ASSESSING THE CAUSAL EFFECTS OF INFLATION EXPECTATIONS ON HOUSEHOLD DECISIONS

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EXPECTATIONS AND DECISIONS

"*When my information changes, I alter my conclusions. What do you do, sir?*"

John Maynard Keynes

- Along just about every dimension of macroeconomic models, optimal decisions depend on expectations about the future:
  - Consumption/saving decisions
  - Investment decisions by households and firms
  - Pricing and wage-setting decisions
  - Employment decisions
  - Policymaking
  - ….
- A key challenge for macroeconomists is identifying and characterizing the role that expectations *actually* play in decision-making.

The Werning (2022) Cautionary Example

The New Keynesian Phillips Curve can be written as

$$\pi_t = \beta E_t \pi_{t+1} + \alpha x_t$$

which suggests that the pass-through of inflation expectations into inflation is approximately 1.

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The New Keynesian Phillips Curve can be written as

$$\pi_t = \alpha E_t \sum_{j=0}^{\infty} \beta^j x_{t+j}$$

which suggests that the pass-through of inflation expectations into inflation is 0.

The Werning (2022) Cautionary Example

- Instead, start with initial FOCs of firm profit maximization and take partial derivatives with respect to inflation expectations *holding everything else constant* ("temporary equilibrium").

$$p_t^* - P_{t-1} = \left(\frac{1}{1-\beta\lambda}\right)\pi^e + a_t$$

$$\Rightarrow \pi_t = \left(\frac{1-\lambda}{1-\beta\lambda}\right)\pi^e + \left(\frac{1}{1-\lambda}\right)a_t$$

$$\Rightarrow \frac{\partial \pi_t}{\partial \pi_t^e} \approx 1$$

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$$\Longrightarrow \frac{\partial \pi_t}{\partial \pi_t^e} \approx 1$$

- To estimate the passthrough of beliefs into decisions, we therefore need:
  - data on individual *expectations*
  - *exogenous* variation in those expectations
  - data on subsequent *decisions* of agents

THE RCT APPROACH

Elicit **prior** expectations and planned decisions

Step 1: Measuring expectations of economic agents using a survey (see e.g. Stantcheva 2022).

THE RCT APPROACH

Elicit **prior** expectations and planned decisions

Information treatment

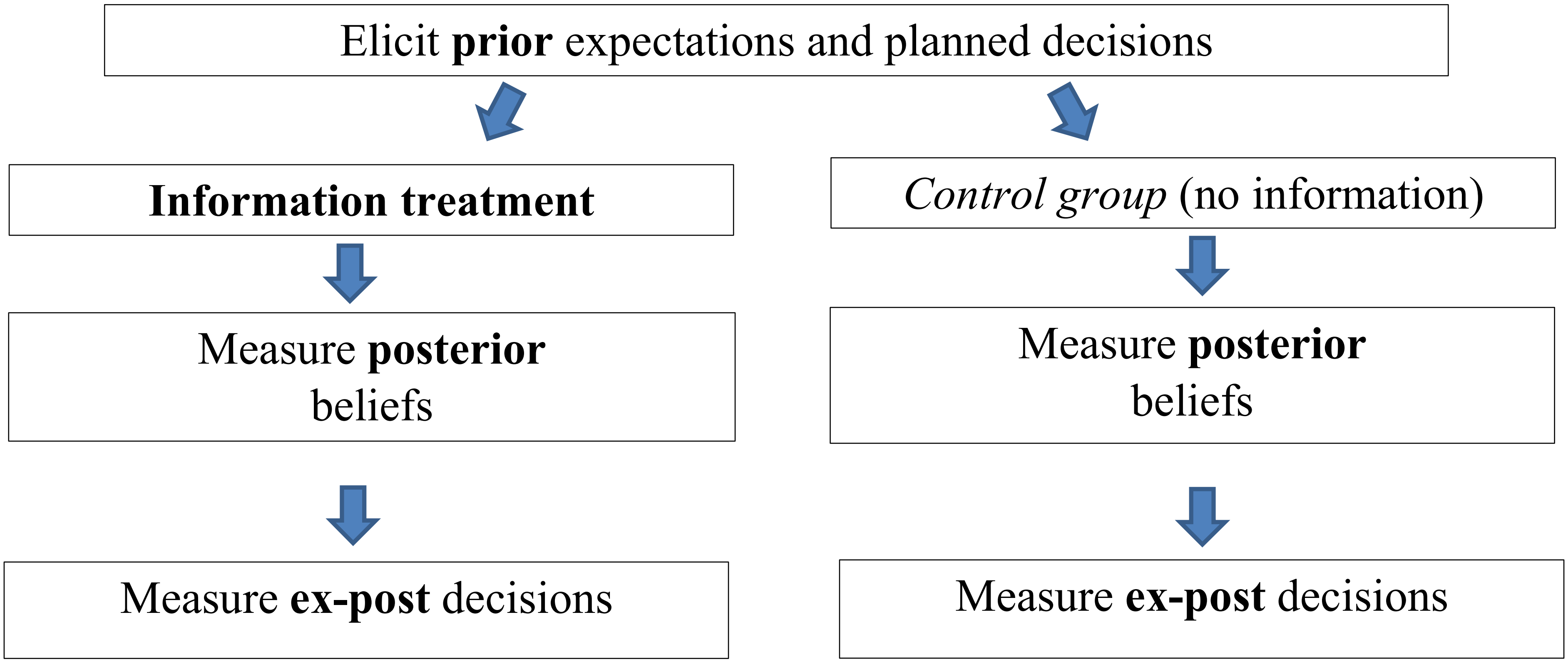
Measure **posterior** beliefs

Control group (no information)

Measure **posterior** beliefs

Step 2: Implement a randomized information treatment that generates exogenous variation in beliefs (see e.g. Haaland et al. 2023).

THE RCT APPROACH



Step 3: Measure ex-post decisions to assess how expectations affect economic decisions.

Example: CGW (2022)

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- **The survey:** Nielsen Homescan Panel participants
  - Around 80,000 representative households participate in the panel
  - We survey these households repeatedly over time, ~20,000/wave
  - We measure inflation expectations using both distributional and point forecasts.
  - We also ask about their recent consumption levels and their planned spending decisions.

EXAMPLE: CGW (2022)

1. **The survey:** Nielsen Homescan Panel participants
2. **The information treatment:** information about inflation/Fed
   a. In 2018Q2, households were *randomly* assigned to either control or one of multiple treatment groups
   b. Some treated households were told about recent inflation rate.
   c. Some treated households were told about Fed's inflation target.
   d. Some treated households were told about Fed's inflation forecast.
   e. Posterior beliefs measured after treatment.

Interpreting Treatment Effects

Simple Bayesian updating predicts:

$$posterior_i = (1 - G) \times prior_i + G \times signal$$

where G will be large when signal is credible and informative and small otherwise. When G is small, posteriors will be close to priors.

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Estimate treatment effect in the survey as follows:

$$posterior_i = \alpha + \beta \times prior_i + \delta \times T_i + \gamma \times (T_i \times prior_i) + error_i$$

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- *Control group:* $T_i = 0,\ posterior_i = prior_i\ \ so\ \hat{\beta} = 1$

INTERPRETING TREATMENT EFFECTS

Simple Bayesian updating predicts:

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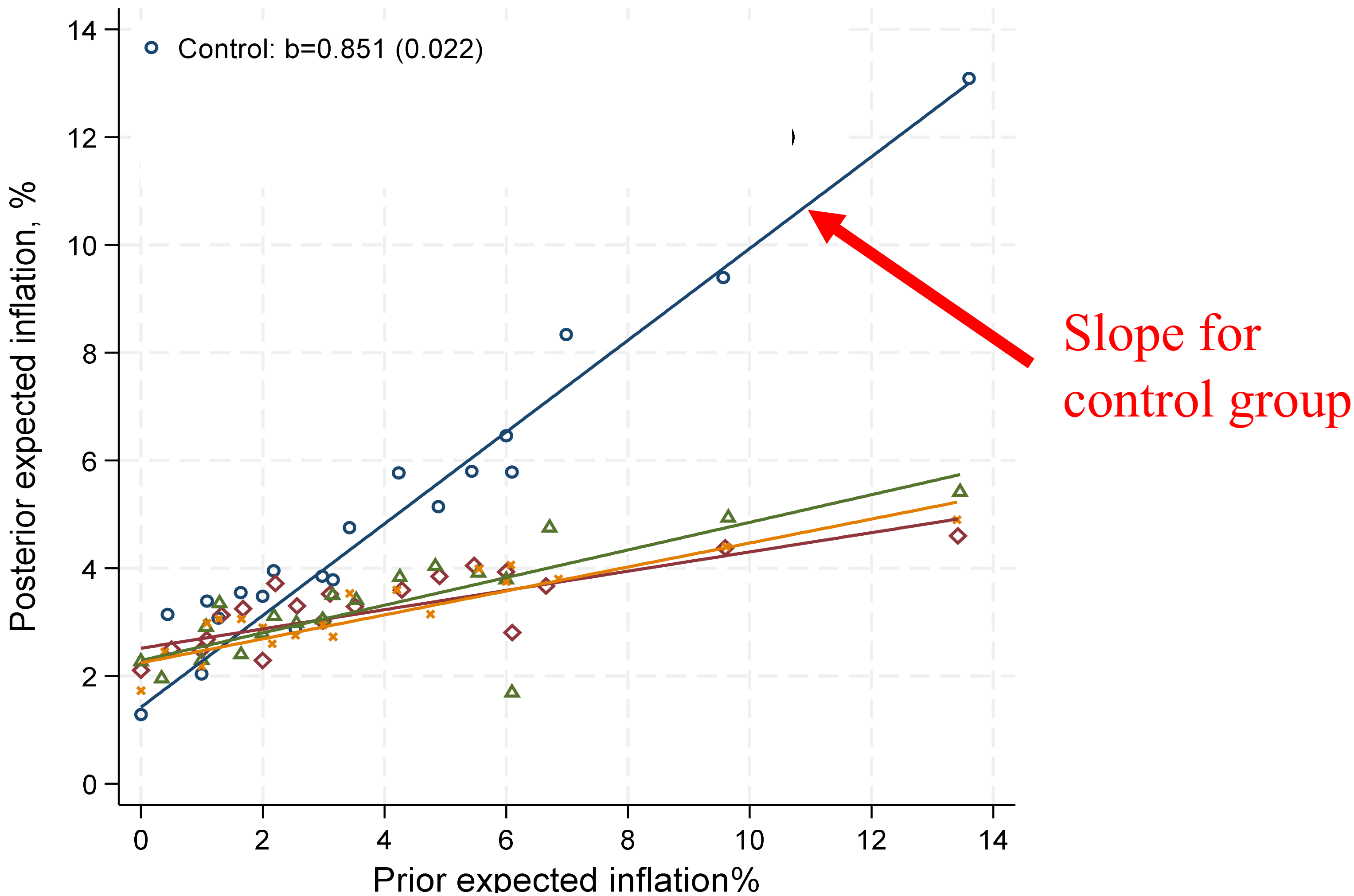
Estimate treatment effect in the survey as follows:

$$posterior_i = \alpha + \beta \times prior_i + \delta \times T_i + \gamma \times (T_i \times prior_i) + error_i$$

- *Control group:* $T_i = 0,\ posterior_i = prior_i\ \ so\ \hat{\beta} = 1$
- *Treatment group:* $T_i = 1,\ posterior_i = (\alpha + \delta) + (\beta + \gamma) \times prior_i,$ so $\hat{\gamma}$ tells us how much less weight treated firms place on their prior (equivalent to $-G$) relative to control.

ILLUSTRATION: NIELSEN RCT 2018Q2 (CGW 2022)



Because different questions are used for priors and posteriors, it is common for the slope coefficient to be less than one for control group.

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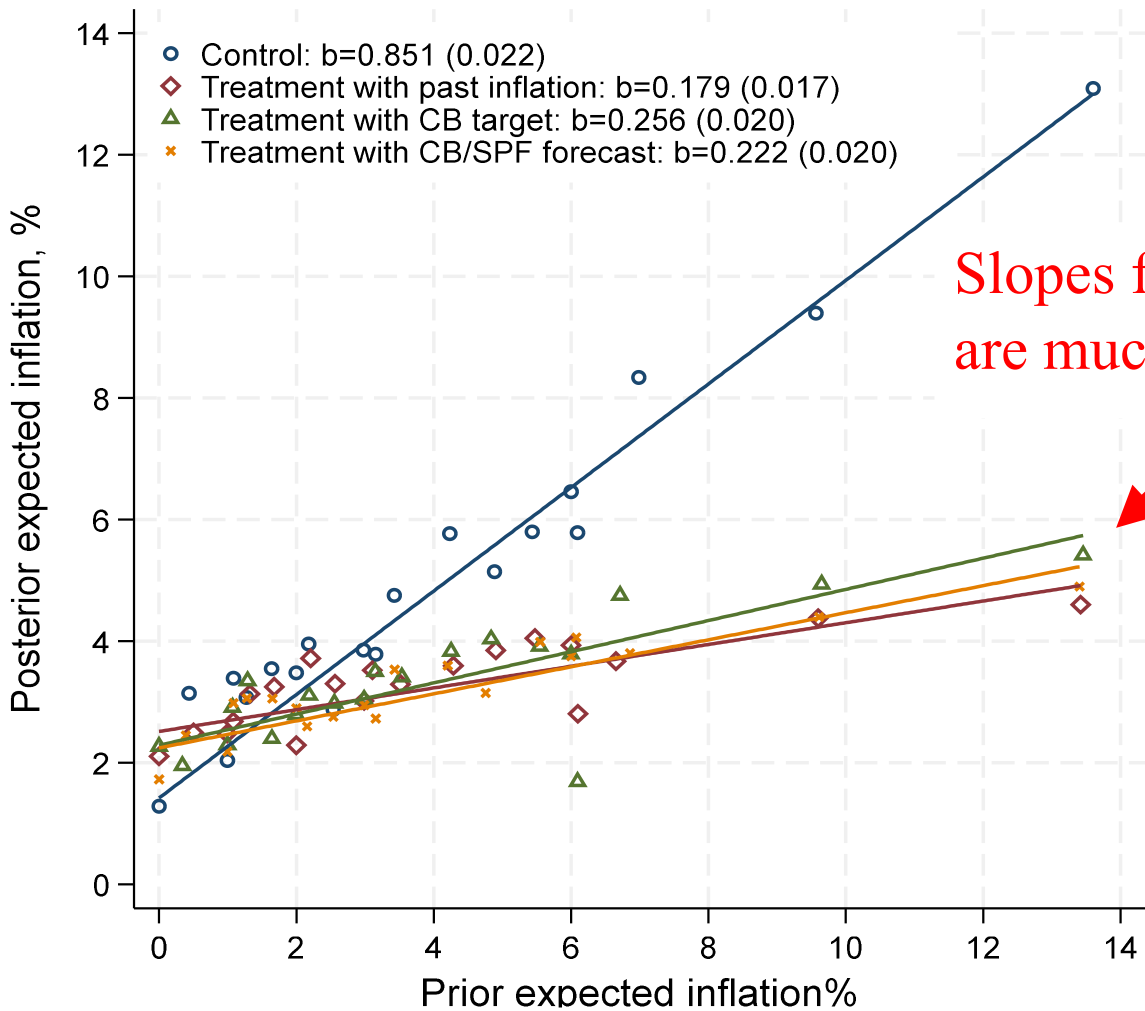

Slopes for treatment groups are much flatter, i.e. $\hat{\gamma} \ll 0$

This is an example of treatments having a very powerful effect on beliefs. We'll focus on $\hat{\gamma}/\hat{\beta}$ (≈ -0.75) as our metric for the strength of the treatment effect.

EXAMPLE: CGW (2022)

1. **The survey:** Nielsen Homescan Panel participants
2. **The information treatment:** information about inflation/Fed
3. **The effects on decisions:** Homescan spending data.
   a. We can measure spending directly via the spending that is measured by Nielsen directly and self-reported measures in survey.

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1. **The survey:** Nielsen Homescan Panel participants
2. **The information treatment:** information about inflation/Fed
3. **The effects on decisions:** Homescan spending data.
   a. We can measure spending directly via the spending that is measured by Nielsen directly and self-reported measures in survey.
   b. We can estimate the *causal* effect of expectations on spending using:

$$\log(spend)_{i,t+h} = \beta E_i^{post}\pi + \gamma E_i^{prior}\pi + \kappa \log(spend)_{it} + Controls_{it} + error_{i,t+h}$$

while instrumenting for posterior inflation expectations using:

$$E_i^{post}\pi = a + \sum_j b_j \times Treat_{i,j} + \sum_j \gamma_j \times Treat_{i,j} \times E_i^{pre}\pi + \psi \times E_i^{pre}\pi + error$$

EXAMPLE: CGW (2022)

Dep. var. is indicated in the title of the panel	Actual spending, horizon, month	
	3 months	6 months
	(1)	(2)
Panel A. Total Spending, scanner		
Posterior inflation expectations		
Observations	13,170	13,132
1st stage F-stat	134.8	128.1

This approach yields very strong instruments for expectations.

EXAMPLE: CGW (2022)

Dep. var. is indicated in the title of the panel	Actual spending, horizon, month	
	3 months	6 months
	(1)	(2)
Panel A. Total Spending, scanner		
Posterior inflation expectations	0.950***	0.864**
	(0.286)	(0.336)
Observations	13,170	13,132
1^{st} stage F-stat	134.8	128.1

This approach yields evidence suggesting positive *causal* link from inflation expectations to total spending of households, but negative w.r.t durables.

EXAMPLES OF THIS CAUSAL APPROACH

- The effects of *inflation expectations*:
  - Firms: CGK (2018), CGR (2020), Abberger et al. (2024)
  - Households: **CGW (2022)**, CGGKR (2024)
- The effects of *macroeconomic uncertainty and expectations*:
  - Firms: Kumar et al. (2024)
  - Households: Roth and Wohlfart (2020), CGGKW (2023)
- The effects of *exchange rate expectations*:
  - On firms: Delgado et al. (2024)
- The effects of *housing price expectations*:
  - Armona et al. (2018), Chopra et al. (2024), Bottan et al. (2024)
- The effects of *financial asset price expectations*:
  - Beutel and Weber (2023), Weber et al. (2023), Gorodnichenko and Yin (2024)

Potential Pitfalls and Challenges

1. Measurement of expectations and survey implementation
2. Where can you run an RCT?
3. Successful information treatments
4. Measurement of outcomes
5. **Interpreting RCT estimates: direct vs. indirect effects**
6. External validity
7. Alternatives
8. Partial vs general equilibrium outcomes

Direct vs Indirect Effects

RCTs estimate a total derivative while Werning focuses on a partial derivative:

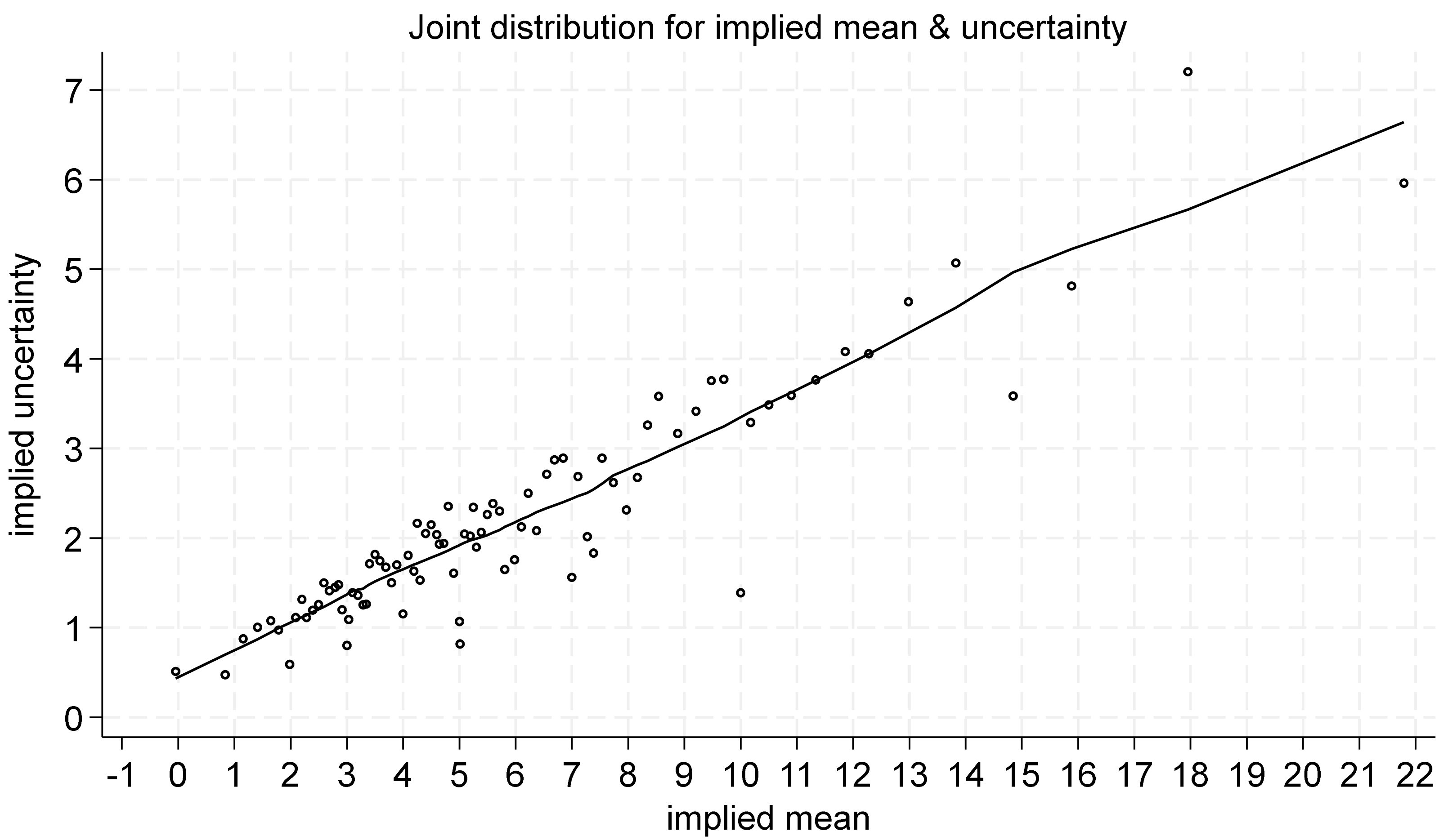
$$\underbrace{\boldsymbol{\frac{d\pi_t}{d\pi^e}}}_{\substack{\textbf{RCT} \\ \text{(total)}}} = \underbrace{\left(\frac{1-\lambda}{1-\beta\lambda}\right)}_{\substack{\text{Werning} \\ \text{(direct)}}} + \underbrace{\left(\frac{1}{1-\lambda}\right)\frac{\partial a_t}{\partial \pi^e}}_{\substack{\text{Other expectations} \\ \text{(indirect)}}}$$

For policy: The total derivative is likely the more relevant metric.

For theory: We want to know the different mechanisms and channels at work.

Georgarakos et al. (2024)

Objective: separate the effect of inflation expectations from inflation uncertainty on household decisions.



Strategy

- Monthly panel from the ECB Consumer Expectations Survey (CES); eleven largest EA countries; ~ 19,000 households

- **September 2023:** RCT is fielded in a 10 min special-purpose survey following the regular survey wave:
  - Measure prior inflation expectations, uncertainty and planned decisions
  - Implement information treatment
  - Measure posterior beliefs, plans and hypotheticals

Strategy

- Monthly panel from the ECB Consumer Expectations Survey (CES); eleven largest EA countries; ~ 19,000 households

- **September 2023:** RCT is fielded in a 10 min special-purpose survey following the regular survey wave:
  - Measure prior inflation expectations, uncertainty and planned decisions
  - Implement information treatment
  - Measure posterior beliefs, plans and hypotheticals

- **October, November, December 2023 & January 2024** regular survey waves:
  - Measure *actual* spending, investment and labour market outcomes

Information Treatments

T1 (first moment): *The average prediction among professional forecasters is that inflation in the euro area will be at 2.5% over the next 12 months.*

T2 (second moment): *Professional forecasters are exceptionally uncertain right now about inflation compared to recent years. As a result, there is a significant difference of 3.1 percentage points between the lowest and the highest predictions about inflation in the euro area over the next 12 months.*

T3 (first and second moment): *The average prediction among professional forecasters is that inflation in the euro area will be at 2.5% over the next 12 months. At the same time, professional forecasters are exceptionally uncertain right now about inflation compared to recent years. As a result, there is a significant difference of 3.1 percentage points between the lowest and the highest predictions about inflation in the euro area over the next 12 months.*

Quantifying Effects on Decisions

$$(Y_i) = \alpha_1 Post_i^{mean} + \beta_1 Post_i^{uncert}$$
$$+\alpha_0 Prior_i^{mean} + \beta_0 Prior_i^{uncert} + Controls + error_i$$

$$Post_i^{mean} = a_0 + \sum_{j=1}^{3} a_j \times I\{i \in Treat\ j\}$$
$$+ \sum_{j=1}^{3} b_j \times I\{i \in Treat\ j\} \times Prior_i^{mean}$$
$$+ \sum_{j=1}^{3} c_j \times I\{i \in Treat\ j\} \times Prior_i^{uncert} + Controls +$$
$$error_i$$

$$Post_i^{uncert} = \tilde{a}_0 + \sum_{j=1}^{3} \tilde{a}_j \times I\{i \in Treat\ j\}$$
$$+ \sum_{j=1}^{3} \tilde{b}_j \times I\{i \in Treat\ j\} \times Prior_i^{mean}$$
$$+ \sum_{j=1}^{3} \tilde{c}_j \times I\{i \in Treat\ j\} \times Prior_i^{uncert} + Controls +$$
$$error_i$$

Quantifying Effects on Decisions: Durable Goods Purchases

	Dependent variable: indicator variable is a durable good is purchased					
	Home	Durable	Car	Holiday package	Luxury items	Other
	(1)	(2)	(3)	(4)	(5)	(6)
Posterior mean						
Posterior uncertainty (log)						
Observations	11,514	11,509	11,504	11,513	11,519	11,481
R-squared	0.00	-0.04	-0.00	0.10	0.02	0.03
1st stage F-stat (mean)	118.5	114.7	117.6	115	117.7	112.4
1st stage F-stat (uncert)	99.38	99.33	98.19	100.5	100.6	100.1
KP Wald test	10.69	9.451	10.46	10.53	10.49	10.32

Information treatments are powerful instruments.

Quantifying Effects on Decisions: Durable Goods Purchases

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	Home	Durable	Car	Holiday package	Luxury items	Other
	(1)	(2)	(3)	(4)	(5)	(6)
Posterior mean						
Posterior uncertainty (log)	**-2.66*** (1.03)**	**-22.59*** (5.70)**	**-2.21* (1.30)**	**-9.61 (6.55)**	**-2.08* (1.06)**	**-6.14* (3.29)**
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Higher inflation uncertainty leads to an immediate and large reduction in purchases of durable goods of different types.

QUANTIFYING EFFECTS ON DECISIONS: DURABLE GOODS PURCHASES

Dependent variable: indicator variable is a durable good is purchased						
	Home	Durable	Car	Holiday package	Luxury items	Other
	(1)	(2)	(3)	(4)	(5)	(6)
Posterior mean	**0.45***	**4.72*****	**0.47**	**1.99**	**0.50***	**0.61**
	(0.27)	**(1.37)**	**(0.31)**	**(1.58)**	**(0.27)**	**(0.85)**
Posterior uncertainty (log)	-2.66***	-22.59***	-2.21*	-9.61	-2.08*	-6.14*
	(1.03)	(5.70)	(1.30)	(6.55)	(1.06)	(3.29)
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Higher inflation expectations lead to a rise in durable goods purchases.

QUANTIFYING EFFECTS ON DECISIONS: DURABLE GOODS PURCHASES

	Dependent variable: indicator variable is a durable good is purchased					
	Home	Durable	Car	Holiday package	Luxury items	Other
	(1)	(2)	(3)	(4)	(5)	(6)
Posterior mean	**-0.27***** **(0.05)**	**-1.12***** **(0.34)**	**-0.26***** **(0.07)**	**-1.29***** **(0.41)**	**-0.19**** **(0.10)**	**-1.22***** **(0.20)**
Observations	11,514	11,509	11,504	11,513	11,519	11,481
R-squared	0.00	-0.04	-0.00	0.10	0.02	0.03
1^{st} stage F-stat (mean)	118.5	114.7	117.6	115	117.7	112.4
1^{st} stage F-stat (uncert)	99.38	99.33	98.19	100.5	100.6	100.1
KP Wald test	10.69	9.451	10.46	10.53	10.49	10.32

The total effect of inflation expectations is negative!

The direct effect is positive but the indirect effect via uncertainty is stronger.

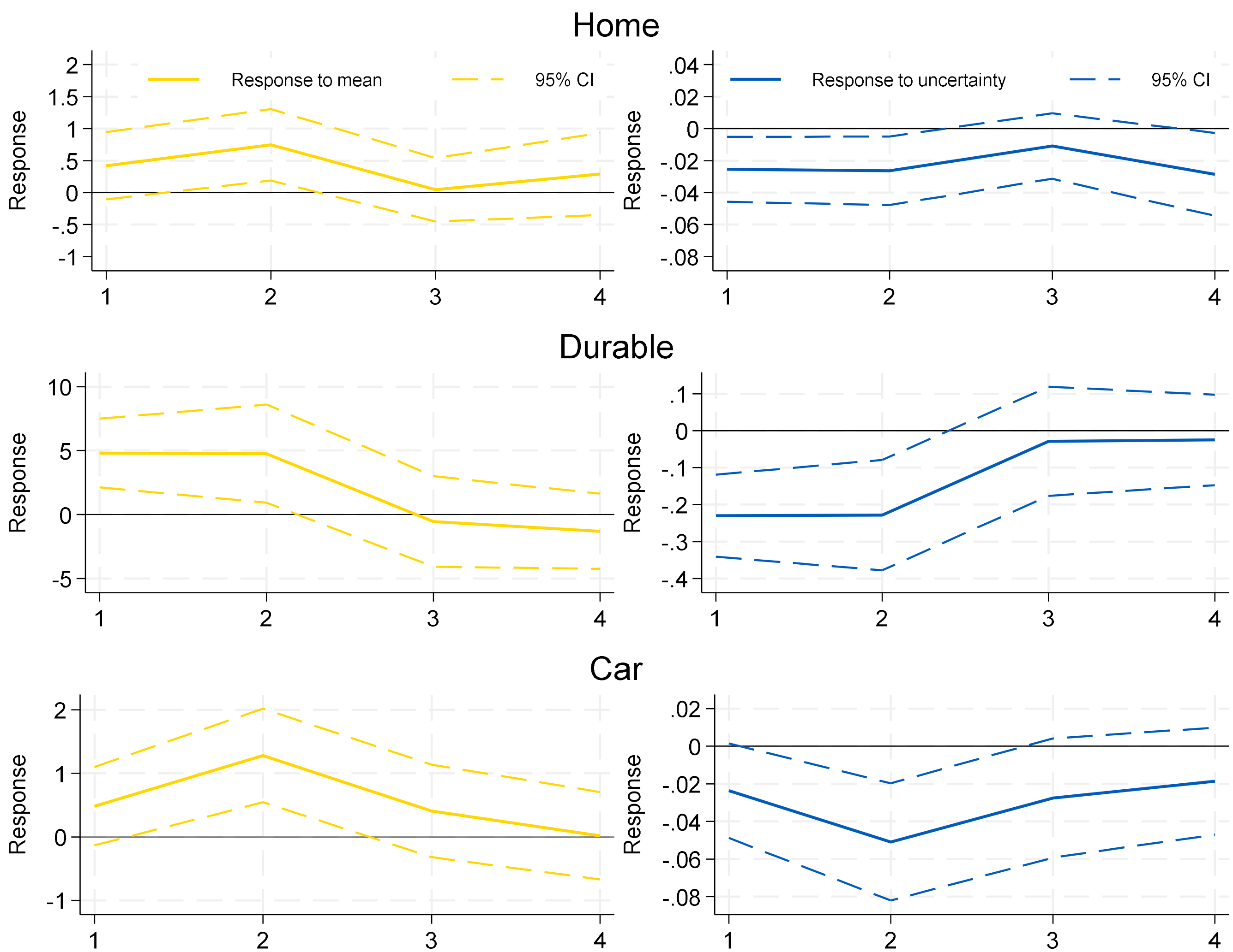
QUANTIFYING EFFECTS ON DECISIONS: DURABLE GOODS PURCHASES

	Dependent variable: indicator variable is a durable good is purchased					
	Home	Durable	Car	Holiday package	Luxury items	Other
	(1)	(2)	(3)	(4)	(5)	(6)
Posterior mean	0.08	-0.01	0.12	0.25	0.22***	0.69***
	(0.08)	(0.33)	(0.08)	(0.27)	(0.08)	(0.22)
Posterior uncertainty (log)	-0.13	3.38**	0.14	0.09	-0.47	-0.79
	(0.43)	(1.65)	(0.31)	(1.35)	(0.34)	(1.07)
Observations	11,514	11,509	11,504	11,513	11,519	11,481
R-squared	0.00	-0.04	-0.00	0.10	0.02	0.03

The RCT/IV approach is essential to the identification.

With OLS, effects are much smaller and generally insignificant.

Quantifying Effects on Decisions: Dynamics of Durable Goods Purchases



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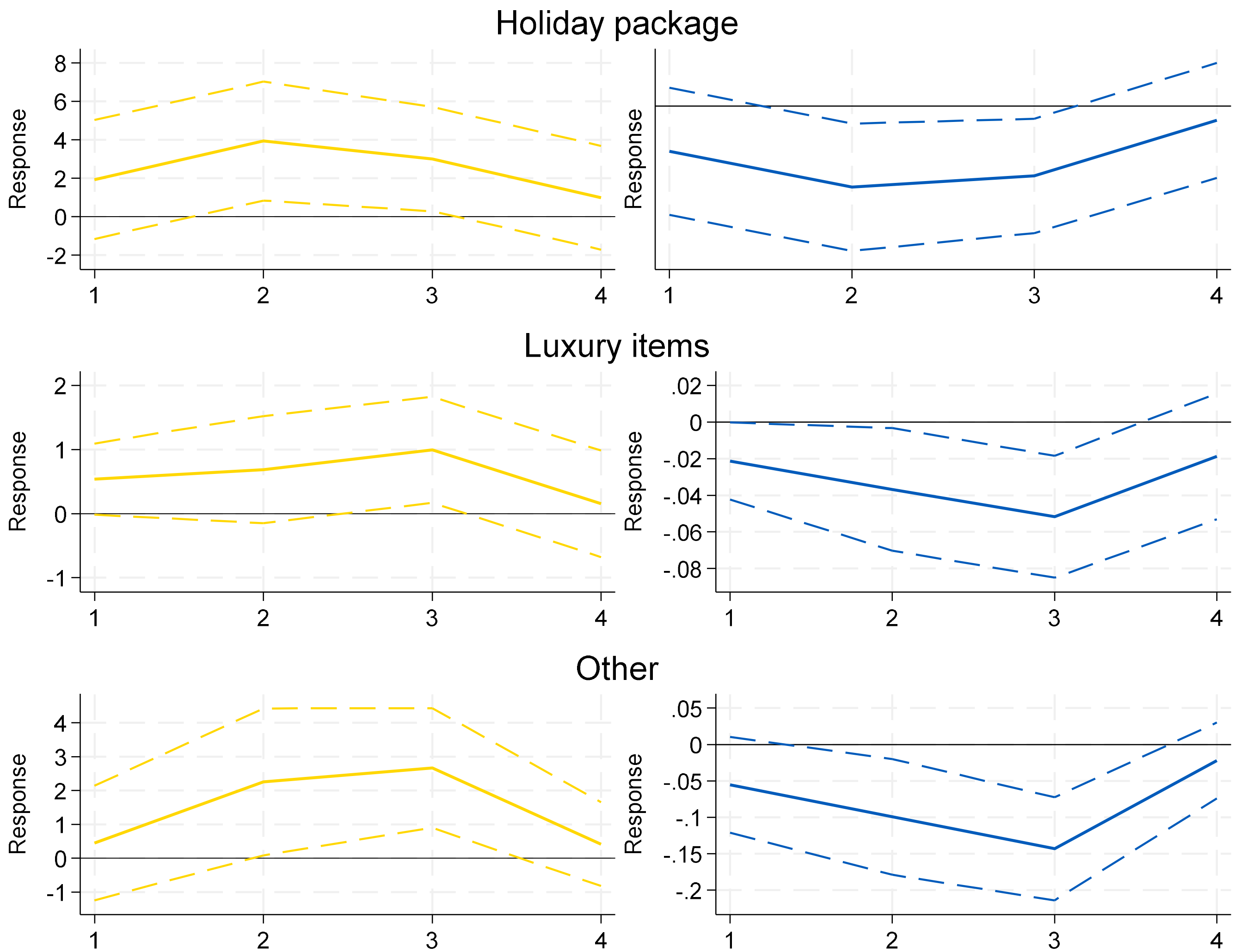

QUANTIFYING EFFECTS ON DECISIONS: *ACTUAL* PORTFOLIO ADJUSTMENT

	Cash	Check/ Saving	Stocks	Mutual funds	Retire-ment	Bonds	Crypto assets	Other
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Post. mean								
Post. uncertainty								
Observations								
R-squared								
F (mean)								
F (uncertainty)								
KP Wald								

We can measure effects on actual portfolios of respondents after two months.

QUANTIFYING EFFECTS ON DECISIONS: *ACTUAL* PORTFOLIO ADJUSTMENT

	Cash	Check/ Saving	Stocks	Mutual funds	Retire-ment	Bonds	Crypto assets	Other
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Post. mean								
Post. uncertainty	1.43	**24.03*** **	-3.69**	10.21***	**-16.20*** **	-8.21***	-0.01	-7.78***
	(1.39)	(6.22)	(1.87)	(2.36)	(4.11)	(1.31)	(0.27)	(2.68)
Observations	9,121	9,121	9,121	9,121	9,121	9,121	9,121	9,121
R-squared	0.07	0.02	0.05	-0.04	-0.05	-0.11	0.01	0.06
F (mean)	101.1	101.1	101.1	101.1	101.1	101.1	101.1	101.1
F (uncertainty)	91.79	91.79	91.79	91.79	91.79	91.79	91.79	91.79
KP Wald	11.30	11.30	11.30	11.30	11.30	11.30	11.30	11.30

Higher uncertainty about inflation leads households to reduce their retirement contributions in favor of holding more liquid assets (consistent with responses for hypothetical allocations).

QUANTIFYING EFFECTS ON DECISIONS: *ACTUAL* PORTFOLIO ADJUSTMENT

	Cash	Check/ Saving	Stocks	Mutual funds	Retire-ment	Bonds	Crypto assets	Other
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Post. Mean	-0.36	**-5.06*** **	0.71	-2.40***	**3.79*** **	1.84***	-0.06	1.76***
	(0.36)	**(1.50)**	(0.45)	(0.54)	**(1.01)**	(0.32)	(0.06)	(0.66)
Post. uncertainty	1.43	24.03***	-3.69**	10.21***	-16.20***	-8.21***	-0.01	-7.78***
	(1.39)	(6.22)	(1.87)	(2.36)	(4.11)	(1.31)	(0.27)	(2.68)
Observations	9,121	9,121	9,121	9,121	9,121	9,121	9,121	9,121
R-squared	0.07	0.02	0.05	-0.04	-0.05	-0.11	0.01	0.06
F (mean)	101.1	101.1	101.1	101.1	101.1	101.1	101.1	101.1
F (uncertainty)	91.79	91.79	91.79	91.79	91.79	91.79	91.79	91.79
KP Wald	11.30	11.30	11.30	11.30	11.30	11.30	11.30	11.30

Higher inflation expectations instead lead to a shift away from liquid assets toward more retirement funds.

QUANTIFYING EFFECTS ON DECISIONS: *EXPECTED* JOB SEARCH

	Job search intensity (# of job application) (1)	(2)	(3)	(4)
Posterior mean	-1.15***			
	(0.42)			
Post. uncertainty	5.56***			
	(1.71)			
Observations	1,411			
R-squared	-0.07			
1^{st} stage F-stat (mean)	11.03			
1^{st} stage F-stat (uncert.)	10.14			
KP Wald	1.887			

Across respondents, higher uncertainty increases expected job search intensity while higher inflation expectations does the reverse.

QUANTIFYING EFFECTS ON DECISIONS: *EXPECTED* JOB SEARCH

	Job search intensity (# of job application)	**Subj. prob. of finding a job in 3 months**		
	(1)	(2)	(3)	(4)
Posterior mean	-1.15***	-10.24**		
	(0.42)	(4.89)		
Post. uncertainty	5.56***	36.50**		
	(1.71)	(17.07)		
Observations	1,411	461		
R-squared	-0.07	-0.07		
1^{st} stage F-stat (mean)	11.03	2.383		
1^{st} stage F-stat (uncert.)	10.14	3.878		
KP Wald	1.887	1.232		

Among the unemployed, this higher search intensity under higher uncertainty leads to a higher expectation of finding a job.

QUANTIFYING EFFECTS ON DECISIONS: *EXPECTED* JOB SEARCH

	Job search intensity (# of job application) (1)	Subj. prob. of finding a job in 3 months (2)	**Subj. prob. of losing a job in 3 months** (3)	**Subj. prob. of looking for a job in 3 months** (4)
Posterior mean	-1.15***	-10.24**	-0.27	-1.81**
	(0.42)	(4.89)	(0.93)	(0.74)
Post. uncertainty	5.56***	36.50**	**1.60**	**5.34***
	(1.71)	(17.07)	**(3.44)**	**(3.04)**
Observations	1,411	461	7,597	7,251
R-squared	-0.07	-0.07	0.03	0.03
1^{st} stage F-stat (mean)	11.03	2.383	70.18	75.18
1^{st} stage F-stat (uncert.)	10.14	3.878	65.76	69.30
KP Wald	1.887	1.232	5.896	9.996

Among the employed, higher uncertainty leads to higher expectation of searching for a new job but not because they expect to lose their job.

QUANTIFYING EFFECTS ON DECISIONS: *EMPLOYMENT OUTCOMES*

	Employed (any)	**Employed (full-time)**	**Employed (part-time)**	**Unemployed**	**Other (out of labor force, laid-off, etc.)**
	(1)	(2)	(3)	(4)	
Four months after treatment					
Posterior mean					
Posterior uncertainty					
Observations					
R-squared					
1st stage F-stat (mean)					
1st stage F-stat (uncert.)					
KP Wald					

QUANTIFYING EFFECTS ON DECISIONS:
EMPLOYMENT OUTCOMES

	Employed (any)	Employed (full-time)	Employed (part-time)	Unemployed	Other (out of labor force, laid-off, etc.)
	(1)	(2)	(3)	(4)	
Four months after treatment					
Posterior mean					
Posterior uncertainty	0.044	**0.161****	**-0.121****	**-0.071*****	0.026
	(0.076)	**(0.082)**	**(0.049)**	**(0.022)**	(0.075)
Observations	8,666	8,666	8,666	8,666	8,666
R-squared	0.41	0.35	0.01	0.02	0.43
1^{st} stage F-stat (mean)	96.75	96.75	96.75	96.75	96.75
1^{st} stage F-stat (uncert.)	85.54	85.54	85.54	85.54	85.54
KP Wald	8.570	8.570	8.570	8.570	8.570

With higher uncertainty, shifts out of UE and PT into FT work, consistent with increased search by employed and unemployed.

QUANTIFYING EFFECTS ON DECISIONS: *EMPLOYMENT OUTCOMES*

	Employed (any)	Employed (full-time)	Employed (part-time)	Unemployed	Other (out of labor force, laid-off, etc.)
	(1)	(2)	(3)	(4)	
Four months after treatment					
Posterior mean	-0.259	-2.327	2.173*	0.822	-0.716
	(1.886)	(2.026)	(1.201)	(0.565)	(1.854)
Posterior uncertainty	0.044	0.161**	-0.121**	-0.071***	0.026
	(0.076)	(0.082)	(0.049)	(0.022)	(0.075)
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With higher inflation expectations, perhaps shift from FT to PT employment.

Summary

- With multiple treatments, we can separate direct and indirect effects of expectations changes on decisions.

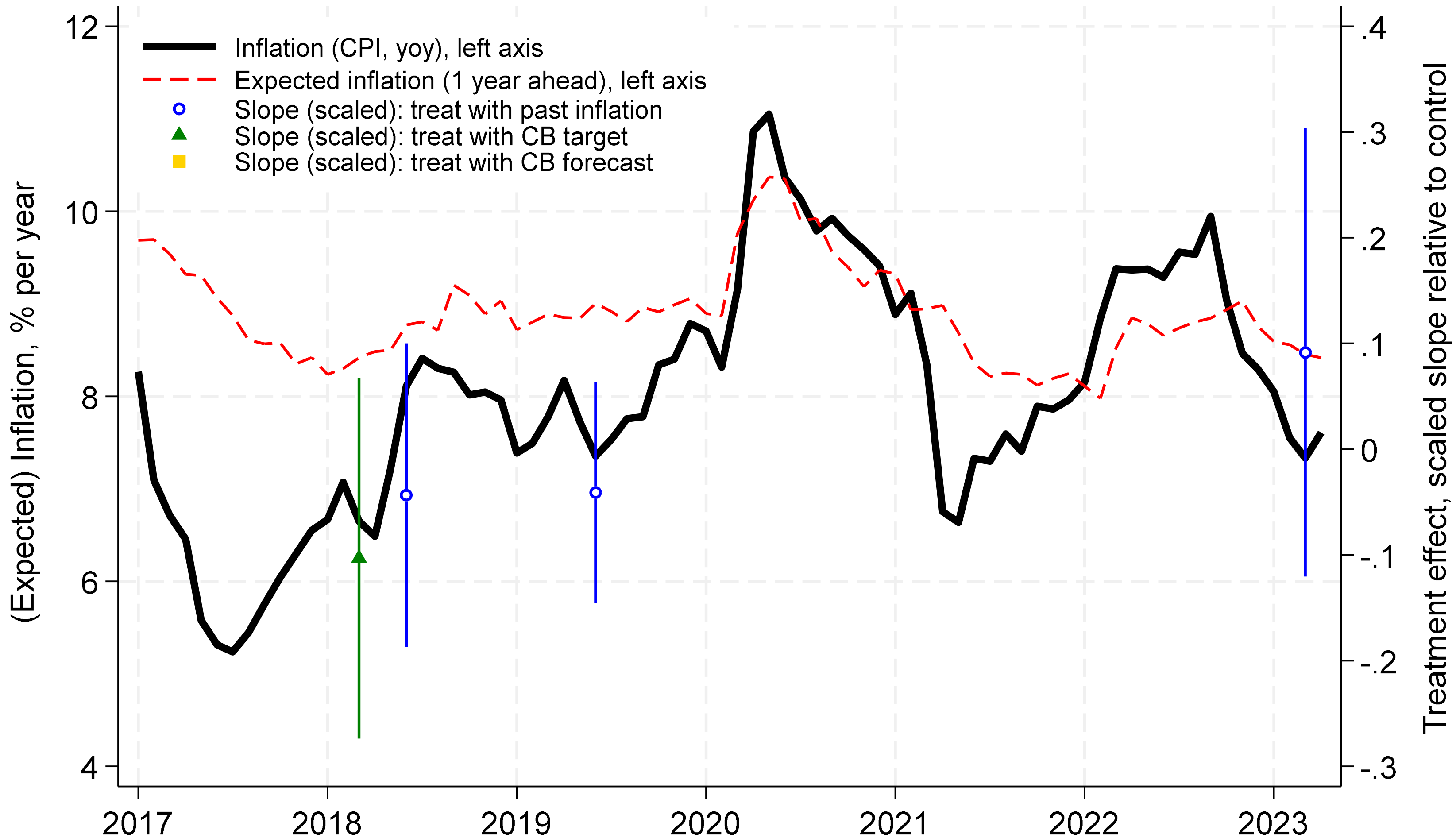
- This is particularly important for inflation expectations, since first and second moments are strongly positively correlated but generally have opposing effects on decisions.

- For policy purposes, the total effect is generally the most relevant statistic. But even in that case, knowing how decisions respond to inflation expectations and uncertainty can be useful in designing communications:
  - To boost spending, we could try to raise inflation expectations *or* reduce inflation uncertainty (doing both would be particularly effective).

Potential Pitfalls and Challenges

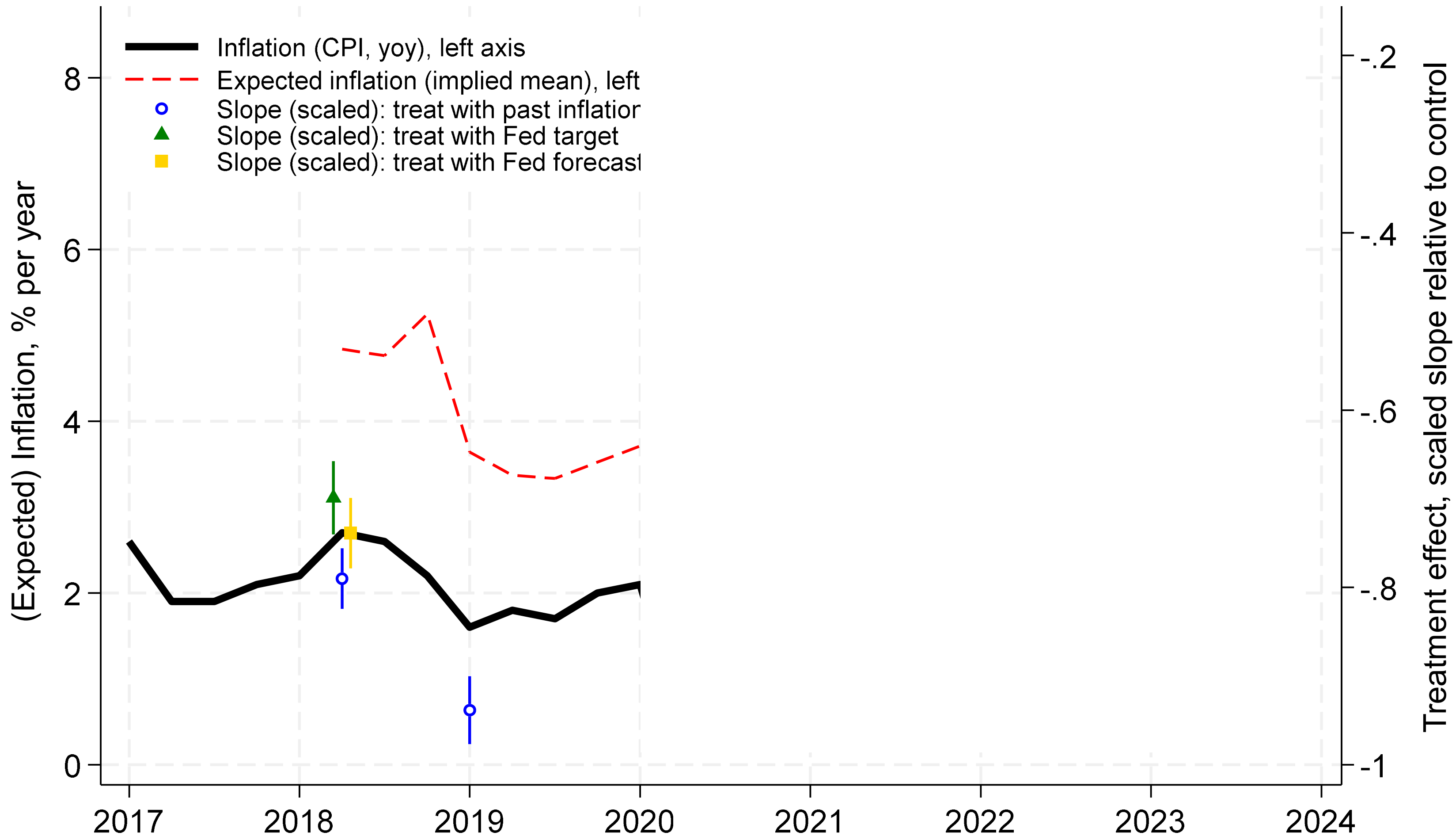
1. Measurement of expectations and survey implementation
2. Where can you run an RCT?
3. **Successful information treatments**
4. Measurement of outcomes
5. Interpreting RCT estimates: direct vs. indirect effects
6. External validity
7. Alternatives
8. Partial vs general equilibrium outcomes

EXAMPLE OF A "FAILED" FIRST STAGE



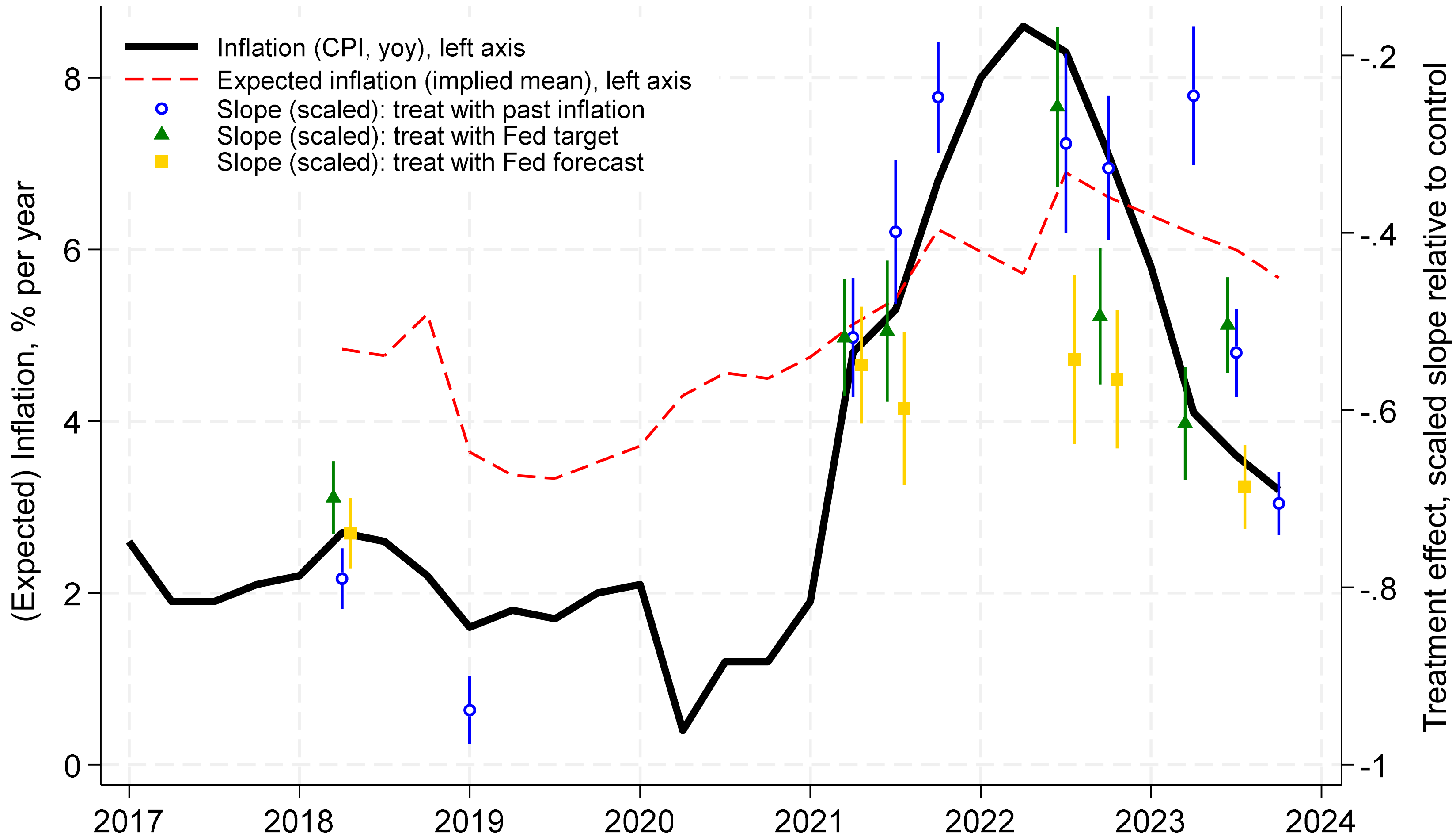
In Uruguay, four different RCTs providing information about inflation or central bank's target/forecast found no effect on firms' inflation expectations.

EXAMPLE OF A CHANGING TREATMENT EFFECT



Among Nielsen households, treatment effects went from large in 2018

EXAMPLE OF A CHANGING TREATMENT EFFECT



Among Nielsen households, treatment effects went from large in 2018 to very small in 2021-2022 when inflation was high.

Potential Pitfalls and Challenges

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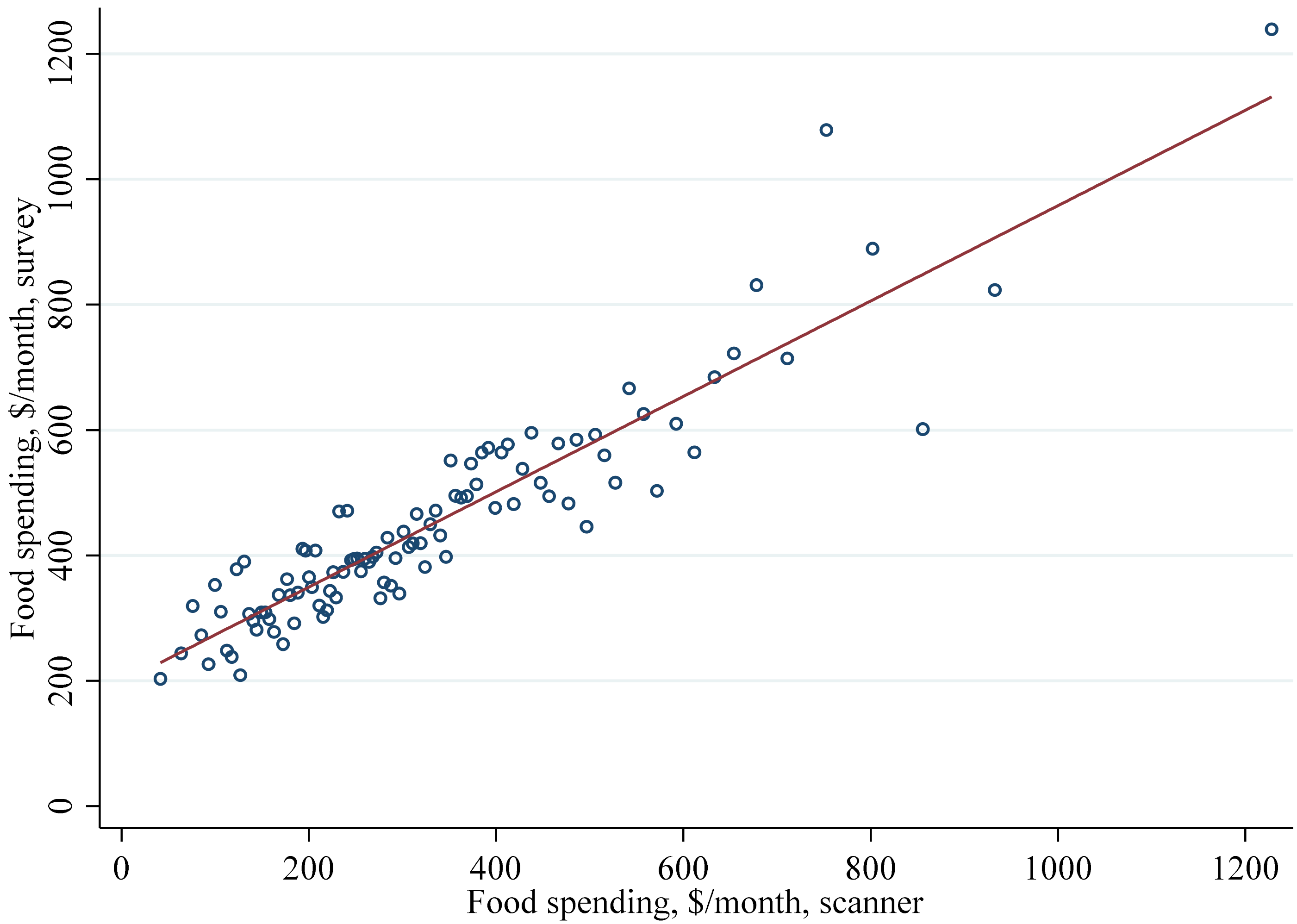
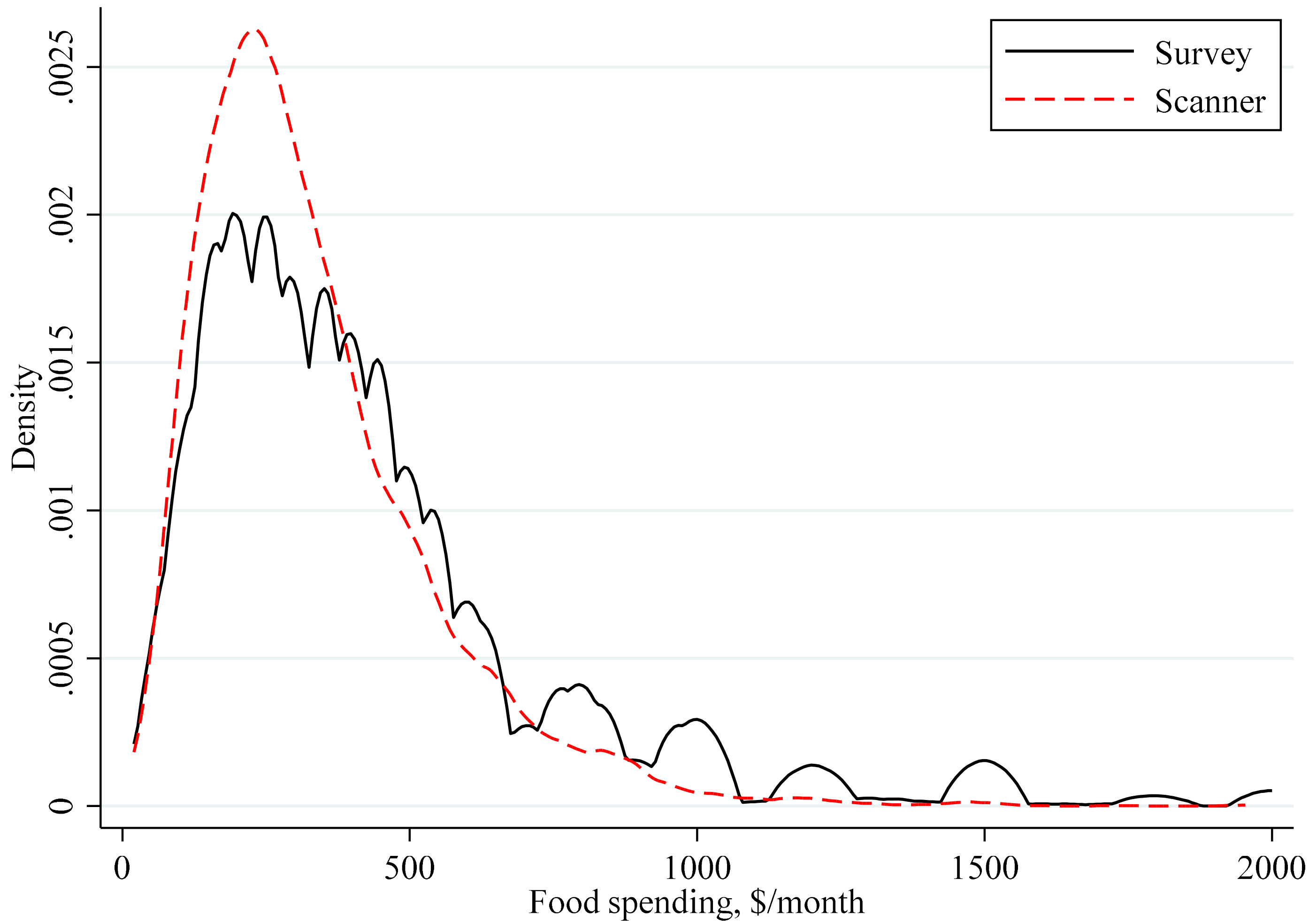
External vs Self-reported Spending



On average, self-reported and scanner measures of spending are closely aligned.

External vs Self-reported Spending



But self-reported spending is much "lumpier" due to rounding.

EXAMPLE: CGW (2022)

Dep. var. is indicated in the title of the panel	Actual spending, horizon, month	
	3 months	6 months
	(1)	(2)
Panel A. Total Spending, survey		
Posterior inflation expectations		
Observations	6,459	6,570
1^{st} stage F-stat	46.97	60.06
Panel B. Total Spending, scanner		
Posterior inflation expectations		
Observations	13,170	13,132
1^{st} stage F-stat	134.8	128.1

Let's compare estimates of effects of inflation expectations on spending using scanner data vs self-reported spending data.

EXAMPLE: CGW (2022)

Dep. var. is indicated in the title of the panel	Actual spending, horizon, month	
	3 months	6 months
	(1)	(2)
Panel A. Total Spending, survey		
Posterior inflation expectations		
Observations	6,459	6,570
1st stage F-stat	46.97	60.06
Panel B. Total Spending, scanner		
Posterior inflation expectations	0.950***	0.864**
	(0.286)	(0.336)
Observations	13,170	13,132
1st stage F-stat	134.8	128.1

This approach yields evidence suggesting positive *causal* link from inflation expectations to total spending of households.

EXAMPLE: CGW (2022)

Dep. var. is indicated in the title of the panel	Actual spending, horizon, month	
	3 months	6 months
	(1)	(2)
Panel A. Total Spending, survey		
Posterior inflation expectations	1.826***	1.015
	(0.690)	(0.638)
Observations	6,459	6,570
1^{st} stage F-stat	46.97	60.06
Panel B. Total Spending, scanner		
Posterior inflation expectations	0.950***	0.864**
	(0.286)	(0.336)
Observations	13,170	13,132
1^{st} stage F-stat	134.8	128.1

The results are much more precise when we have access to external sources of information on decisions instead of self-reported outcomes.

POTENTIAL PITFALLS AND CHALLENGES

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Complementary Approach: Hypotheticals

An alternative to the 3-step RCT procedure described here is to ask survey participants directly how they would react if they held different beliefs (see Coliarieti et al. 2024):

"*For this next question, we would like you to think about the ways in which uncertainty about the overall economy may (or may not) affect the decisions in your firm. In particular, for each of the following options, please provide an answer ranging from "much more likely" to "much less likely" that best describes how you would be affected by an [increase/decrease] in macroeconomic uncertainty.*"

Complementary Approach: Hypotheticals

Outcomes we observe	increase	decrease	p-val(equal)	=RCT?
To hire more employees	-1.29	1.71	0.00	Yes
	(0.02)	(0.01)		
To raise my price(s)	-1.23	1.67	0.00	Yes
	(0.02)	(0.01)		
To purchase more machinery/physical equip.	-1.32	1.64	0.00	Yes
	(0.03)	(0.02)		
To open/invest in new facilities	-1.28	1.70	0.00	Yes
	(0.02)	(0.01)		
To do more advertising	1.60	-1.64	0.09	Yes
	(0.02)	(0.02)		
To increase average wages	-0.59	0.62	0.25	Zero
	(0.02)	(0.02)		
To introduce new products/services	-1.11	1.62	0.00	Zero
	(0.02)	(0.02)		
To engage in more R&D	-1.48	1.47	0.65	Zero
	(0.02)	(0.02)		
To see my operating margins increase	-1.73	1.67	0.00	No/Zero
	(0.01)	(0.01)		

Hypotheticals seem to deliver the same qualitative outcome as RCTs!

Complementary Approach: Hypotheticals

Hypotheticals/vignettes/strategic surveys:

- Can be implemented in surveys that do not allow RCTs
- Do not require follow-up surveys
- Do not require external data on decisions
- Do not require same large samples as for RCTs
- Are immune to concerns about power of the first stage
- Can be written to measure either partial or total effects
- Can be written to provide either qualitative or quantitative estimates, measure non-linearities and asymmetric effects.

But it remains to be established under what conditions hypotheticals and RCTs will systematically yield the same results.

Conclusion

- Applying randomized information treatments to surveys of economic agents can provide new answers to fundamental questions in macroeconomics with sharper causality than other strategies in the face of otherwise daunting identification issues.

- This strategy has already been applied to a number of areas with success, but there is room to apply these methods far more systematically.

- However, RCTs are not a panacea. They can only identify partial equilibrium responses. We still need models and aggregate data to go from partial equilibrium elasticities to general equilibrium effects.