

# **Measuring and Reducing Non-Response and Linkage Non-Consent Bias**

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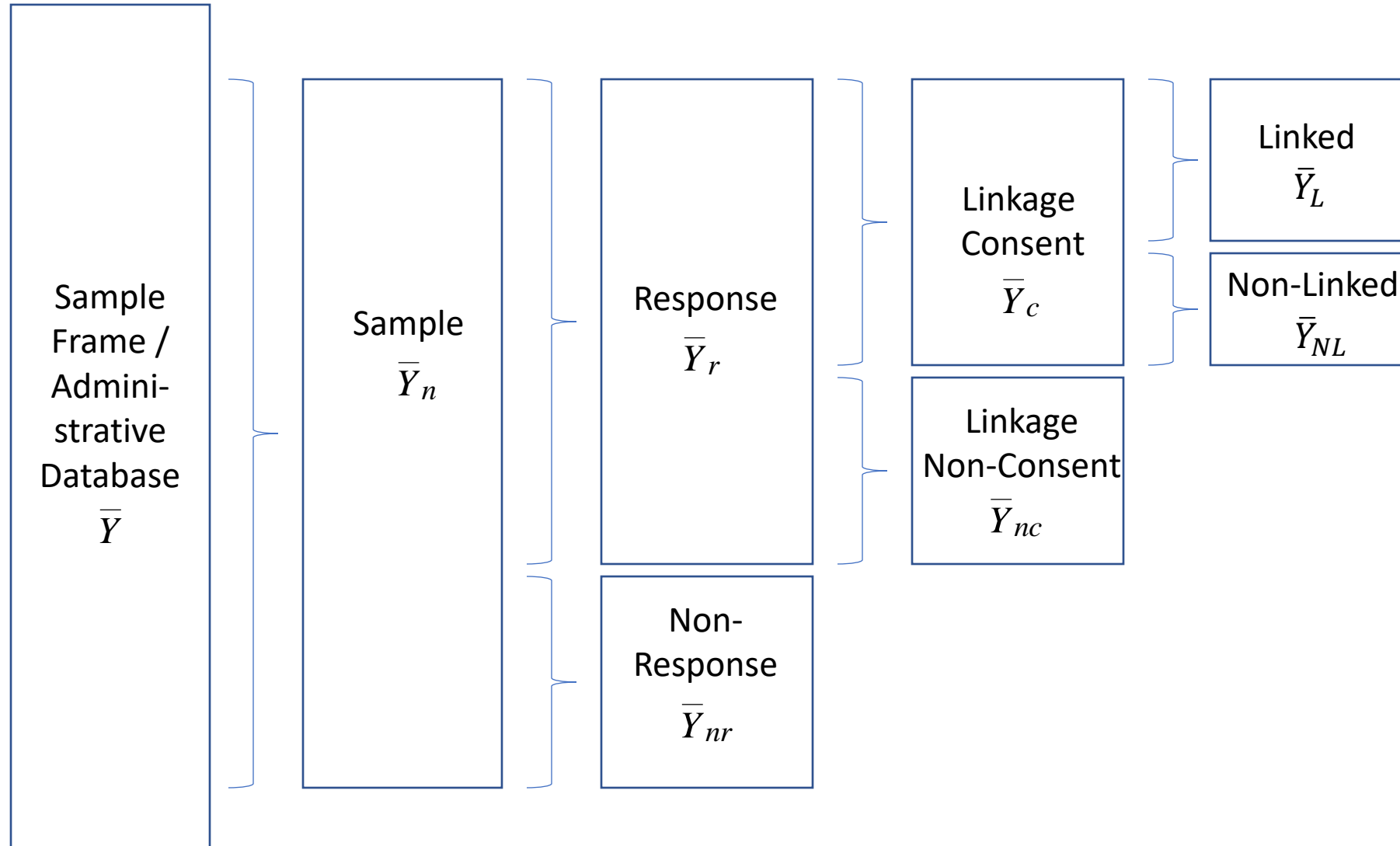
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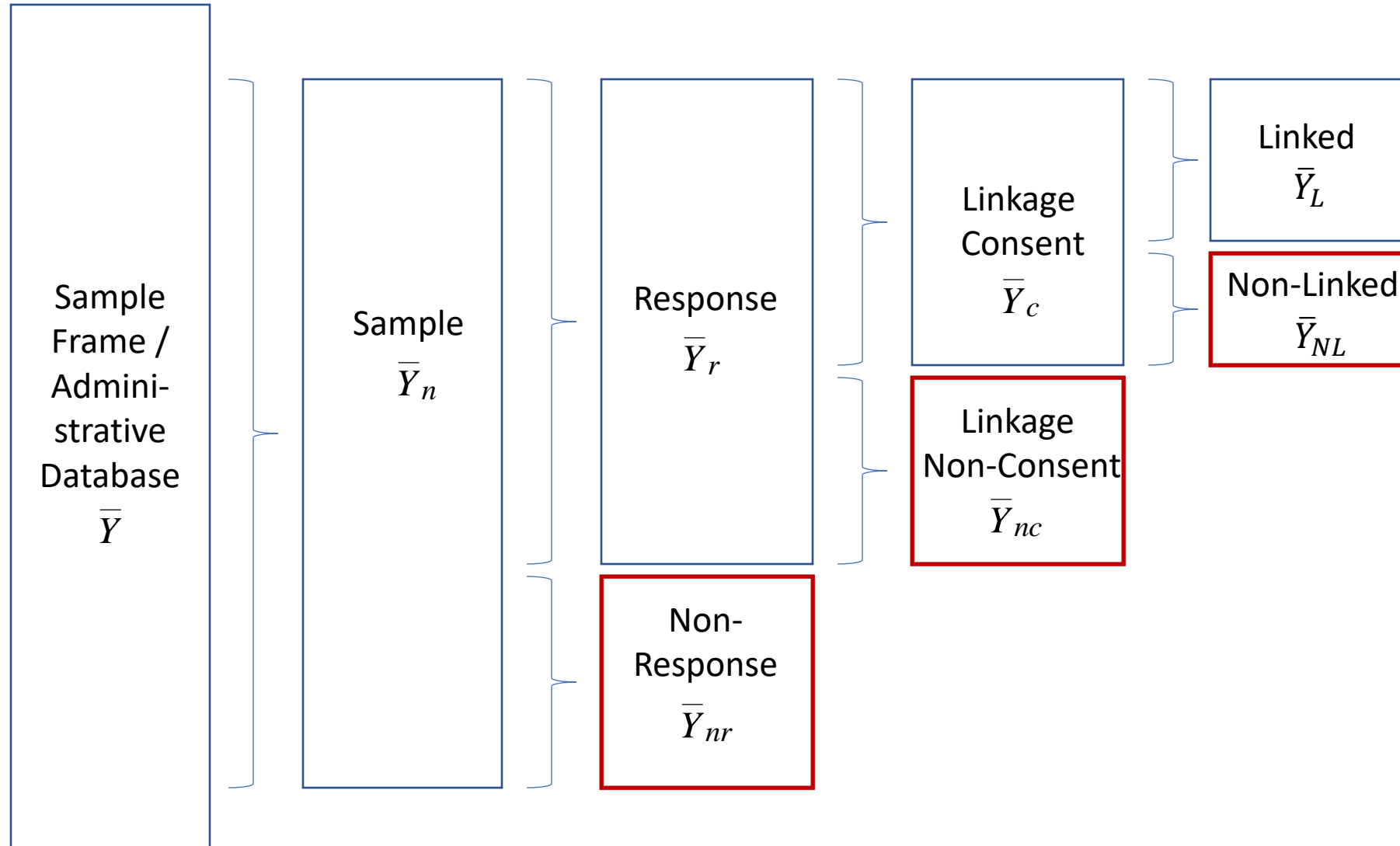
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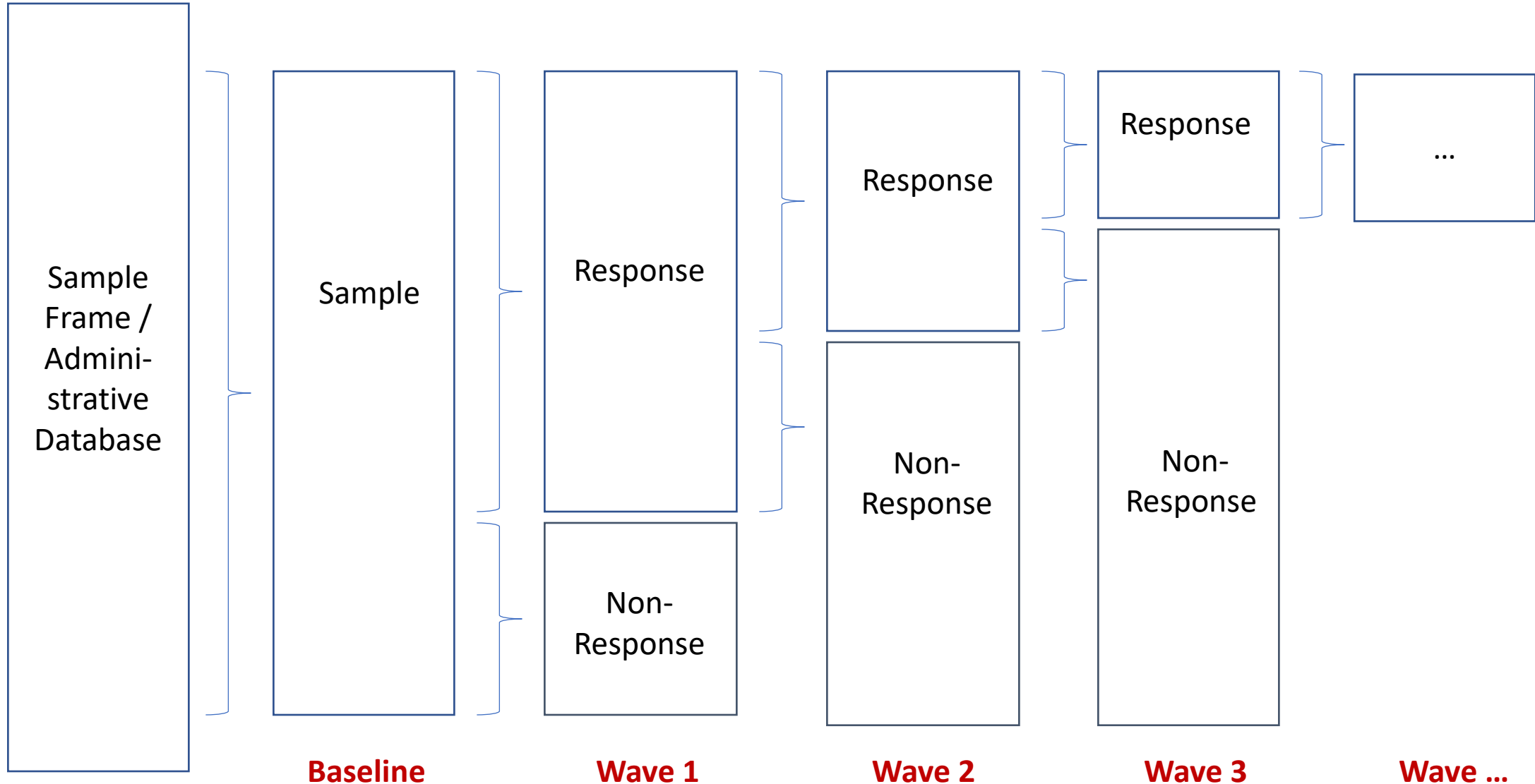
# Conceptual Pathway to Response and Data Linkage



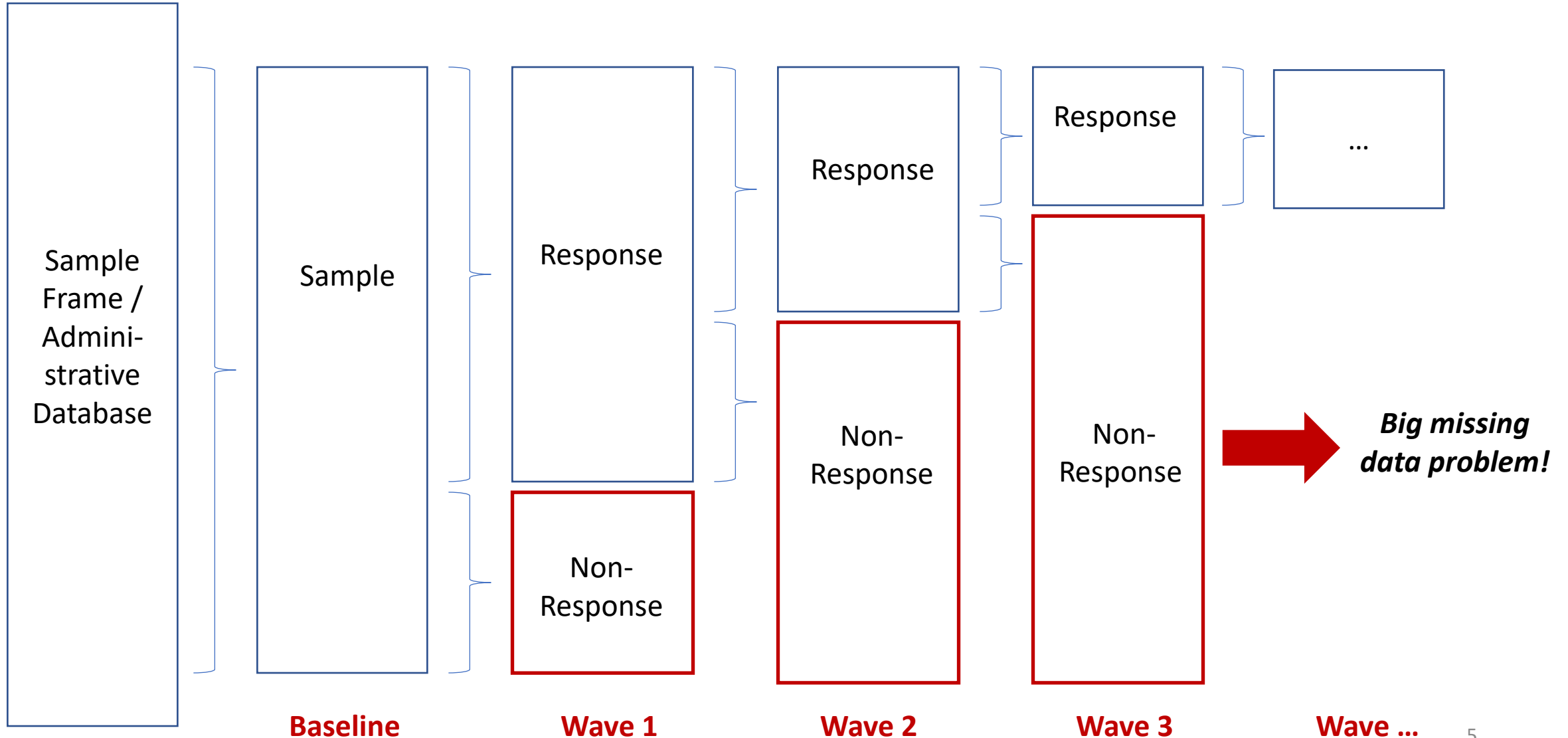
# Conceptual Pathway to Response and Data Linkage



# Conceptual Pathway to Panel Response



# Conceptual Pathway to Panel Response



# Auxiliary Data Sources

- Auxiliary data used to identify and correct both types of bias
- Non-Response
  - Administrative data
  - Frame data
  - Paradata
  - Commercial data
  - Previous wave(s) survey data
- Linkage Non-Consent
  - Same as non-response, and current-wave survey data

# Magnitude of Non-Response and Linkage Non-Consent Bias

Two Examples

# Sakshaug and Kreuter (2012)

CATI/CAPI cross-sectional survey of welfare benefit recipients in Germany

- Administrative records available for drawn sample

<i>Characteristics</i>	<i>Non-Response Bias</i>	<i>Non-Consent Bias</i>	<i>Measurement Bias</i>
Age (years)	0.1	-0.3*	-0.0
Foreign (%)	-5.6*	-0.9*	-2.5*
Unemployment benefit (%)	3.2*	-0.3	-7.5*
Disability (%)	0.4	0.0	6.1*
Employment status (%)	1.0	0.3	-1.0
Monthly income (EUR)	-71.4*	1.7	402.4*

\*  $p < 0.05$

Non-response bias larger than linkage non-consent bias

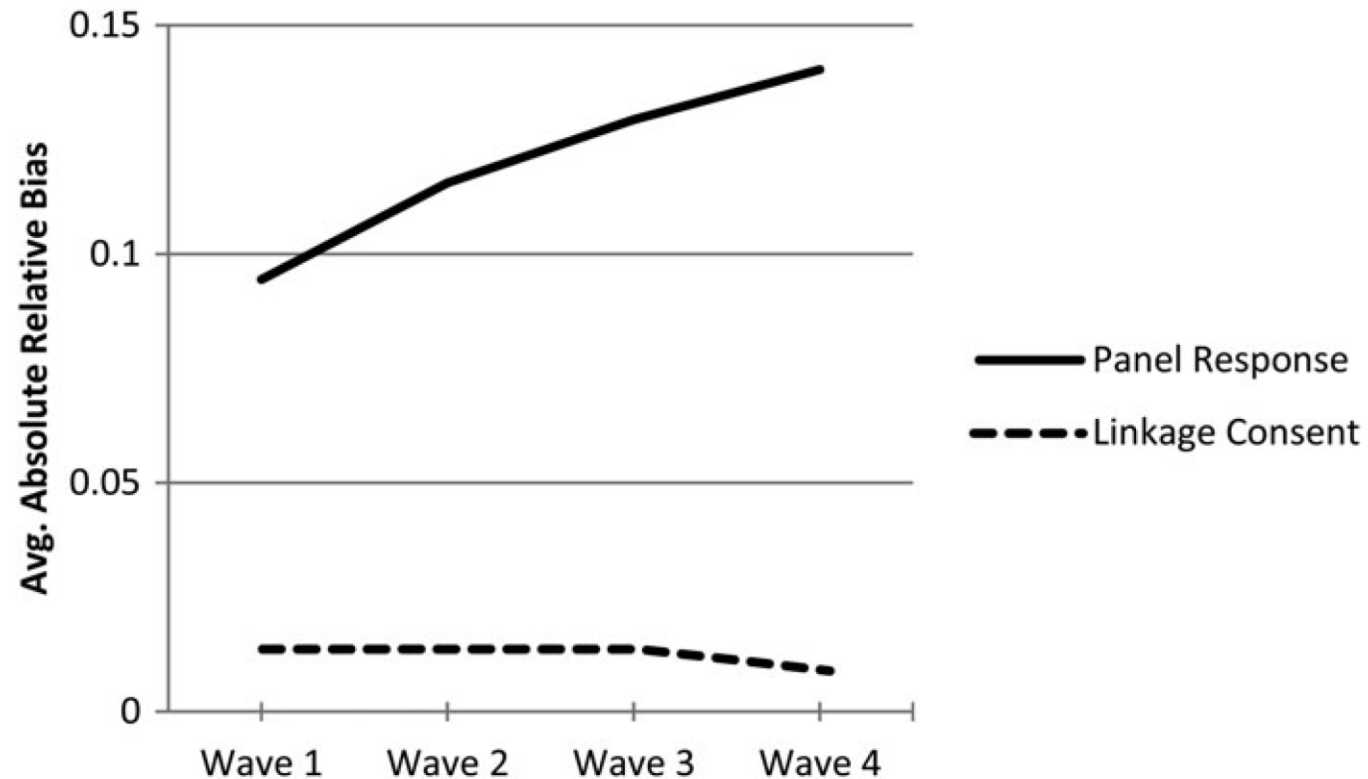
- Measurement bias (mostly) larger than both



# Sakshaug and Huber (2016)

CATI panel survey of employees in Germany

- Administrative data available for drawn sample



**Figure 4. Absolute Relative Bias Averaged across Six Cross-Sectional Items by Wave**

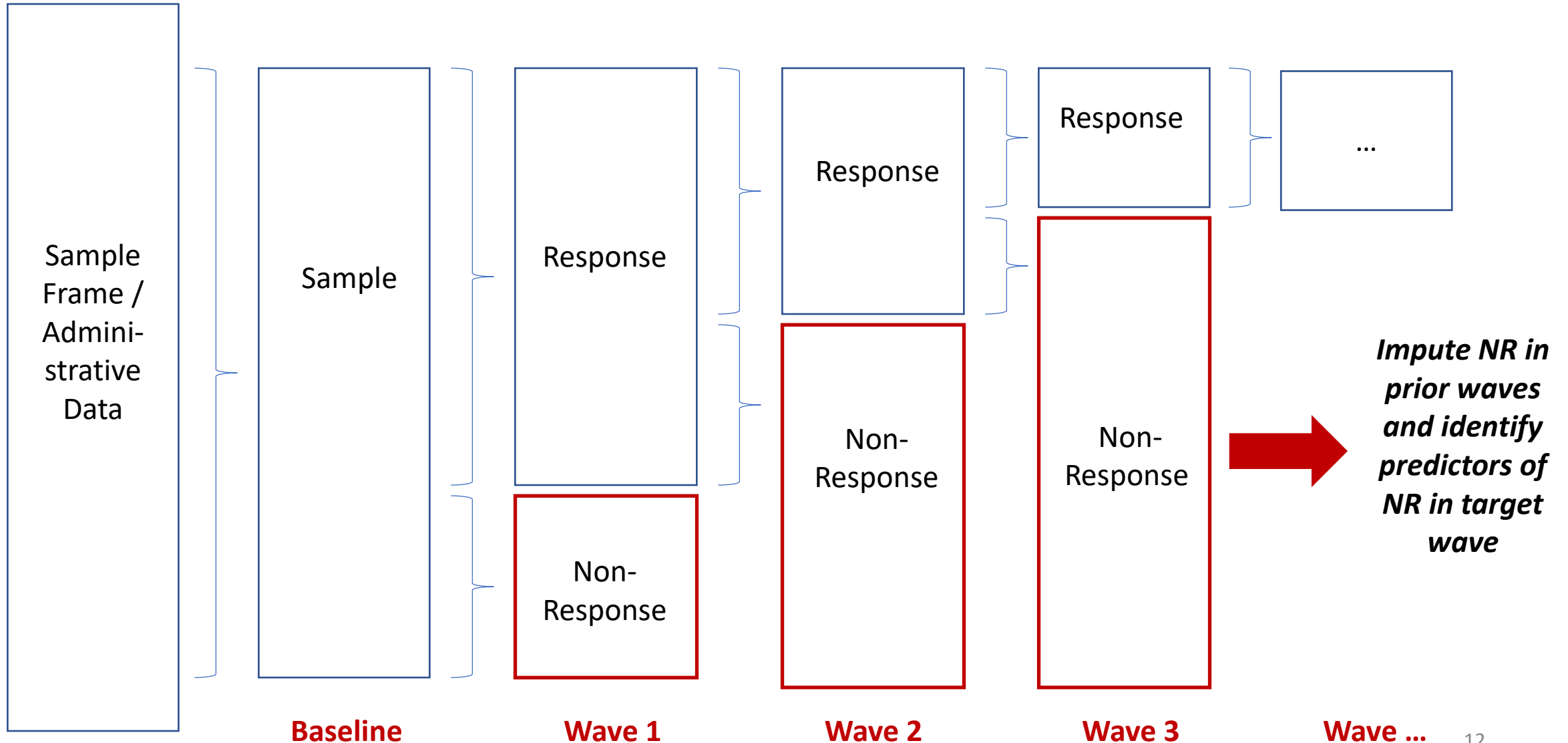
# Adjusting for Panel Non-Response Bias

Using Previous Wave(s) Survey Data

# Silverwood et al. (2020)

- Data-driven multiple imputation (MI) approach for non-response bias adjustment
- Applied to UCL Next Steps Cohort Study
- Aim: Adjust for cumulative non-response bias in Wave 8 (Age 25) by using survey data from Waves 1-7
- Approach capitalizes on rich survey data collected in earlier waves
  - 868 eligible predictor variables
- Method: Multiply impute NR in Waves 1-7, apply variable selection to identify predictors of Wave 8 NR, and use retained predictors to multiply impute Wave 8 outcomes

# Data Driven Approach for Non-Response Bias Adjustment



# Silverwood et al. (2020)

	Wave 1 Rs		Wave 8 Rs			NR bias	
<i>Characteristics</i>			<i>Complete case analysis</i>	<i>MI approach</i>		<i>Before MI</i>	<i>After MI</i>
Male (%)	51.5		45.0	46.6		-6.5	<b>-4.9</b>
Non-white British (%)	14.1		12.8	14.3		-1.3	<b>0.2</b>
Single parent HH (%)	23.5		19.5	23.3		4.0	<b>-0.2</b>
Ever suspended (%)	11.1		7.3	10.5		-3.8	<b>-0.6</b>
Attend university (%)	36.9*		44.5	38.2		7.6	<b>1.3</b>
Income (GBP)	33,022		34,756	32,673		1734	<b>-349</b>

\* External benchmark (estimated)

# Adjusting for Panel Non-Response Bias

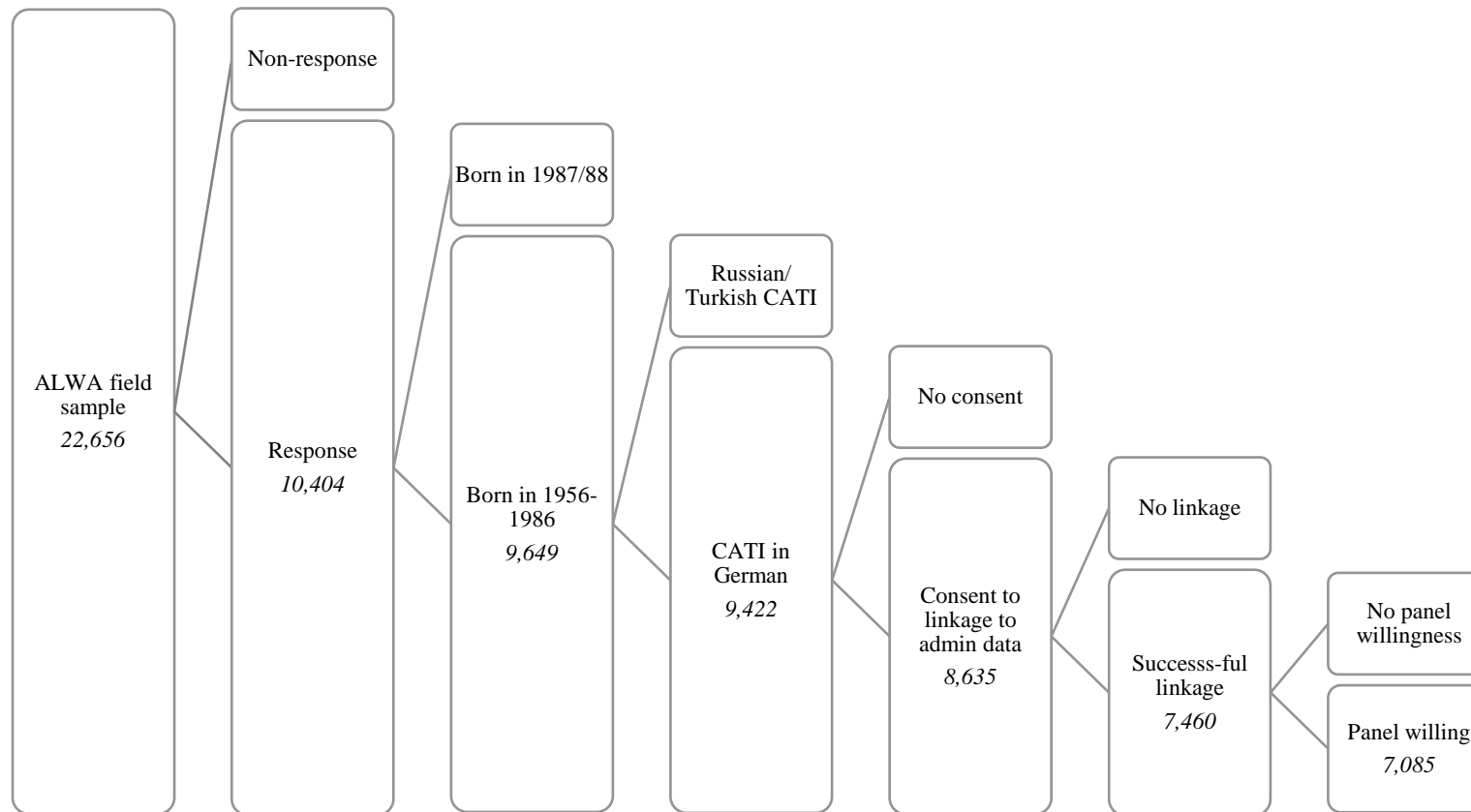
Using Linked Administrative Data in a Piggyback Longitudinal Survey

# Piggyback Longitudinal Surveys

- Several longitudinal studies recruit respondents from independent cross-sectional surveys
  - US National Health Interview Survey → US Medical Expenditure Panel Survey-Household Component
  - Health Surveys for England → English Longitudinal Study of Ageing
  - German General Social Survey → GESIS Panel
- Some of these cross-sectional surveys perform administrative data linkages (given respondent consent)
- Idea: Use existing linkages from cross-sectional survey to measure and adjust for NR bias in piggyback longitudinal survey
- Challenge: Not all cross-sectional respondents are “panel willing” or consent to linkage
  - Further adjustments for multiple sources of selection

# Büttner, Sakshaug, and Vicari (forthcoming)

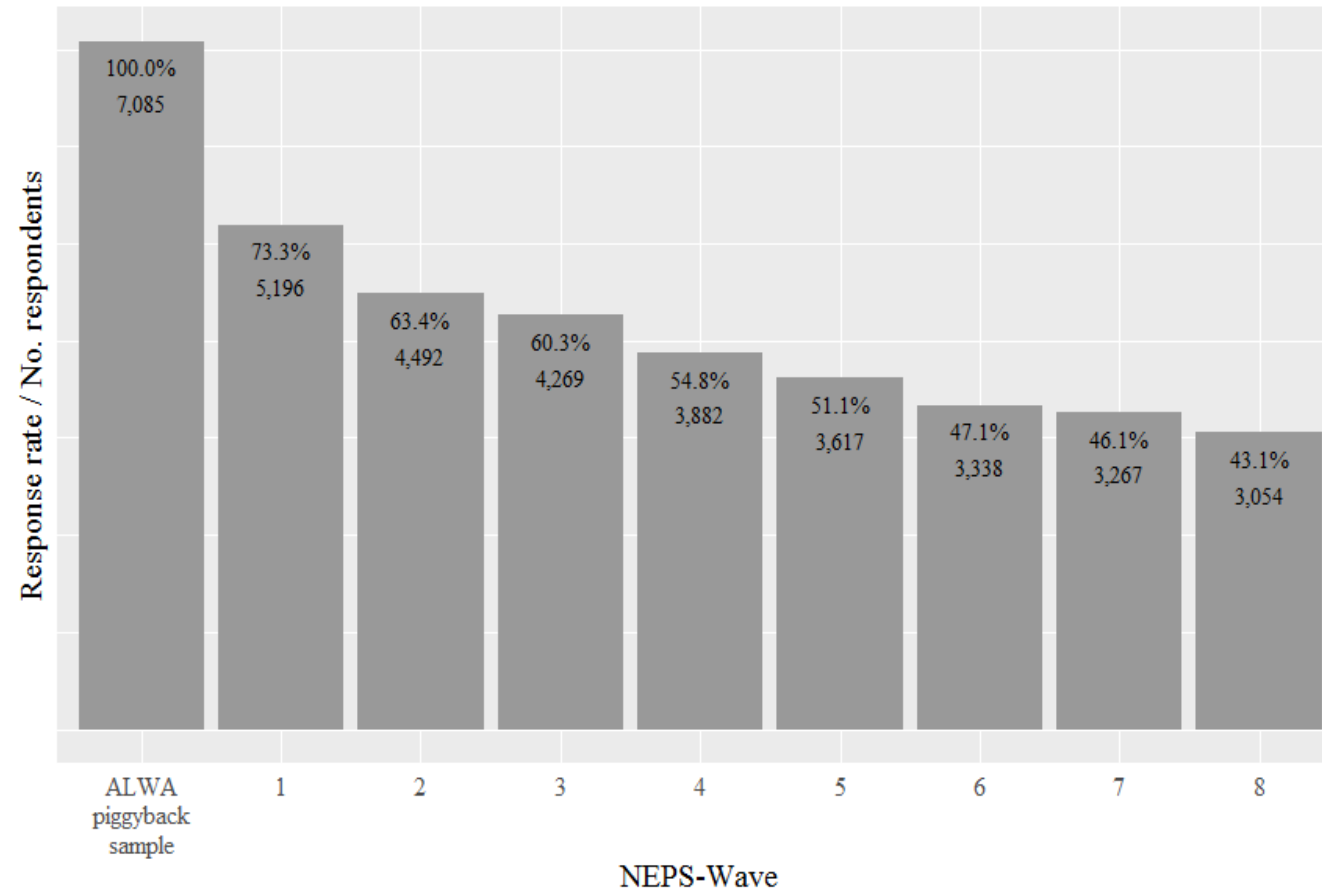
- Cross-sectional survey: “Working and Learning in a Changing World” (ALWA)
- Linked administrative data: “Integrated Employment Biographies”



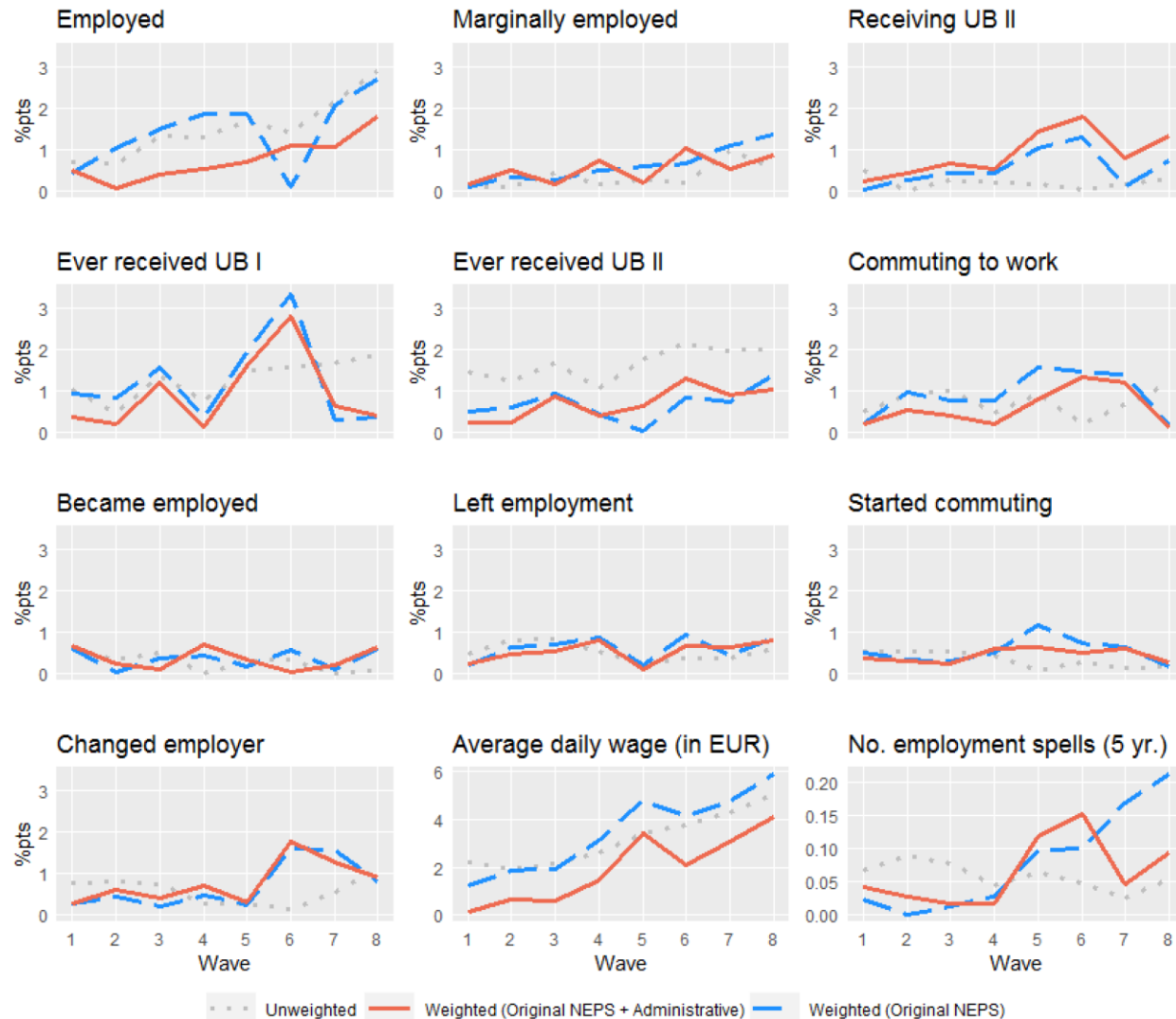


# Büttner, Sakshaug, and Vicari (forthcoming)

- Piggyback longitudinal survey: “National Educational Panel Study” (NEPS)



# Absolute Attrition Bias by Wave and Weighting Scheme



- Linked administrative variables significant predictors in multiple waves' response models
- Current- and between-wave information associated with attrition
- Incorporating linked admin data in weighting adjustment reduces NR bias for some variables

Büttner, Sakshaug, and Vicari (forthcoming)

# Reducing (the Risk of) Linkage Non-Consent Bias

Survey Design Strategies

# Linkage Non-Consent Bias

- Some statistical adjustment methods for non-consent/linkage bias
  - Weighting (Yang, Fricker, and Eltinge 2019)
  - Imputation (Zhang, Parker, and Schenker 2016)
  - Statistical matching (Gessendorfer et al. 2018)
- Other approaches try to maximize consent rates at the design stage
  - Placement of consent Q in questionnaire
    - E.g. Beginning, middle, end
  - Framing of consent Q
    - E.g. Gain framing / loss framing

# Consent Placement Studies

- Sakshaug and Vicari (2018) – Web survey of establishments
  - **Beginning: 61.3%**
  - Middle: 52.3%
  - End: 45.2%
- Sala, Knies, and Burton (2014) – CAPI survey of households
  - **“In context”: 65%**
  - End: 58%
- Sakshaug, Tutz, and Kreuter (2013) – CATI survey of employed/unemployed persons
  - **Beginning: 95.6%**
  - End: 86.0%

# Consent Framing Studies

Gain/benefit framing: *“To keep the interview as short as possible...”*

- Sakshaug et al. (2019) – CATI employee survey
  - Gain vs. neutral: no effect overall; **4-10 percentage points higher for “busy” respondents**
- Sakshaug, Tutz, and Kreuter (2013) – CATI survey of employed/unemployed persons
  - Gain vs. neutral: no effect
- Sakshaug and Kreuter (2014) – Web survey of employed/unemployed persons
  - **Gain: 61.6%**
  - Neutral: 55.4%

Loss framing: *“The answers you provided will be less useful if we cannot link...”*

- Kreuter, Sakshaug, and Tourangeau (2016) – CATI survey of US registered voters
  - Gain: 56.1%
  - **Loss: 66.8%**

# Interaction between Placement and Framing

Telephone survey		Gain	Loss	Total
Placement	Beginning	91.7	87.1	<b>89.1</b>
	End	72.3	74.6	<b>73.6</b>
Total		82.9	80.9	81.8
Web survey		Gain	Loss	Total
Placement	Beginning	80.5	85.9	<b>83.1</b>
	End	<b>65.6</b>	<b>76.6</b>	<b>71.5</b>
Total		73.4	81.0	77.3

Positive effect of placement (“beginning”) in both surveys

- Irrespective of framing
- Difference between 12-16 %-points

In Web survey, interaction between framing and placement

- Loss framing increases consent, but only at “end” of iw

Sakshaug et al. (2019)

# Conclusions

- Linkage consent biases exist, but are small relative to non-response biases
- Using rich survey and/or linked-administrative data useful for measuring/adjusting for panel non-response bias
- Linkage consent rates improved by asking consent question at the beginning of questionnaire (as opposed to end placement)
- Consent question framing effects are less consistent, except in Web surveys



# Thank you

Questions? Comments? Collaborations?

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