sample selection bias.

The replication data are not the full sample of the MSC between 2008M12–2015M12 but a subsample that excludes respondents with missing responses in variables of their interest; i.e., interest rate expectations, inflation expectations, and readiness to spend on houses, cars, and durable goods. Since a subsample with no DK responses is not useful for our purpose, we obtain the original data from the websites of the MSC, FRED, and ALFRED (ArchivaL FRED), and construct the full sample by ourselves. We reconstructed the replication data for double check, and successfully recovered all variables in Table 1 with correct

Table 3: Summary statistics

Variable	N	Mean	SD	Min	Max	NA
px1	14386	3.45	4.07	−25	25	1151
px5	14231	3.17	2.91	−15	25	1306
MPN	15537	0.000 71	0.19	−1	1	0
IN	15537	0.0077	0.23	−1	1	0
age	15537	56.70	16.15	18	97	0
hsize	15537	2.40	1.31	1	10	0
female	15537					
... No	7503	0.48				
... Yes	8034	0.52				
ytl4	15537					
... 1	3343	0.22				
... 2	3804	0.24				
... 3	4124	0.27				
... 4	4266	0.27				
edu	15537					
... 1	687	0.044				
... 2	3418	0.22				
... 3	8298	0.53				
... 4	3134	0.20				

Table 4: Missing responses for the percentage of inflation

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

values.

The MSC re-interviews respondents six months after their first interviews. Hence one can construct a rotating panel with two waves. Following Sheen and Wang (2023), we use only wave 2 data to include a lagged dependent variable (wave 1 inflation expectations) as an explanatory variable, and exclude respondents with missing news or demographic variables. However, contrary to Sheen and Wang (2023), we keep respondents with missing responses in interest rate expectations, inflation expectations, and readiness to spend on durables. Thus our sample includes DK responses in numerical inflation expectations. Table 3 shows summary statistics of our sample.

Following Sheen and Wang (2023), we further drop respondents with missing wave 1 inflation expectations, since they appear on the right-hand side of the regression equation. Table 4 is a cross table of the counts of observed/missing responses in the two waves for the percentage of inflation. Our sample sizes are 14160 (=13426+734) for short-run expectations and 14023 (=13234+789) for medium-run expectations.

Table 5: ML estimates of the probit selection equations

	px1	px5
MPN	−0.13 (0.13)	−0.15 (0.16)
IN	−0.03 (0.12)	−0.10 (0.12)
Lpx1	−0.02 (0.00)***	
MPN:Lpx1	0.01 (0.02)	
IN:Lpx1	−0.02 (0.02)	
Lpx5		−0.03 (0.01)***
MPN:Lpx5		0.02 (0.03)
IN:Lpx5		0.01 (0.02)
ytl42	0.19 (0.05)***	0.20 (0.05)***
ytl43	0.39 (0.06)***	0.34 (0.05)***
ytl44	0.44 (0.06)***	0.40 (0.06)***
age	−0.01 (0.00)***	−0.01 (0.00)***
femaleTRUE	−0.37 (0.04)***	−0.28 (0.04)***
hsize	−0.03 (0.02)*	−0.03 (0.02)
edu2	0.44 (0.08)***	0.33 (0.08)***
edu3	0.47 (0.08)***	0.34 (0.08)***
edu4	0.45 (0.09)***	0.33 (0.09)***
IP	0.04 (0.03)	0.02 (0.03)
UR	−0.03 (0.01)	−0.03 (0.01)*
CPI	−0.10 (0.06)	−0.04 (0.06)
abs_dCPI	−0.12 (0.09)	−0.12 (0.08)
(Intercept)	1.91 (0.17)***	2.26 (0.17)***
Num. obs.	14160	14023

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$
Numbers in parentheses are asymptotic standard errors.

4.2 Exclusion restriction

Though not necessary for identification, for precise estimation of a sample selection model, it is useful to have a variable that affects selection but not outcome directly (exclusion restriction); see, e.g., Wooldridge (2010, p. 806). Assuming that higher inflation uncertainty increases the likelihood of DK responses but not the level of inflation expectations, we use the absolute difference of the CPI inflation rate in the previous month as our exclusion restriction.

Table 5 shows the ML estimates of the probit selection equations for `px1` and `px5`. We see that `px1` and `px5` tend to be observable for respondents with higher income and education, and tend to be missing for those with higher wave 1 inflation expectations, old, and female. We find that `px1` and `px5` tend to be missing when the absolute difference of the CPI inflation rate in the previous month is large, but the effects are insignificant. We still use this variable as our exclusion restriction, since it is better to have one than nothing.

4.3 Classical estimation

We use our full sample and reestimate the linear regression models for `px1` and `px5` in Table 2 by OLS as benchmarks. Then we estimate the sample selection models with the previous exclusion restriction for `px1` and `px5` by the ML and Heckit estimators, using an R package `sampleSelection` developed by Toomet

Table 6: Alternative estimates of the 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)**
ytl42	−0.43 (0.10)***	−0.43 (0.10)***	−0.56 (0.14)***
ytl43	−0.65 (0.10)***	−0.65 (0.10)***	−0.87 (0.19)***
ytl44	−0.85 (0.11)***	−0.85 (0.11)***	−1.09 (0.20)***
age	0.01 (0.00)***	0.01 (0.00)***	0.01 (0.00)***
femaleTRUE	0.31 (0.06)***	0.31 (0.07)***	0.49 (0.15)***
hsize	0.08 (0.03)**	0.08 (0.03)**	0.10 (0.03)**
edu2	−0.08 (0.19)	−0.08 (0.19)	−0.44 (0.33)
edu3	−0.25 (0.18)	−0.26 (0.19)	−0.64 (0.34)
edu4	−0.51 (0.20)*	−0.51 (0.20)*	−0.88 (0.34)**
IP	0.42 (0.05)***	0.41 (0.05)***	0.39 (0.05)***
UR	−0.05 (0.02)*	−0.05 (0.02)*	−0.03 (0.03)
CPI	1.15 (0.11)***	1.15 (0.11)***	1.19 (0.11)***
(Intercept)	2.52 (0.31)***	2.53 (0.31)***	2.90 (0.42)***
sigma		3.68 (0.02)***	3.86
rho		−0.01 (0.05)	−0.72
invMillsRatio			−2.77 (2.00)
Adj. R^2	0.11		0.11
Num. obs.	13426	14160	14160
Censored		734	734
Observed		13426	13426

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$
Numbers in parentheses are asymptotic standard errors.

and Henningsen (2008).

Table 6 compares the alternative estimates of the outcome equation for `px1`. We find that OLS and ML give almost identical results, whereas ML and Heckit give somewhat different results. The ML estimate of the correlation coefficient ρ between the errors in the selection and outcome equations is almost 0 ($\hat{\rho} = -0.01$), which means that the two equations are almost independent and hence DK responses are ignorable. On the other hand, the Heckit estimate of ρ is far away from 0 ($\hat{\rho} = -0.72$), though the coefficient on the inverse Mills ratio term does not significantly differ from 0.

Table 7 compares the alternative estimates of the outcome equation for `px5`. We find here again that OLS and ML give almost identical results, whereas ML and Heckit give somewhat different results. The ML estimate of ρ is almost 0 ($\hat{\rho} = -0.01$), whereas the Heckit estimate of ρ lies outside $[-1, 1]$ ($\hat{\rho} = -1.30$). Importantly, the coefficient on the inverse Mills ratio term significantly differs from 0, meaning that DK responses are nonignorable for medium-run inflation expectations.

The difference between the ML and Heckit estimates raises a concern about which is a better estimate. The ML estimator is asymptotically efficient under the correct specification of a bivariate normal distribution with homoscedastic errors, whereas the Heckit estimator is consistent under weaker assumptions,

Table 7: Alternative estimates of the 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)
ytl42	−0.19 (0.07)**	−0.20 (0.07)**	−0.41 (0.11)***
ytl43	−0.17 (0.07)*	−0.17 (0.07)*	−0.48 (0.14)***
ytl44	−0.22 (0.08)**	−0.22 (0.08)**	−0.57 (0.15)***
age	−0.00 (0.00)	−0.00 (0.00)	0.01 (0.00)*
femaleTRUE	0.20 (0.05)***	0.20 (0.05)***	0.42 (0.09)***
hsize	0.03 (0.02)	0.03 (0.02)	0.05 (0.03)*
edu2	−0.17 (0.14)	−0.18 (0.14)	−0.58 (0.21)**
edu3	−0.23 (0.13)	−0.23 (0.13)	−0.65 (0.21)**
edu4	−0.31 (0.14)*	−0.32 (0.14)*	−0.74 (0.22)***
IP	−0.02 (0.03)	−0.02 (0.03)	−0.05 (0.04)
UR	0.05 (0.02)**	0.05 (0.02)**	0.07 (0.02)***
CPI	0.15 (0.08)*	0.15 (0.08)*	0.16 (0.09)
(Intercept)	2.00 (0.22)***	2.00 (0.22)***	2.22 (0.27)***
sigma		2.62 (0.02)***	3.17
rho		−0.01 (0.05)	−1.30
invMillsRatio			−4.13 (1.42)**
Adj. R^2	0.11		0.11
Num. obs.	13234	14023	14023
Censored		789	789
Observed		13234	13234

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$
Numbers in parentheses are asymptotic standard errors.

requiring only a univariate normal distribution for the selection equation; see Olsen (1980) and Carlson and Zhao (2025). Thus one may conclude that the Heckit estimator is more reliable. However, OLS, ML, and Heckit estimators are all not robust to outliers. Hence we need further analyses.

4.4 Robust estimation

We reestimate the sample selection models for `px1` and `px5` by a robust Heckit estimator, using an R package `ssmrob` developed by Zhelonkin and Ronchetti (2021). For both the selection and outcome equations, we set the bound for the Huber function as $K := 1.345$, which is the default value in the `ssmrob` package and also a common choice in the literature. The resulting robust estimator has 95% asymptotic efficiency relative to the ML estimator if the true distribution is normal; see de Menezes, Prata, Secchi, and Pinto (2021, p. 10) and references there.

We set $w_1(.) := 1$ since we need no weight for the selection equation. Let $\boldsymbol{X}$ be the $n \times k$ matrix of regressors in the outcome equation including the inverse Mills ratio term. Let $\boldsymbol{H} := \boldsymbol{X}(\boldsymbol{X}'\boldsymbol{X})^{-1}\boldsymbol{X}$ be the hat matrix. For the outcome equation, we set for $i = 1, \ldots, n$,

$$w_2(\boldsymbol{x}_i) := \sqrt{1 - h_{ii}}$$

where $h_{ii} := \boldsymbol{x}_i'(\boldsymbol{X}'\boldsymbol{X})^{-1}\boldsymbol{x}_i$ is the ith diagonal entry of $\boldsymbol{H}$. Naghi, Váradi, and Zhelonkin (2024, p. 4) note that this weight function is simple and stable when regressors include dummy variables.

Table 8 compares the classical ($K := 100$) and robust ML estimates of the probit selection equations for `px1` and `px5`, respectively. When $K := 100$, the Huber function does not bind, and the estimates are identical to the classical ML estimates in Table 5. The `ssmrob` package uses White's heteroscedasticity-consistent standard errors, but they look identical to the usual standard errors in Table 5. Comparing the classical and robust estimates, we find no qualitative difference for both `px1` and `px5`.

Table 9 compares the classical and robust Heckit estimates of the outcome equations for `px1` and `px5`, respectively. When $K := 100$, the Huber function does not bind, and the estimates are identical to the classical Heckit estimates in Tables 6 and 7, though the standard errors now differ from those in Tables 6 and 7. Comparing the classical and robust estimates, we find the following:

1. For both `px1` and `px5`, the estimates of the coefficients on the news variables, wave 1 inflation expectations, cross terms, and macroeconomic variables do not change qualitatively.

2. For both `px1` and `px5`, the estimates of the coefficients on the demographic variables become insignificant. Hence the classical Heckit estimates may not be robust.

3. The estimates of the coefficients on the inverse Mills ratio terms become insignificant not only for `px1` but also for `px5`. Thus sample selection bias may not be a problem in this application.

To summarize, we find that the classical Heckit estimates may not be reliable and that sample selection bias disappears if we use a robust Heckit estimator.

Table 8: Robust ML estimates of the probit selection equations

	px1		px5	
	$K = 100$	$K = 1.345$	$K = 100$	$K = 1.345$
MPN	−0.13 (0.13)	−0.03 (0.16)	−0.15 (0.16)	−0.17 (0.18)
IN	−0.03 (0.12)	−0.02 (0.13)	−0.10 (0.12)	−0.12 (0.14)
Lpx1	−0.02 (0.00)***	−0.02 (0.00)***		
MPN:Lpx1	0.01 (0.02)	−0.01 (0.03)		
IN:Lpx1	−0.02 (0.02)	−0.02 (0.02)		
Lpx5			−0.03 (0.01)***	−0.03 (0.01)***
MPN:Lpx5			0.02 (0.03)	0.01 (0.04)
IN:Lpx5			0.01 (0.02)	0.01 (0.03)
ytl42	0.19 (0.05)***	0.21 (0.05)***	0.20 (0.05)***	0.21 (0.05)***
ytl43	0.39 (0.06)***	0.37 (0.06)***	0.34 (0.05)***	0.32 (0.06)***
ytl44	0.44 (0.06)***	0.42 (0.07)***	0.40 (0.06)***	0.41 (0.07)***
age	−0.01 (0.00)***	−0.01 (0.00)***	−0.01 (0.00)***	−0.01 (0.00)***
femaleTRUE	−0.37 (0.04)***	−0.36 (0.04)***	−0.28 (0.04)***	−0.29 (0.04)***
hsize	−0.03 (0.02)*	−0.04 (0.02)*	−0.03 (0.02)	−0.03 (0.02)
edu2	0.44 (0.08)***	0.40 (0.08)***	0.33 (0.08)***	0.30 (0.08)***
edu3	0.47 (0.08)***	0.42 (0.08)***	0.34 (0.08)***	0.30 (0.08)***
edu4	0.45 (0.09)***	0.42 (0.09)***	0.33 (0.09)***	0.30 (0.10)**
IP	0.04 (0.03)	0.03 (0.03)	0.02 (0.03)	0.02 (0.03)
UR	−0.03 (0.01)	−0.02 (0.02)	−0.03 (0.01)*	−0.03 (0.01)*
CPI	−0.10 (0.06)	−0.12 (0.07)	−0.04 (0.06)	−0.03 (0.07)
abs_dCPI	−0.12 (0.09)	−0.09 (0.10)	−0.12 (0.08)	−0.10 (0.09)
(Intercept)	1.91 (0.17)***	1.95 (0.19)***	2.26 (0.17)***	2.29 (0.19)***
Num. obs.	14160	14160	14023	14023

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$
Numbers in parentheses are White's standard errors.

Table 9: Robust Heckit estimates of the outcome equations

	px1		px5	
	$K = 100$	$K = 1.345$	$K = 100$	$K = 1.345$
MPN	0.22 (0.25)	0.12 (0.19)	−0.03 (0.30)	0.15 (0.22)
IN	0.64 (0.19)***	0.60 (0.14)***	0.58 (0.21)**	0.43 (0.19)*
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)		
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)
ytl42	−0.56 (0.17)***	−0.31 (0.32)	−0.41 (0.14)**	−0.38 (0.20)
ytl43	−0.88 (0.23)***	−0.41 (0.48)	−0.48 (0.17)**	−0.44 (0.27)
ytl44	−1.09 (0.24)***	−0.55 (0.51)	−0.57 (0.19)**	−0.48 (0.31)
age	0.01 (0.00)***	0.01 (0.01)	0.01 (0.00)*	0.01 (0.01)
femaleTRUE	0.49 (0.17)**	0.13 (0.39)	0.42 (0.11)***	0.26 (0.20)
hsize	0.10 (0.03)**	0.02 (0.05)	0.05 (0.03)*	0.04 (0.03)
edu2	−0.45 (0.40)	0.11 (0.73)	−0.58 (0.27)*	−0.41 (0.35)
edu3	−0.64 (0.40)	0.04 (0.75)	−0.65 (0.27)*	−0.41 (0.36)
edu4	−0.88 (0.40)*	−0.12 (0.75)	−0.74 (0.28)**	−0.44 (0.37)
IP	0.39 (0.07)***	0.29 (0.06)***	−0.05 (0.05)	−0.04 (0.04)
UR	−0.03 (0.02)	−0.05 (0.03)	0.07 (0.02)***	0.08 (0.02)***
CPI	1.19 (0.15)***	0.89 (0.15)***	0.16 (0.09)	0.13 (0.07)
(Intercept)	2.90 (0.49)***	2.16 (0.80)**	2.22 (0.32)***	1.77 (0.32)***
sigma	3.86	3.70	3.17	3.13
IMR1	−2.78 (2.49)	0.61 (6.23)	−4.13 (1.92)*	−3.90 (3.54)
Num. obs.	14160	14160	14023	14023
Censored	734	734	789	789
Observed	13426	13426	13234	13234

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$
Numbers in parentheses are White's standard errors.

Throughout our analyses, however, we find no evidence that monetary condition news directly influences household inflation expectations. Hence our analyses supports the conclusion by Sheen and Wang (2023) that households did not adjust their inflation expectations upon hearing monetary condition news during the zero lower bound period.

5 Discussion

We reestimated a regression model in Sheen and Wang (2023) using a sample selection model to see if ignoring DK responses causes sample selection bias, addressing their mistreatment of skipped responses as well. The results were mixed. The ML estimator gave no evidence of sample selection bias, whereas the Heckit estimator gave an evidence of sample selection bias for medium-run inflation expectations. However, the latter evidence disappeared when we used a robust Heckit estimator.

Empirical researchers may find these mixed results disappointing. However, we believe that the results are interesting from a methodological point of view. The difference between the ML and Heckit estimates suggests that the standard sample selection model is not exactly correct, whereas the difference between the classical and robust Heckit estimates suggests that the classical estimate may suffer from outliers. Thus we propose handling DK responses as follows:

1. Do not simply discard DK responses. Estimate a sample selection model to check if DK responses are ignorable. Compare the OLS, ML, Heckit, and robust Heckit estimates.

2. If there is no evidence of sample selection bias at all, then use the OLS estimate. Otherwise proceed as follows:

   (a) If the ML, Heckit, and robust Heckit estimates coincide, then use the ML estimator, which is most efficient if the standard sample selection model is exactly correct.

   (b) If the ML and Heckit estimates differ, but the classical and robust Heckit estimates coincide, then use the classical Heckit estimator, which may be consistent even when the ML estimator is not, and more efficient than the robust Heckit estimator under correct specification.

   (c) If the classical and robust Heckit estimates differ, then use the robust Heckit estimator, which is robust to outliers.

This procedure is useful not only for handling DK responses in inflation expectations, but also for handling missing responses in general.

6 Conclusion

DK responses are common in surveys on inflation expectations. Ignoring them in a regression analysis may cause sample selection bias. One can use a sample selection model to avoid the bias. If nonrobustness of the standard estimators is a concern, then one can use a robust Heckit estimator.

This paper assumes that the specification of the standard sample selection model is approximately correct (local misspecification). If this model specification is not correct even approximately (global misspecification), then one may prefer a semi/non-parametric approach; e.g., Das, Newey, and Vella (2003) and Newey (2009). However, a semi/non-parametric estimator is not robust if it has an unbounded influence function. Robust semi/non-parametric estimation of a sample selection model is a possible topic for future work.

This paper still ignores two types of missing responses: (1) DK responses in the regressors and (2) unit nonresponses. If DK responses in the regressors are exogeneous, then ignoring them does not cause sample selection bias. One can include them using DK dummies to improve efficiency, but such regressors may cause conditional heteroscedasticity.[11] If DK responses appear on both sides of the regression equation, then we have a sample selection model with conditional heteroscedasticity, and we must use a generalized Heckit estimator; see Carlson (2024). If DK responses in the regressors are endogenous, then we need ML or IV estimation.

Many empirical works in economics ignore unit nonresponses, and treat the data as simple random samples. One can use the design weights to adjust for various factors including unit nonresponses. Although such weights are useful, sample selection bias remains if unit nonresponses are nonignorable. Correcting for the bias requires some information on nonrespondents; e.g, Korinek, Mistiaen, and Ravallion (2007) use the geographic structure of nonresponse rates to estimate the response probability function for reweighting, and Akande, Madson, Hillygus, and Reiter (2021) use the population counts of some demographic variables to impute missing values. Addressing the issue of nonignorable unit nonresponses may further change the results of Sheen and Wang (2023), and of many other empirical works as well.

This paper treats DK responses as item nonresponses. However, the two are not identical for the percentage of inflation in the MSC, since respondents can choose DK to the question on the percentage of inflation only if they choose "up" or "down" to the question on the direction of inflation; i.e., DK responses have some qualitative information in this case. Hence a promising direction for future work is to combine the qualitative and quantitative information, which is a kind of mixed methods research advocated by Creswell (2022).

Acknowledgements

We thank Edda Claus for her invaluable comments. This work was supported by JSPS KAKENHI Grant Number JP21K01434.

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[11] In general, including DK dummies as regressors do not improve efficiency, and mistreatment of them may cause omitted variable bias; see Jones (1996).

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