Salience, Myopia and Complex Dynamic Incentives: Evidence from Medicare Part D

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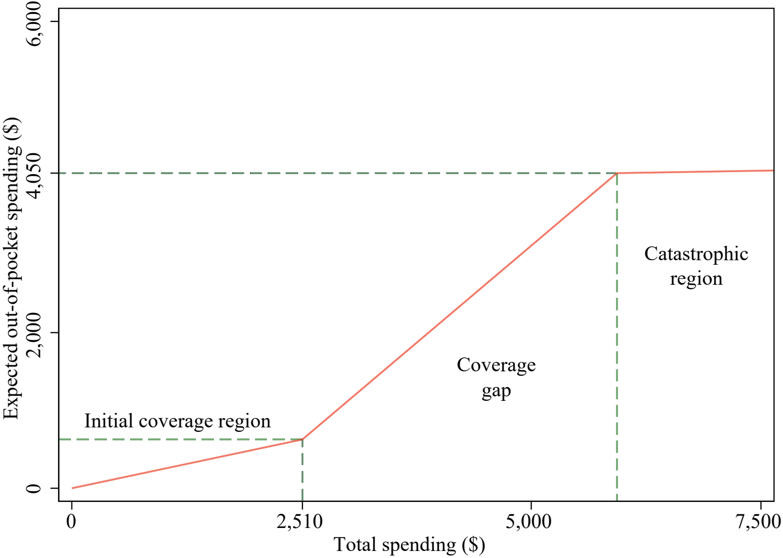
Introduction

- In 2006, U.S. Medicare system added Part D
  - Largest benefit change to Medicare since inception
  - Added drug coverage to existing healthcare benefits
  - Very popular with Medicare enrollees
- Perhaps biggest criticism is non-linear price structure
  - Insurance stops when spending reaches “doughnut hole”
  - 2008 coverage gap starts at $2,510 in *total* expenditures
  - Lasts until $4,050 in *out-of-pocket* expenditures
- Coverage gap is very unpopular
  - One-third of Part D enrollees entered doughnut hole in 2008
  - 2010 Affordable Care Act phases it out

2008 Medicare Part D benefit structure



Non-linear price schedules and rationality

- With non-linear prices, a rational, forward-looking enrollee must forecast future expenditures to make a fill decision
  - I.e., if she forecasts that she will end the year in the doughnut hole, she might choose cheaper drugs before the doughnut hole
  - More generally: end-of-year price distribution matters most
- Not acting rationally leads to *behavioral hazard*
  - Means suboptimal behavioral resulting from mistakes or biases
- Relevant because studies find that Part D enrollees do not act fully rationally in Part D plan choice
- More generally, many health insurance contracts have non-linear price schedules
  - Out-of-pocket maxima, deductibles, etc.
  - Findings on behavioral hazard important more generally

Goals of this study

1. To develop robust tests for whether purchase behavior of Part D enrollees deviates from neoclassical model
2. To understand sources and magnitudes of behavioral hazard and how this influences outcomes

Overview of study

- Construct two dynamic models of drug consumption
  - Quasi-hyperbolic discounting (Laibson, 1997, etc.)
  - Price salience (Chetty et al, 2009; Bordalo et al, 2012)
  - $\Rightarrow$ Neoclassical model is limiting case of both models
- Derive and compute implications of models
- Test for deviations from neoclassical model
  - Test based on a discontinuity design
  - Examine enrollees who arrive *near* doughnut hole early in the year
  - They should expect to reach doughnut hole by end of year
  - Under only neoclassical model, no change in behavior upon crossing into doughnut hole
- Structurally estimate parameters of model
  - Develop behavioral dynamic estimation framework
  - Show identification of discount factor and behavioral parameters
  - Use to evaluate importance of behavioral hazard and implications of counterfactual policies

More general takeaways

- Both test of neoclassical model and structural estimation framework may be useful more broadly
- Lots of recent interest in understanding implications of non-linear pricing
- Many papers reject neoclassical model with non-linear pricing:
  - Brot-Goldberg et al. (2015): high deductible health plans
  - Ito (2014): electricity
  - Grubb and Osborne (2014): cell phone contracts
- We develop robust tests of neoclassical model
- Framework that allows for both price salience and quasi-hyperbolic discounting

Relation to literature

- Most related to Abaluck et al. (2015), Einav et al. (2015)
- Both develop models of Part D choices with myopia
- Abaluck et al. model choice of plan enrollment
  - Methods abstract away from uncertainty in spending during a year
  - Similar question, but our methods and modeling are very different
- Einav et al. (similarly) model drug choices within a year
  - Complementary tests: we test for violations of neoclassical model, they test for forward-looking behavior
  - They estimate geometric discounting with (annual) $\delta = 0.12$
  - We provide behavioral explanations for findings

Remainder of talk

1. Model
2. Data
3. Reduced form evidence
4. Structural estimation
5. Results and counterfactuals
6. Conclusions

Overview of model

- Develop dynamic framework to consider drug purchases of Part D enrollee within a calendar year
- Consider two behavioral models (and limiting case of neoclassical model)
  1. Quasi-hyperbolic discounting
     - Agents are present-biased and discount future more than would geometric discounters
     - Purchases at $t + 1$ discounted at rate $\beta\delta$; at $t + 2$ by $\beta\delta^2$
     - Consider both “sophisticates” and “naïfs” version of model
  2. Price salience model
     - Decision made prior to point of sale, e.g., in physician’s office
     - Enrollee with last purchase in initial coverage region assesses probability σ that different coverage region exists
- Difference across models:
  - In salience model, prices are only fully salient in first Rx inside doughnut hole
  - Quasi-hyperbolic discounter lowers spending on Rx that moves her inside doughnut hole

Enrollee optimization

- Time period is a week
  - Each week, there are a number, $0, \ldots, \overline{N}$ of health shocks
  - Let n denote the health shock within a week
  - Let Q_n denote conditional probability of receiving another health shock in week
- Each health shock is for one of H potential diseases/drug classes
  - Health shock h has baseline health cost c_h
  - Disease h treated with one of J_h potential drugs or outside option
  - Gross flow utility from consuming drug j:

$$c_h + \phi_{hj} + \varepsilon_{hj}$$

  - Flow utility from outside option, option 0:

$$c_h + \varepsilon_{h0}$$

- Unobservables are distributed type 1 extreme value

Main identifying assumption

Assumption (1)

With probability 1, enrollees in our sample expect that, even if they change their purchase for any one health shock:

(a) *they will reach the doughnut hole start of $2,510 in total spending, and*

(b) *they will not reach the sample minimum catastrophic region start of $4,010 in out-of-pocket spending.*

- Our sample is based on enrollees who start some week between the end of March and the end of July with $\geq$ $2,000 in spending but $<$ $2,510
  - 95% of enrollees in sample spend more than $2,510
- Let m denote amount left to spend until reaching doughnut hole
  - State space is (m, n) ex ante to receiving a health shock

Effective prices

- With quasi-hyperbolic discounting:

$$p^{eff}(m, p_{hj}, oop_{hj}) = \begin{cases} p_{hj}, \text{ if } 0 \leq m < oop_{hj} \\ oop_{hj} + p_{hj} - m, \text{ if } oop_{hj} \leq m < p_{hj} \\ oop_{hj}, \text{ if } p_{hj} \leq m. \end{cases}$$

- With price salience:

$$p^{eff}(m, p_{hj}, oop_{hj}) = \begin{cases} p_{hj}, \text{ if } m = 0 \\ \sigma p_{hj} + (1-\sigma) oop_{hj}, \text{ if } 0 < m < oop_{hj} \\ \sigma(oop_{hj} + p_{hj} - m) + (1-\sigma) oop_{hj}, \\ \quad \text{ if } oop_{hj} \leq m < p_{hj} \\ oop_{hj}, \text{ if } p_{hj} \leq m \end{cases}$$

- oop = out-of-pocket price, p = full price
- For ease of notation, let outside good price be 0
- Disutility from price is a function $\alpha(p^{eff})$
  - We use a linear spline in estimation

Enrollee optimization

- Choice specific value function for sophisticates model:

$$\overline{u}_j(m,n,h) + \varepsilon_{hj} \equiv \phi_{hj} - \alpha(p^{eff}(m, p_{hj}, oop_{hj})) - c_h + \beta V(\max\{m - p_{hj}, 0\}, n+1) + \varepsilon_{hj}$$

(Function for salience model analogous, but with σ instead of β)

- Probability of purchase:

$$s(m,n,h,j) = \frac{\exp(\overline{u}_j(m,n,h))}{\sum_{k=0}^{J_h} \exp(\overline{u}_k(m,n,h))}$$

- Ex ante value function for sophisticates / salience model:

$$V(m,n) = (1-Q_n)\delta V(m,0) + Q_n \sum_{h=1}^{H} P_h \sum_{j=0}^{J_h} s(m,n,h,j) \times [\phi_{hj} - c_h - \alpha(p^{eff}(m, p_{hj}, oop_{hj})) + V(\max\{m-p_{hj}, 0\}, n+1) - \log s(m,n,h,j) + \gamma]$$

- Naïfs use neoclassical value function

Neoclassical model results

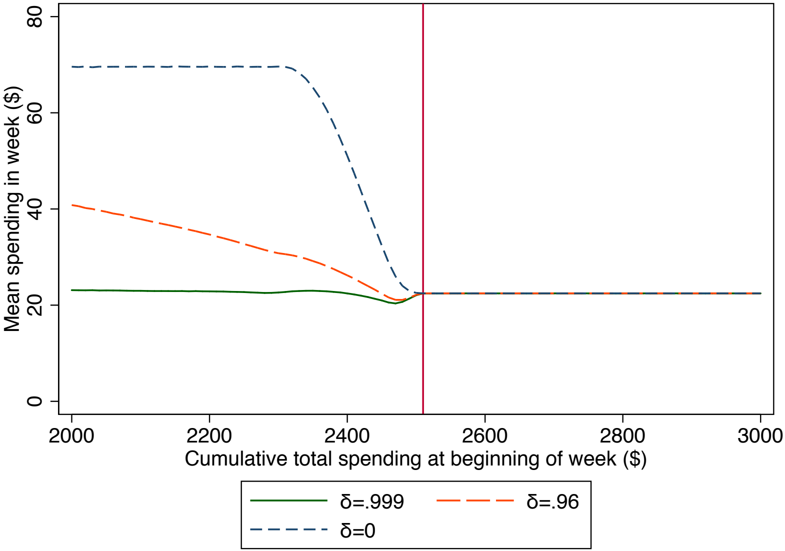
Proposition (1)

Consider a neoclassical dynamically-optimizing Part D enrollee for whom Assumption 1 holds and for whom $\beta/\sigma = \delta = 1$. Suppose further that there is a common full price $\overline{p}$ and out-of-pocket price $\overline{oop}$ that is charged for every (inside-good) drug and that price disutility is linear so that $\alpha(p) \equiv \overline{\alpha}p$.
Then, the purchase probability of each drug is the same across ex ante states.

Intuition:

- Part D insurance is very similar to a lump-sum payment
- What about case where value of drug is in between $\overline{oop}$ and $\overline{p}$?
    - Assumption 1 rules this out (with supporting evidence from data)
- What about drugs with different prices?
    - Simulation evidence...

Stylized spending, geometric discounting model



Behavioral model results

Proposition (2)

Assume conditions of Proposition 1 except for $\beta/\sigma = 1$. Then,

(a) *at doughnut hole, shares $s(0, n, h, j)$ are the same across models*

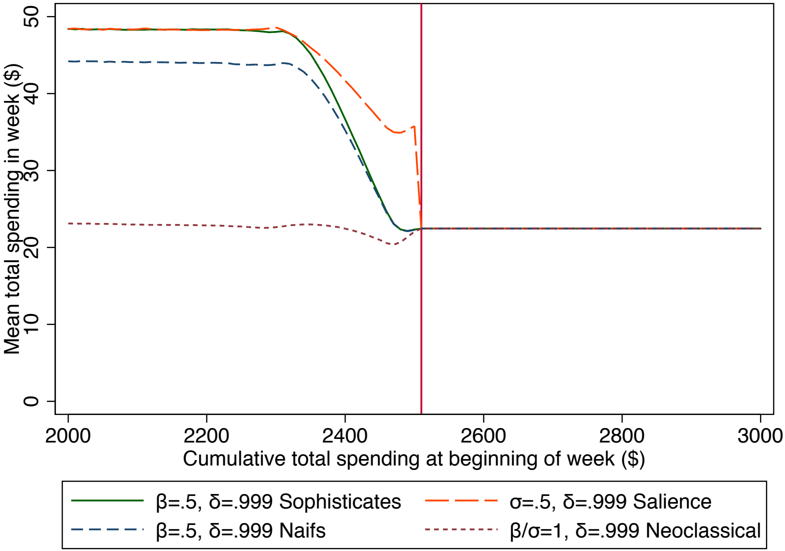
(b) *under the behavioral models, $s(m, n, h, j) = s(m', n', h, j)$ $> s(0, n'', h, j)$ if $m, m' \geq \overline{p}$*

(c) *purchase probabilities $s(m, n, h, j)$ will be the same for the sophisticates and salience models if $m \geq \overline{p}$ and $\beta = \sigma$*

Intuition:

- The decision process is different before and inside the doughnut hole
- Before the doughnut hole, the total subsidy is discounted by (or salient with) factor β (σ)
- The same effective discount factor/salience level of β/σ holds for all pre-doughnut hole states

Stylized spending across different behavioral models



Data

- Part D claims data on employer-sponsored plans
- Data are from 2008, 3rd year of Part D program
- From Express Scripts, a large benefits manager
- Focus on plans that have a standard “doughnut hole” design:
  - Claims from 5 plans and 2 employers covering 28,543 enrollees
  - Each plan has coverage gap starting at $2,510 in total price
  - Falsification from plan with coverage gap at $4,000
- Employer-sponsored plans – important segment of Part D
  - Almost 7m enrollees or 15% of Part D enrollment in 2008
  - Use most enrollees for the employers in our sample
    - Drop some plans with more generous coverage
  - Minimizes selection issues
  - This segment has higher income than average

Data (continued)

- For each claim, our Express Scripts data contain:
    - Enrollee identifier; date; drug name, type, and NDC code
    - Out-of-pocket price and total price billed to insurance company
- We create drug classes based on drug function
    - Lump together drug classes and drugs with small number of prescriptions over the year
- Combine data with Johns Hopkins ACG score:
    - Patient's score provides expected pharmaceutical cost
    - In our case, input is individual Rx claims for Jan. - Mar 29. 2008
    - Structural estimation stratifies all parameters by ACG score
- Sample
    - Keep patients who reach $2,000 in total spending between Sun. Mar. 30 and Sat. Jul. 26, 2008
    - Keep weeks from first complete week over $2,000 to last week starting under $3,000
    - One observation is an enrollee/week

Table 1: plan characteristics and enrollment

Plan	A	B	C	D	E	F
Employer	1	1	1	2	2	3
% of employees from employer	26	45	9	79	21	46
Deductible ($)	275	100	100	0	200	0
Coverage gap start (total $)	2,510	2,510	2,510	2,510	2,510	4,000
Catastrophic start (out-of-pocket $)	4,050	4,050	4,050	4,010	4,010	4,050
Total enrollment	7,541	12,858	2,431	4,062	1,058	35,395
% hitting $2,510	20	13	16	16	13	20
% hitting catastrophic	2	1	1	1	1	0
Estimation sample:						
Enrollment	620	644	126	304	49	2,981
% hitting $2,510	96	94	95	97	94	97
% hitting catastrophic	11	6	9	10	12	0
Mean total spending ($)	4,284	3,867	4,009	4,246	3,974	4,072
Mean out-of-pocket ($)	2,373	2,010	2,125	2,045	2,071	1,026
Mean age	74	73	73	75	75	78
Percent female	62	58	53	62	59	64
Mean ACG score	1.04	1.17	1.18	0.91	1.07	0.67

Note: plan A provides generic coverage in deductible region; plan F used for falsification exercise only and also provides generic coverage in doughnut hole.

Table 2: most common drug classes in sample

Indicator	Number Rx	% of obs.	Most common Rx
Cholesterol Lowering	2,201	9.4	Simvastatin
Renin-Angiotensin System Blocker	1,851	7.9	Lisinopril
Beta-Blocker	1,288	5.5	Metoprolol
Opioid	1,233	5.2	Hydrocodon
Antidepressant	1,220	5.2	Sertraline
Diuretic	1,214	5.2	Furosemide
Calcium Channel Blocker	957	4.1	Amlodipine
Insulin Sensitizer	815	3.5	Metformin
Gastroesophageal Reflux & Peptic Ulcer	799	3.4	Omeprazole
Hypothyroidism	798	3.4	Levothyroxine

Testing for deviations from neoclassical model

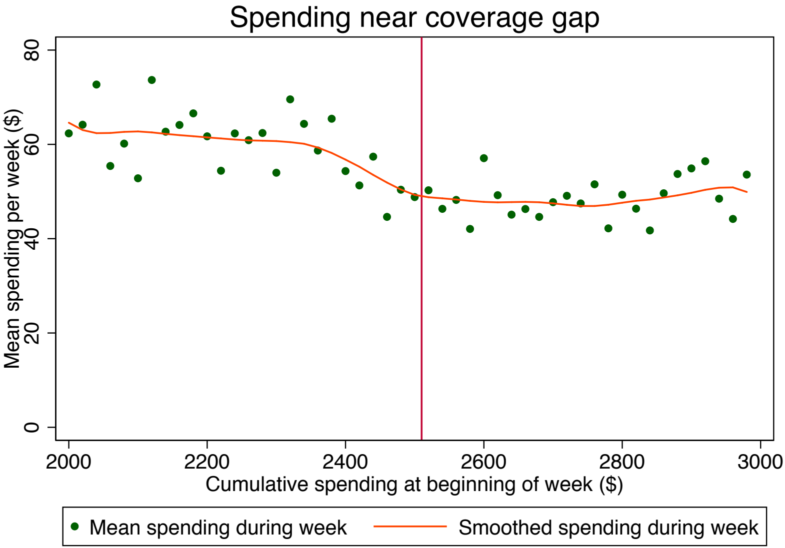
- Estimate a series of regressions on sample of enrollees near doughnut hole early in year (starting at $2,000 in total spending)
  - For this sample, same future price but different current prices
    - Neoclassical model: should react principally to future price
  - Compare *same* individual before and during gap
  - Discontinuity approach minimizes impact of other factors
- Using this sample, linear regressions of form:

$$Y_{it} = FE_i + \lambda_1 1\{0 < m_{it0} \leq \$110\} + \lambda_2 1\{m_{it0} = 0\} + v_{it}$$

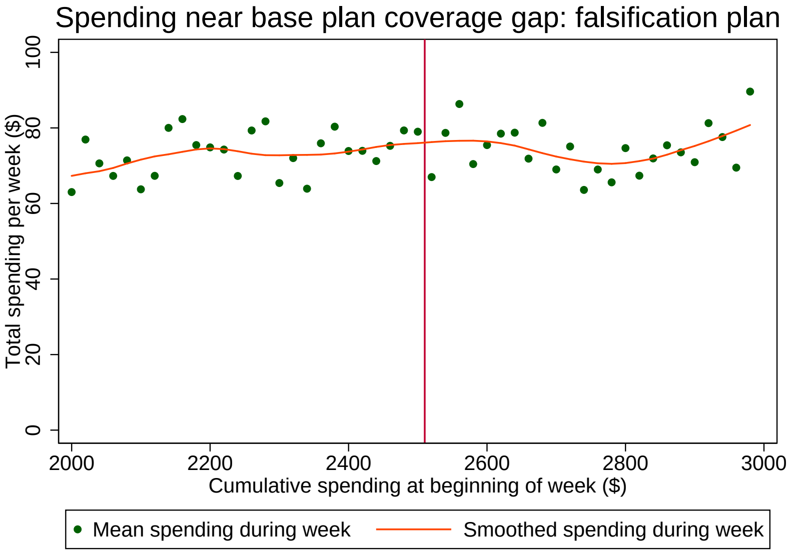
where:

  - Y_{it} include variables such as # of Rxs in week
  - FE_i are individual fixed effects
  - $1\{m_{it0} = 0\}$ – indicator for in doughnut hole at beginning of week
  - $1\{0 < m_{it0} \leq \$110\}$ – "near doughnut hole" indicator at beginning of week – not reported in tables
- For behavioral models (but not geometric model with low discount factor): flat spending in some pre-doughnut hole region

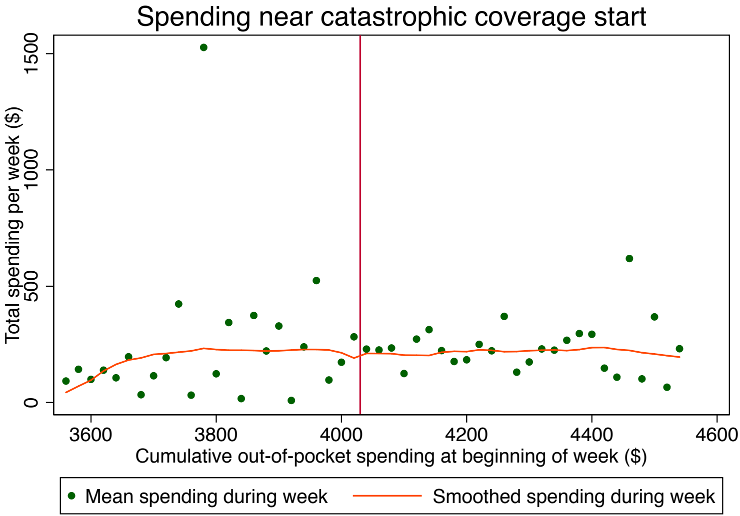
Total spending: base sample



Total spending: falsification plan F

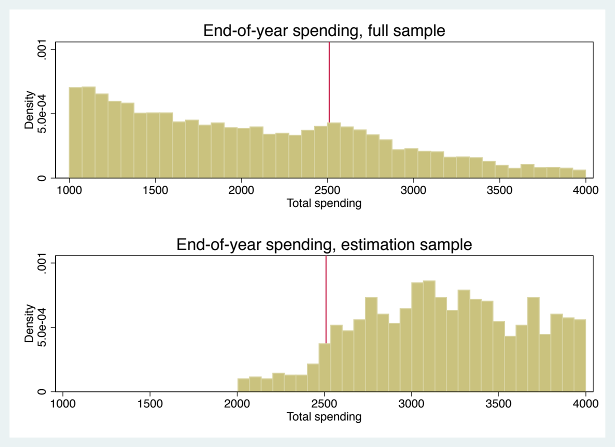


Total spending near catastrophic start: base sample



Note: sample is enrollees near catastrophic region early in year.

Do people end year at coverage gap start?



- Full sample has “bunching” right at doughnut hole
- Estimation sample does not: assumption that enrollees here end year inside doughnut hole seems reasonable

Behavior for sample arriving near coverage gap

Dependent variable:	Mean value before \$2,400	Beginning of week spending in: \$2,510 - 2,999
Mean spending in week	61.97	-17.46^{**} (1.38)
Mean price per Rx	79.47	-9.77^{**} (1.37)
Number of Rxs	0.84	-0.18^{**} (0.02)
Number of branded Rxs	0.30	-0.08^{**} (0.01)
Number of generic Rxs	0.54	-0.10^{**} (0.01)
Expensive Rxs	0.12	-0.04^{**} (0.00)
Medium Rxs	0.23	-0.06^{**} (0.01)
Inexpensive Rxs	1.10	-0.01 (0.01)

Note: N=28,543 except for "Mean spending per Rx" regression when N=10,846

- Each regression includes individual fixed effects and \$2,400-2,509 indicator
- Sample extends from \$2,000 - 3,000 in beginning of week spending
- Inexpensive drugs: $<$ \$50; expensive drugs: $\geq$ \$150

Takeaway: big drops, particularly on expensive drugs, in doughnut hole

Behavior near coverage gap with variation in pre-coverage gap region

Dependent variable:	Mean value before \$2,400	Beginning of week spending in: \$2,510 - 2,999	\$2,200 - 2,399
Mean spending in week	61.97	−17.79** (1.76)	−0.68 (2.25)
Mean price per Rx	79.47	−8.97** (1.72)	1.64 (2.13)
Number of Rxs	0.84	−0.20** (0.02)	−0.03 (0.03)
Number of branded Rxs	0.30	−0.08** (0.01)	0.01 (0.01)
Number of generic Rxs	0.54	−0.12** (0.02)	−0.04* (0.02)
Expensive Rxs	0.12	−0.04** (0.01)	−0.00 (0.01)
Medium Rxs	0.23	−0.06** (0.01)	0.00 (0.01)
Inexpensive Rxs	1.10	−0.02* (0.01)	−0.01 (0.02)

- Each regression includes individual fixed effects and \$2,400-2,509 indicator
- Sample extends from \$2,000 - 3,000 in beginning of week spending
- Inexpensive drugs: $<$ \$50; expensive drugs: $\geq$ \$150

Takeaway: spending flat in \$2,000 to \$2,399 region

Table 6: Largest and smallest changes in drug classes near coverage gap

Dependent variable Number of Rxs for:	Mean value before $2,400	Beginning of week spending in: $2,510 - 2,999
Cholesterol Lowering	0.081	-0.0177^{**} (0.0034)
Beta-Blocker	0.046	-0.0135^{**} (0.0023)
Gastroesophageal Reflux & Peptic Ulcer	0.032	-0.0130^{**} (0.0022)
Renin-Angiotensin System Blocker	0.065	-0.0120^{**} (0.0029)
Antidepressant	0.045	-0.0102^{**} (0.0024)
Anti-Glaucoma	0.010	0.0001 (0.0014)
Antidiarrheal	0.001	0.0002 (0.0004)
Diuretic & Renin-Angiotensin System Blocker	0.002	0.0003 (0.0005)
Folic Acid Antagonist Antibiotic	0.003	0.0005 (0.0008)
Antiarrhythmic	0.002	0.0007 (0.0005)

- Each regression includes individual fixed effects and $2,400-2,509 indicator
- Sample extends from $2,000-3,000 in beginning of week spending

Takeaway: similar drops except for opioids (which alleviate pain)

Interpretation of reduced form evidence

- Reaction to current price is evidence against neoclassical model with traditional discount factor
- Lack of significance in $2,200-2,399 region rules out geometric discounting with low (but positive) discount factor
- We don't account for catastrophic region:
  - 9% of enrollees in our sample eventually do end up there
  - Rationally, spending should be higher in catastrophic region
  - Reaching doughnut hole implies higher probability of reaching catastrophic region
  - This will bias doughnut hole coefficients higher, towards zero
- Falsification exercise
  - No change at $2,510
- Seniors provided good information about doughnut hole
  - See Part D statement
- Evidence from national sample: 83.4% hit doughnut hole in 2007
  - They weren't uninformed, just not sure how to act

Portion of Part D statement provided to seniors

STAGE 1 **Yearly Deductible**	(Because there is no deductible for this plan, this payment stage does not apply to you.)
	You are in this stage:
STAGE 2 **Initial Coverage**	• You begin in this payment stage when you fill your first prescription of the year. During this payment stage, the plan pays its share of the cost of your drugs and you (or others on your behalf) pay your share of the cost. • You generally stay in this stage **until the amount of your year-to-date "total drug costs" reaches $2,850.00.** As of **08/30/2014**, your year-to-date "total drug costs" was **$321.05**. (See definitions in Section 3).
What happens next?	
Once you have **an additional $2,528.95 in "total drug costs,"** you move to the next payment stage (stage 3, Coverage Gap).	
STAGE 3 **Coverage Gap**	• During this payment stage, you (or others on your behalf) receive a discount on brand name drugs and you pay up to 72% of the costs of generic drugs. • You generally stay in this stage until the amount of your year-to-date "out-of-pocket costs" (see Section 3) reaches **$4,550.00.** When this happens, you move to payment stage 4, Catastrophic Coverage.
STAGE 4 **Catastrophic Coverage**	• During this payment stage, the plan pays most of the cost for your covered drugs. • You generally stay in this stage for the rest of the plan year (through December 31, 2014).

Overview of structural estimation

- We separate the individuals into groups based on ACG score
  - Variation across groups in all parameters
- Basic idea of estimation: nested fixed point with maximum likelihood
  - Solve dynamic decision process
  - Match choice predictions to data
- Central complication: we do not observe all health shocks
  - Only observe health shocks when individual purchases drug
  - Modeling of outside option central to identification: individuals choose outside option more in doughnut hole
- Result is a problem with unobserved heterogeneity
  - Complicates specification and computation of likelihood
  - Can't use conditional choice probability estimators
  - Develop method to integrate over number of health shocks and places of diseases
  - Efficient method is important because we have 200+ parameters

See details of structural estimation algorithm

Identification of structural model

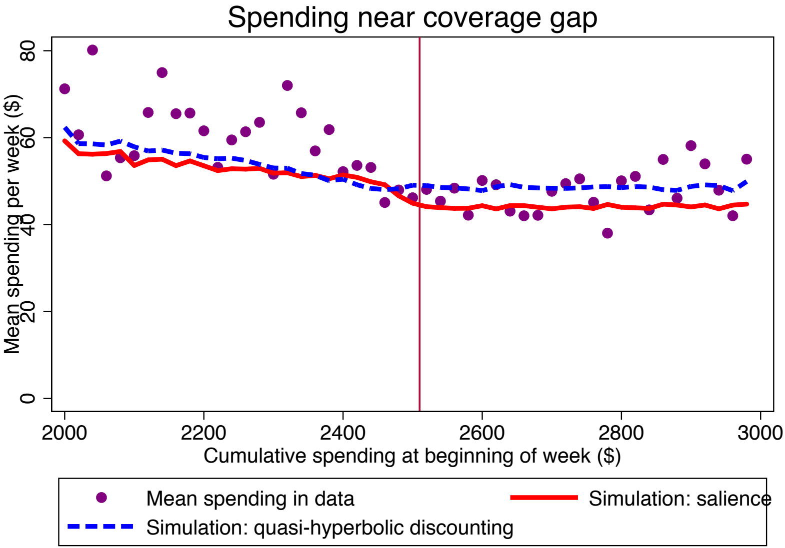
- Identification of discount factor δ:
  - An exclusion restriction can be used to identify both δ and choice-specific value functions (Magnac and Thesmar, 2002)
  - Intuitively, in the geometric discounting case, suppose that there is:
    - Drug 1: price \$100 and \$25 copay
    - Drug 2: price \$40 and \$10 copay
  - Then, at state $m = \$20$, no insurance subsidy from drug 1
    - Drug 1 utility same as inside doughnut hole
    - This provides exclusion restriction and identifies δ
    - ϕ and price parameters identified concurrently
- To identify β/σ:
  - β is ratio of time t tradeoff between t and $t+1$ to time t tradeoff between $t+1$ and $t+2$ (Laibson, 1997)
  - Given δ, behavior at states with two vs. one purchase occasion until doughnut hole identify β/σ
- Overall: need to identify flow utility (including price elasticity) accurately to identify discount factor
- Proposition 3 provides formal proof of identification for simple case

Structural estimation results

Model:	Quasi-hyperbolic discounting: naïfs	Quasi-hyperbolic discounting: sophisticates	Price salience
Price $<$ \$20	-0.116^{**} (0.006)	-0.116^{**} (0.006)	-0.148^{**} (0.007)
Price $\in$ [\$20, \$50)	-0.012^{**} (0.002)	-0.012^{**} (0.002)	-0.014^{**} (0.002)
Price $\in$ [\$50, \$150)	-0.013^{**} (0.008)	-0.013^{**} (0.008)	-0.018^{**} (0.0009)
Price $\geq$ \$150,	-0.006^{**} (0.001)	-0.006^{**} (0.001)	-0.003^{*} (0.001)
Behavioral: β or σ	0 (–)	0 (–)	0 (–)
Discount factor: δ	–	–	–
log L	$-95{,}594.6$	$-95{,}594.6$	$-95{,}456.7$
log L $\beta/\sigma = .1, \delta = .1$	$-95{,}604.8$	$-95{,}604.5$	$-95{,}462.0$
P-value for LM test	0.00	0.00	0.00
log L $\beta/\sigma = .3, \delta = .995$	$-95{,}672.5$	$-95{,}563.8$	$-95{,}532.9$
P-value for LM test	0.00	0.00	0.00

- Price coefficients similar across ACG scores
    - Imply elasticity of $-.54$ over 52 weeks
    - Big heterogeneity: medium-priced Rxs *increase* with price increase
    - Abaluck et al. $-.09$; Einav et al. $-.50$; Karaca-Mandic et al. $-.95$
- Salience model—with no future salience—fits data the best
    - Enrollees not paying attention to doughnut hole prices

Fit of quasi-hyperbolic discounting and price salience models



Counterfactuals

- Use mix of estimation sample and other enrollees from our data
  - Chosen so that 33% hit doughnut hole (2008 Medicare Part D)
  - Use 32% estimation sample, 68% others
  - Use middle ACG scores, salience model
  - Results robust to other ACG scores
- Simulate optimizing behavior for 52 week model
  - Finite horizon Bellman equation here
  - Explicitly allow catastrophic coverage
  - Use estimated structural parameters
- Examine outcomes and welfare
  - Welfare measures assume geometric 5% discounting over year
- Two sets of counterfactuals
  1. Importance of moral hazard and behavioral hazard
  2. Counterfactual policies
     - Eliminating the coverage gap
     - Generic-only coverage in doughnut hole

Moral hazard and behavioral hazard

Statistic (per week)	Baseline: $\sigma = 0$ future not salient Case 1	Neoclassical model (no behavioral hazard) Case 2	No insurance (no moral hazard) Case 3
Number of Rxs	0.59	0.57	0.42
Number of branded Rxs	0.16	0.13	0.11
Number of generic Rxs	0.35	0.38	0.25
Expensive Rxs	0.08	0.06	0.05
Medium Rxs	0.17	0.15	0.13
Inexpensive Rxs	0.33	0.36	0.25
Enrollee spending ($)	15.82	10.91	26.61
Insurer spending ($)	25.39	24.17	0.00
Total spending ($)	41.20	35.08	26.61
Enrollee welfare	1.21	1.27	0.63

- Moral hazard: extra spending from health insurance
  - Without insurance, total spending would decline 35%
- Behavioral hazard: extra spending from no salience
  - Forward looking consumers would reduce total spending 15% and own spending 31%

Closing the doughnut hole

Statistic (per week)	Baseline: future not salient Policy 1	No doughnut hole Policy 2	No doughnut hole w/ constant insurer spending Policy 3	No doughnut hole for generics only Policy 4
Number of Rxs	0.59	0.63	0.62	0.61
Number of branded	0.16	0.18	0.17	0.16
Number of generic	0.35	0.37	0.37	0.39
Expensive Rxs	0.08	0.10	0.08	0.08
Medium Rxs	0.17	0.18	0.16	0.17
Inexpensive Rxs	0.33	0.35	0.38	0.36
Enrollee spending ($)	15.71	12.83	14.88	14.25
Insurer spending ($)	25.55	32.49	25.55	27.23
Total spending ($)	41.26	45.32	40.43	41.48
Enrollee welfare	1.21	1.35	1.31	1.29
Coinsurance rate	from data	from data	37%	from data

- No doughnut hole: total spending ↑ 10% (insurer spend ↑ 31%)
  - Comparables: Abaluck et al.: 6%, Einav et al.: 10%
- 37% coinsurance for revenue-neutral doughnut hole elimination
- Generic-only coverage: total spending almost unchanged

Conclusions

- We develop a modeling framework to understand behavior with complex insurance contracts
- Discontinuity-based test of neoclassical model:
  - Uses sample of enrollees who expect to end up in doughnut hole
  - People lower consumption upon reaching coverage gap
    - Strong evidence against neoclassical model
  - Also can reject geometric discounting model with low discount factor because spending flat in region before doughnut hole
- Develop structural estimation with quasi-hyperbolic discounting or price salience
  - First structural, dynamic estimation of price salience model
- Findings:
  - Salience model fits data best, with $\sigma = 0$
  - Closing coverage gap would:
    - Raise total spending 10%; or
    - Necessitate 37% coinsurance for budget neutrality
    - Generic-only gap coverage much cheaper

Likelihood with known disease occurrences

- We first illustrate likelihood for simpler case where all health shocks are known
- Denote individuals $i = 1, \ldots, I$, time by t
- Let N_{it} indicate observed health shocks
- Variables now indexed by g: Q_{gn}, $\overline{N}_g$, P_{gh}, and $s(g, m, n, h, j)$
- Likelihood for i and t can be written as:

$$\ln L_{it} = \sum_{n=0}^{N_{it}} \ln(1\{n = N_{it}\}(1 - Q_{g(i)n}) + \\ 1\{n < N_{it}\} Q_{g(i)n} P_{g(i)h_{itn+1}} s(g(i), m_{itn+1}, n+1, h_{itn+1}, j_{itn+1})).$$

- For each observed disease n:
  - Conditional probability of seeing that additional disease ($Q_{g(i)n}$)
  - Conditional probability of the observed disease ($P_{g(i)h_{itn+1}}$)
  - Conditional probability of observed drug for that disease ($s()$)
- If no more diseases, conditional probability is $(1 - Q_{g(i)n})$

Idea with unknown disease occurrences

- Compute probabilities P and Q from data on the same enrollees, but earlier in the year (expenditures $<$ \$2,000)
  - Simplifies identification and computation task of likelihood estimator
- Specify all possibilities over when observed health shocks could have occurred and over number of health shocks
- Example: enrollee purchases drugs A then B, and has maximum 4 health shocks, $\overline{N}_{g(i)} = 4$
  - Possible health shock times (with A before B): $(1,2),(1,3),(1,4),(2,3),(2,4),(3,4)$
  - Possible number of health shocks: $(1,2) = \{2,3,4\}$, $(1,3) = \{3,4\}$, $(1,4) = \{4\}$, etc.
- Conditional on any possibility of when observed health shocks occur, model fits earlier likelihood
- Use methods in Gowrisankaran (1999) to enumerate possible health shock times in closed form
  - Define this set as $\mathcal{L}(N)$

Likelihood function

$$\ln L_{it} = \log \left(\sum_{l_1,\dots,l_{\hat{N}_{it}} \in \mathcal{L}(\hat{N}_{it})} \sum_{N_{it}=l_{\hat{N}_{it}}}^{\overline{N}_{g(i)}} \left(\prod_{n=0}^{N_{it}-1} Q_{g(i)n} \right) (1 - Q_{g(i)N_{it}}) \right.$$

$$\prod_{n=1}^{\hat{N}_{it}} P_{g(i)h_{itn}} s\left(g(i), m_{itn}, l_n, h_{itn}, j_{itn}\right))$$

$$\left. \prod_{n=1, n\neq l_1,\dots,n\neq l_{\hat{N}_{it}}}^{N_{it}} \left(\sum_{h=1}^{H} P_{g(i)h} s\left(g(i), \min_{\tilde{n} \text{ s.t. } l_{\tilde{n}} < n} m_{it\tilde{n}}, n, h, 0 \right) \right) \right)$$

- First line: sum over when observed health shocks occur and number of health shocks, probability of seeing this many shocks
- Second line: probability of observed health shocks and drugs chosen
- Third line: probability of unobserved health shocks

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