Myopia and Complex Dynamic Incentives: Evidence from Medicare Part D

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Introduction

- Part D is the largest and most important benefit change to Medicare since its inception
  - Part D added drug coverage to existing hospital and physician/outpatient benefits
  - Signed by President George W. Bush with bipartisan support
  - Cost to Medicare was $66.5 billion in 2012
- Program lowered out-of-pocket costs and increased prescription drug consumption
- Part D is popular, enrolling over 43 million beneficiaries
Coverage gap

- Biggest criticism is “donut hole” benefit structure
- Insurance stops when spending reaches “donut hole”
  - 2008 coverage gap starts at $2,510 in total expenditures
- Benefits don’t restart until catastrophic coverage
  - 2008 catastrophic limit is $4,050 in out-of-pocket expenditures
- Coverage gap is very unpopular
  - One-third of Part D enrollees entered donut hole in 2008
  - Critics suggest that it leads to adverse consequences for health by reducing consumption of medications (Liu et al., 2011)
  - 2010 Affordable Care Act phases it out
- Creates a complex dynamic decision problem for enrollees
Rational model versus reality

- Rational model: what matters most is expected end-of-year price
  - Rational individuals will gain only a small time value of money from changing behavior in coverage gap
- Does rational model accurately reflect enrollee behavior?
  - Some studies find (partly) myopic part D plan choices
  - But other studies find some rationality
    - Ketcham et al., 2012, Einav et al, 2013, Ketcham et al., 2014
- Suggests need to examine rationality in this market further
  - Rationality here implies dynamic optimization
  - Dynamic optimization required for many health insurance contracts
    - Deductibles, out-of-pocket maximums, donut holes, ...
Goals of this study

1. To analyze the extent to which part D enrollees act myopically in their choice of drugs

2. To evaluate the extent to which myopia creates “behavioral hazard” and how this influences outcomes
Overview of study

- Construct a dynamic model of drug consumption
  - Model allows for non-rational behavior, notably quasi-hyperbolic discounting
- Develop simple and robust test of myopia
  - Test based on a regression discontinuity design
  - Examine enrollees who arrive near donut hole early in the year
  - Rationally, they should expect to reach donut hole by end of year
- Structurally estimate parameters of model
  - Use to evaluate importance of behavioral hazard and implications of counterfactual policies
  - Challenging because “outside option” not observed
  - Develop methods to efficiently handle missing outside option
- Both test of myopia and structural estimation framework may be more broadly applicable in understanding insurance
Relation to literature

- Study most closely related to papers examining Part D:
  - Einav et al., 2013, Abaluck et al., 2013, etc.
  - We develop complementary tests to literature
  - Einav et al. estimates a structural dynamic model with annualized discount factor 0.12
    - We propose a test for low discount factors or myopia
    - Our modeling framework more similar to standard dynamic multinomial choice models
    - Identification uses actual price data and period near donut hole

- Also relates to literature examining hyperbolic discounting:
  - Agents play a game against future versions of themselves
  - Our empirical modeling builds on Fang and Wang (2013) and others
Remainder of talk

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

- Model focuses on the dynamic decision of a single enrollee
  - Structural estimation section discusses aggregation
- We model a Medicare Part D enrollee who reaches $2,000 in expenditures between April and July
  - We consider decision process after reaching near the donut hole
  - Assume that these individuals will end the year in the donut hole
  - Assumption is close to correct (empirical evidence later)
  - Implication: donut hole is absorbing state
- Each week, enrollee faced with a distribution of health shocks
  - At any point in time, enrollee calculates conditional distribution of future health shocks
  - Conditional on type, each health shock is an independent draw
  - Maximum $\bar{N}$ health shocks in a week
- Let $Q_n, n = 0, \ldots \bar{N}$ denote conditional probability of observing another health shock
Health shocks and drugs

- Each health shock corresponds to a drug class
  - E.g., opioids or insulin sensitizers
  - Each health shock $h$ occurs with probability $P_h$
- Each health shock has associated drugs $j = 1, \ldots, J_h$ plus the outside option $j = 0$, which involves no treatment
- Flow utility from any drug treatment is a function of:
  - $\gamma_{hj}$ – perceived mean utility fixed effects
  - price $p_{hj}$ or $oop_{hj}$, with parametrization $\alpha(p)$
    - We use a linear spline with kink points at $20, 50, 100$ and coefficients $\bar{\alpha}$
    - Allow for flexible impact of price on decisions
  - $i.i.d.$ shocks $\varepsilon_{hj}$
- Flow utility before donut hole: $\gamma_{hj} - \alpha(oop_{hj}) + \varepsilon_{hj}$
- Flow utility in donut hole: $\gamma_{hj} - \alpha(p_{hj}) + \varepsilon_{hj}$
- Outside option has utility $\varepsilon_{h0}$
  - Substitution to outside good in donut hole is important
Our problem is dynamic because filling a Rx moves you closer to coverage gap

At any week $t$, individual discounts future utility as:
- $\beta$ for treatments this week
- $\beta \delta$ for treatments at $t + 1$
- $\beta \delta^2$ for treatments at $t + 2$, etc.

Agents at time $t$ value $t + 1$ and $t + 2$ payoffs similarly (by $1/\delta$)
- But, upon getting to $t + 1$, they heavily discount $t + 2$ payoffs (by $1/\beta \delta$)
- They would like to commit to future actions but can’t

Agents are “sophisticates” who know their $\beta$ and $\delta$

They optimize at each state, taking as given future actions
- Thus, agents play an equilibrium against future selves
- Can model this similarly to a Bellman (Fang and Wang, 2013)
Implications of model: no discounting

- Consider a simple case with one health shock and one drug
  - \( H = 1, J = 1, \overline{\alpha}(p) = \alpha p \)
- Let \( p_{11} = 100.4 \) and \( oop_{11} = 25.1 \)
  - Numbers chosen to divide easily into $2,510 threshold
- First 25 drugs consumed are insured and the rest aren’t
- Consider first: \( \beta = \delta = 1 \)
  - For tractability, assume decision ends at far-away finite time
  - All that matters is end-of-year price
  - Decision same as with no insurance and $1,882.5 fixed subsidy!
  - Takeaway: no change in behavior upon crossing donut hole
    - Reminder: we’re considering only people who know they will hit the donut hole at some point
- What about multiple drugs/drug classes?
  - More complicated intuition but similar idea
- What about case where drug valuation is in between \( oop \) and \( p \)?
  - Spending would stop at coverage gap
  - Not true in our data!
Implications of model: geometric discounting, $\delta > 0$

Geometric discounting case is $\beta = 1, 0 < \delta < 1$

- Compare 25th drug purchase (last insured one) to 26th one:
  - By purchasing at 25th time, enrollee pays $25.1 immediately and then moves up $75.3 payment by one purchase occasion
  - At 26th time, enrollee pays full $100.4 immediately
  - Difference in utility: $75.3(1 - \delta^t)\alpha$
    - $t$ is time between 25th and 26th purchases $\rightarrow$ small

  Implication: can only explain sizable purchase probability differences with very elastic demand or very low discount factor

- Now compare 24th to 26th purchase:
  - Enrollee gets the same time value of $75.3$
  - But time period she gets it some longer $t'$
  - Difference in utility: $75.3(1 - \delta^{t'})\alpha$

  Implication: increase from 24th to 26th purchase is roughly twice increase from 25th to 26th purchase

- Overall, geometric discounting yields continued decrease in purchases towards donut hole
Implications of model: myopia

- Myopia is:
  - $\beta < 1$ or $\delta = 0$ (total myopia)

- Compare again 25th drug purchase to 26th one:
  - Difference is still value of $75.3$ over period between purchases
  - But, $75.3$ is now discounted by $\beta \delta^t$, where $t$ is expected time till next purchase
  - Difference in utility is now $75.3(1 - \beta \delta^t)\alpha$

  Implication: $\beta \ll 1$ can yield substantial utility difference

- Now compare 24th to 26th purchase:
  - $75.3$ is now discounted by $\beta \delta^{t'}$
  - Difference in utility is now $75.3(1 - \beta \delta^{t'})\alpha$
  - Importantly, $75.3(1 - \beta \delta^t)\alpha \approx 75.3(1 - \beta \delta^{t'})\alpha$

  Implication: myopia allows for 24th and 25th purchases to have similar probabilities and a big drop at 26th

- Graphic case using also $\gamma_{11} = 1$, $\alpha = 0.02$, $Q_0 = 1$, $Q_1 = 0$
Spending from stylized case

Simulated spending from stylized model

- **β=0** (complete myopia)
- **β=0.5, δ=0.999** (β-δ case)
- **β=1, δ=0.96** (geometric but low δ)
- **β=1, δ=0.999** (geometric)
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 “donut hole” design:
  - Claims from 5 plans and 2 employers covering 32,463 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
Our Express Scripts data contain:
- All claims from each enrollee
- Enrollee identifier and date
- Drug name, type, and NDC code
- Out-of-pocket price and total price billed to insurance company

Combine data with ACG score data:
- Developed by Johns Hopkins
- 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
Construction of sample and variables

  - Both reduced-form and structural estimation driven by regression discontinuity of people near coverage gap start
  - One observation is an enrollee/week
  - We keep weeks starting with first complete week over $2,000
  - Sample extends to last week in year that starts under $3,000
- Structural estimation (and some reduced form evidence) classify each drug into a disease category
  - Use drug function not disease because of choice model framework
  - E.g., calcium channel blockers and renin-angiotensin system blockers are each classes, though both used for hypertension
  - Lump together drug classes with fewer than 100 Rxs over the whole year
  - Lump together drugs within a disease class so that there are at least 50 Rxs over the whole year
    - Structural estimation models fixed effects for each drug
## Table 1: plan characteristics and enrollment

<table>
<thead>
<tr>
<th>Plan</th>
<th>A</th>
<th>B</th>
<th>C</th>
<th>D</th>
<th>E</th>
<th>F</th>
</tr>
</thead>
<tbody>
<tr>
<td>Employer % of employees from employer</td>
<td>26</td>
<td>45</td>
<td>9</td>
<td>79</td>
<td>21</td>
<td>46</td>
</tr>
<tr>
<td>Deductible ($)</td>
<td>275</td>
<td>100</td>
<td>100</td>
<td>0</td>
<td>200</td>
<td>0</td>
</tr>
<tr>
<td>Donut hole start (total $)</td>
<td>2,510</td>
<td>2,510</td>
<td>2,510</td>
<td>2,510</td>
<td>2,510</td>
<td>4,000</td>
</tr>
<tr>
<td>Catastrophic start (out-of-pocket $)</td>
<td>4,050</td>
<td>4,050</td>
<td>4,050</td>
<td>4,010</td>
<td>4,010</td>
<td>4,050</td>
</tr>
<tr>
<td>Total enrollment</td>
<td>7,541</td>
<td>12,858</td>
<td>2,431</td>
<td>4,062</td>
<td>1,058</td>
<td>35,395</td>
</tr>
<tr>
<td>% hitting $2,510</td>
<td>20</td>
<td>13</td>
<td>16</td>
<td>16</td>
<td>13</td>
<td>20</td>
</tr>
<tr>
<td>% hitting catastrophic</td>
<td>2</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>0</td>
</tr>
<tr>
<td>Estimation sample: Enrollment</td>
<td>672</td>
<td>717</td>
<td>149</td>
<td>326</td>
<td>52</td>
<td>3,341</td>
</tr>
<tr>
<td>% hitting $2,510</td>
<td>96</td>
<td>95</td>
<td>96</td>
<td>97</td>
<td>94</td>
<td>98</td>
</tr>
<tr>
<td>% hitting catastrophic</td>
<td>12</td>
<td>8</td>
<td>9</td>
<td>10</td>
<td>12</td>
<td>0</td>
</tr>
<tr>
<td>Mean total spending ($)</td>
<td>4,543</td>
<td>4,135</td>
<td>4,082</td>
<td>4,232</td>
<td>3,982</td>
<td>4,150</td>
</tr>
<tr>
<td>Mean out-of-pocket ($)</td>
<td>2,398</td>
<td>2,038</td>
<td>2,160</td>
<td>2,032</td>
<td>2,068</td>
<td>1,032</td>
</tr>
<tr>
<td>Mean age</td>
<td>74</td>
<td>73</td>
<td>72</td>
<td>75</td>
<td>75</td>
<td>78</td>
</tr>
<tr>
<td>Percent female</td>
<td>62</td>
<td>57</td>
<td>54</td>
<td>62</td>
<td>56</td>
<td>64</td>
</tr>
<tr>
<td>Mean ACG score</td>
<td>1.07</td>
<td>1.18</td>
<td>1.22</td>
<td>0.94</td>
<td>1.14</td>
<td>0.67</td>
</tr>
</tbody>
</table>

Note: plan A provides generic coverage in deductible region; plan F used for falsification exercise only and also provides generic coverage in donut hole.
Table 2: most common drug classes in sample

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

Total number of drug classes: 70
Testing for low discount factors and hyperbolic discounting

- Estimate a series of regressions on sample of enrollees near donut hole early in the year (starting at $2,000 in total spending)
  - For this sample, same future price but different current prices
  - Rationally, should react principally to future price
  - RDD approach minimizes possibility that factors other than donut hole influence our findings
- Using this sample, linear regressions of form:

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

where:

- the unit of observation is an enrollee \( i \) over a week \( t \)
- \( Y_{it} \) include variables such as # of Rxs in week
- \( FE_i \) are individual fixed effects
- \( 1\{m_{it0} = 0\} \) – indicator for in donut hole at beginning of week
- \( 1\{0 < m_{it0} \leq $110\} \) – “near donut hole” indicator at beginning of week – not reported in tables
- Start with “lowess” non-parametric regressions
Total spending: base sample

Spending near coverage gap

- Mean spending during week
- Smoothed spending during week

Cumulative spending at beginning of week ($) vs. Total spending per week ($)

Legend:
- Mean spending during week
- Smoothed spending during week
Total spending: falsification plan F

Spending near base plan coverage gap: falsification plan

Cumulative spending at beginning of week ($)

Mean spending during week

Smoothed spending during week
Total spending near $4,000: falsification plan F

Note: sample is enrollees near F coverage gap early in year.
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 donut hole
- Estimation sample does not
Table 4: Behavior for sample arriving near coverage gap

<table>
<thead>
<tr>
<th>Dependent variable:</th>
<th>Mean value before $2,400</th>
<th>Beginning of week spending in: $2,510 - 2,999</th>
</tr>
</thead>
<tbody>
<tr>
<td>Total drug spending in week</td>
<td>61.83</td>
<td>$-17.62^{**}$ (1.39)</td>
</tr>
<tr>
<td>Mean total price per Rx</td>
<td>79.47</td>
<td>$-9.83^{**}$ (1.37)</td>
</tr>
<tr>
<td>Number of Rxs</td>
<td>0.84</td>
<td>$-0.18^{**}$ (0.02)</td>
</tr>
<tr>
<td>Number of branded Rxs</td>
<td>0.30</td>
<td>$-0.08^{**}$ (0.01)</td>
</tr>
<tr>
<td>Number of generic Rxs</td>
<td>0.54</td>
<td>$-0.10^{**}$ (0.01)</td>
</tr>
<tr>
<td>Expensive Rxs</td>
<td>0.12</td>
<td>$-0.04^{**}$ (0.00)</td>
</tr>
<tr>
<td>Medium Rxs</td>
<td>0.23</td>
<td>$-0.06^{**}$ (0.01)</td>
</tr>
<tr>
<td>Inexpensive Rxs</td>
<td>1.10</td>
<td>$-0.01$ (0.01)</td>
</tr>
</tbody>
</table>

Note: $N=30,305$ except for “Mean spending per Rx” regression when $N=11,197$
- 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: big drops, particularly on expensive drugs, at donut hole
**Table 5: Behavior near coverage gap with variation in pre-coverage gap region**

<table>
<thead>
<tr>
<th>Dependent variable:</th>
<th>Mean value before $2,400</th>
<th>Beginning of week spending in:</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>$2,510 - 2,999</td>
</tr>
<tr>
<td>Total drug spending in week</td>
<td>61.83</td>
<td>$-18.03** (1.78)</td>
</tr>
<tr>
<td>Mean total price per Rx</td>
<td>79.47</td>
<td>$-9.01** (1.72)</td>
</tr>
<tr>
<td>Number of Rxs</td>
<td>0.84</td>
<td>$-0.20** (0.02)</td>
</tr>
<tr>
<td>Number of branded Rxs</td>
<td>0.30</td>
<td>$-0.08** (0.01)</td>
</tr>
<tr>
<td>Number of generic Rxs</td>
<td>0.54</td>
<td>$-0.12** (0.02)</td>
</tr>
<tr>
<td>Expensive Rxs</td>
<td>0.12</td>
<td>$-0.04** (0.01)</td>
</tr>
<tr>
<td>Medium Rxs</td>
<td>0.23</td>
<td>$-0.06** (0.01)</td>
</tr>
<tr>
<td>Inexpensive Rxs</td>
<td>1.10</td>
<td>$-0.02* (0.01)</td>
</tr>
</tbody>
</table>

- 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:** no pattern of sustained drops approaching donut hole
### Table 6: Largest and smallest changes in drug classes near coverage gap

<table>
<thead>
<tr>
<th>Dependent variable</th>
<th>Mean value before $2,400</th>
<th>Beginning of week spending in: $2,510 - 2,999</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cholesterol Lowering</td>
<td>0.080</td>
<td>$-0.0176** (0.0034)</td>
</tr>
<tr>
<td>Beta-Blocker</td>
<td>0.046</td>
<td>$-0.0136** (0.0023)</td>
</tr>
<tr>
<td>Gastroesophageal Reflux &amp; Peptic Ulcer</td>
<td>0.031</td>
<td>$-0.0129** (0.0023)</td>
</tr>
<tr>
<td>Renin-Angiotensin System Blocker</td>
<td>0.065</td>
<td>$-0.0124** (0.0029)</td>
</tr>
<tr>
<td>Antidepressant</td>
<td>0.045</td>
<td>$-0.0105** (0.0024)</td>
</tr>
<tr>
<td>Ophthalmic Antibiotic</td>
<td>0.002</td>
<td>$0.0000 (0.0006)</td>
</tr>
<tr>
<td>Antidiarrheal</td>
<td>0.001</td>
<td>0.0002 (0.0004)</td>
</tr>
<tr>
<td>Folic Acid Antagonist Antibiotic</td>
<td>0.003</td>
<td>0.0003 (0.0008)</td>
</tr>
<tr>
<td>Diuretic &amp; Renin-Angiotensin System Blocker</td>
<td>0.002</td>
<td>0.0003 (0.0005)</td>
</tr>
<tr>
<td>Antiarrhythmic</td>
<td>0.002</td>
<td>0.0007 (0.0005)</td>
</tr>
</tbody>
</table>

- 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)
Table B1: is there substitution from branded to generics and from expensive to other drugs?

<table>
<thead>
<tr>
<th>Regressor</th>
<th>Branded</th>
<th>Generic</th>
<th>Expensive</th>
<th>Medium</th>
<th>Inexpensive</th>
</tr>
</thead>
<tbody>
<tr>
<td>Frac branded</td>
<td>1.45**</td>
<td>−1.50**</td>
<td>−</td>
<td>−</td>
<td>−</td>
</tr>
<tr>
<td></td>
<td>(.038)</td>
<td>(.054)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Frac branded × donut hole</td>
<td>−.065</td>
<td>.085</td>
<td>−</td>
<td>−</td>
<td>−</td>
</tr>
<tr>
<td></td>
<td>(.042)</td>
<td>(.060)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Frac expensive</td>
<td>−</td>
<td>−</td>
<td>1.47**</td>
<td>.168*</td>
<td>−1.79**</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>(.051)</td>
<td>(.065)</td>
<td>(.078)</td>
</tr>
<tr>
<td>Frac expensive × donut hole</td>
<td>−</td>
<td>−</td>
<td>−.065</td>
<td>.170**</td>
<td>.056</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>(.042)</td>
<td>(.054)</td>
<td>(.084)</td>
</tr>
<tr>
<td>Donut hole ($2,510 - 2,999)</td>
<td>−.045*</td>
<td>−.041</td>
<td>−.031**</td>
<td>−.072**</td>
<td>−.002</td>
</tr>
<tr>
<td></td>
<td>(.019)</td>
<td>(.036)</td>
<td>(.011)</td>
<td>(.018)</td>
<td>(.027)</td>
</tr>
<tr>
<td>N</td>
<td>11,197</td>
<td>11,197</td>
<td>11,197</td>
<td>11,197</td>
<td>11,197</td>
</tr>
</tbody>
</table>

Takeaways:

- Significant evidence of substitution from expensive to medium-priced drugs
- Evidence based on drug classes with lots of expensive drugs
Interpretation of reduced form evidence

- Reaction to current price is evidence of low discount factor or myopia
- 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:
  - 10% of enrollees in our sample eventually do end up there
  - Rationally, spending should be higher in catastrophic region
  - Reaching donut hole implies higher probability of reaching catastrophic region
  - This will bias donut hole coefficients higher, which is towards zero
- Falsification exercise
  - No change at $2,510
- Behavior near catastrophic start looks more geometric
- Seniors provided good information about donut hole
  - See Part D statement
Portion of Part D statement provided to seniors

<table>
<thead>
<tr>
<th>STAGE 1</th>
<th>Yearly Deductible</th>
</tr>
</thead>
<tbody>
<tr>
<td>(Because there is no deductible for this plan, this payment stage does not apply to you.)</td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>STAGE 2</th>
<th>Initial Coverage</th>
</tr>
</thead>
<tbody>
<tr>
<td>• 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.</td>
<td></td>
</tr>
<tr>
<td>• You generally stay in this stage until the amount of your year-to-date &quot;total drug costs&quot; reaches $2,850.00. As of 08/30/2014, your year-to-date &quot;total drug costs&quot; was $321.05. (See definitions in Section 3).</td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>What happens next?</th>
</tr>
</thead>
<tbody>
<tr>
<td>Once you have an additional $2,528.95 in &quot;total drug costs,&quot; you move to the next payment stage (stage 3, Coverage Gap).</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>STAGE 3</th>
<th>Coverage Gap</th>
</tr>
</thead>
<tbody>
<tr>
<td>• 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.</td>
<td></td>
</tr>
<tr>
<td>• You generally stay in this stage until the amount of your year-to-date &quot;out-of-pocket costs&quot; (see Section 3) reaches $4,550.00. When this happens, you move to payment stage 4, Catastrophic Coverage.</td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>STAGE 4</th>
<th>Catastrophic Coverage</th>
</tr>
</thead>
<tbody>
<tr>
<td>• During this payment stage, the plan pays most of the cost for your covered drugs.</td>
<td></td>
</tr>
<tr>
<td>• You generally stay in this stage for the rest of the plan year (through December 31, 2014).</td>
<td></td>
</tr>
</tbody>
</table>
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 up 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 donut 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
Identification of structural model

- Identification conditional on per-period profits:
  - Laibson, 1997 shows how to identify $\beta$ and $\delta$
  - $\beta\delta$ identified by time $t$ tradeoff between $t$ and $t + 1$
  - $\delta$ identified by time $t$ tradeoff between $t + 1$ and $t + 2$
  - Divide by $\delta$ to get $\beta$

- Analog in our model (from simple example):
  - Difference between 25th and 26th purchase identifies $\beta\delta^t$
  - Difference between 24th and 26th purchase identifies $\beta\delta^{t'}$
    - Caveat: at $\delta = 0$ or $\beta = 0$, can’t separate them

- How to simultaneously identify per-period profits?
  - Magnac and Thesmar (2002) argue that this is difficult, in general
  - Intuition: high $\alpha$ and low $\beta\delta$ have similar implications
    - Both predict big drop in quantity upon entry into donut hole
  - Heterogeneity provides identification in our case
    - E.g., different drugs have different substitutes within their classes
    - Formally, our model satisfies Magnac and Thesmar Prop. 4

- Overall takeaway: identification of price elasticity necessary to identify discount factor
### Structural estimation results

<table>
<thead>
<tr>
<th>Estimation sample:</th>
<th>Lowest ACG</th>
<th>Middle ACGs</th>
<th>Highest ACG</th>
</tr>
</thead>
<tbody>
<tr>
<td>Price spline: &lt; $20</td>
<td>$-0.110^{**}$ (0.011)</td>
<td>$-0.120^{**}$ (0.006)</td>
<td>$-0.127^{**}$ (0.014)</td>
</tr>
<tr>
<td>Price spline: &lt; $50</td>
<td>$-0.011^{**}$ (0.004)</td>
<td>$-0.007^{**}$ (0.002)</td>
<td>$-0.017^{**}$ (0.005)</td>
</tr>
<tr>
<td>Price spline: &lt; $100</td>
<td>$-0.019^{**}$ (0.003)</td>
<td>$-0.016^{**}$ (0.01)</td>
<td>$-0.022^{**}$ (0.003)</td>
</tr>
<tr>
<td>Price spline: ≥ $100</td>
<td>$-0.006^{**}$ (0.002)</td>
<td>$-0.007^{**}$ (0.001)</td>
<td>$-0.005^{**}$ (0.002)</td>
</tr>
<tr>
<td>Hyperbolic term $\beta$</td>
<td>0 (−)</td>
<td>0 (−)</td>
<td>0 (−)</td>
</tr>
<tr>
<td>Geometric term $\delta$</td>
<td>–</td>
<td>–</td>
<td>–</td>
</tr>
<tr>
<td>$\ln L$</td>
<td>$-27,995.3$</td>
<td>$-98,888.8$</td>
<td>$-20,672.6$</td>
</tr>
<tr>
<td>$\ln L, \beta = 0.1, \delta = 0.4$</td>
<td>$-27,997.8$</td>
<td>$-98,899.1$</td>
<td>$-20,674.8$</td>
</tr>
<tr>
<td>$\ln L, \beta = 0.1, \delta = 0.999$</td>
<td>$-27,999.1$</td>
<td>$-98,911.1$</td>
<td>$-20,677.8$</td>
</tr>
<tr>
<td>$\ln L, \beta = 1, \delta = 0.1$</td>
<td>$-28,016.9$</td>
<td>$-98,979.8$</td>
<td>$-20,693.5$</td>
</tr>
<tr>
<td>Number of drug FEs</td>
<td>125</td>
<td>254</td>
<td>142</td>
</tr>
<tr>
<td>N</td>
<td>4,898</td>
<td>20,091</td>
<td>8,592</td>
</tr>
</tbody>
</table>

- **Price coefficients similar across ACG scores**
  - Imply elasticity of $-0.32$ over 52 weeks
  - Big heterogeneity: medium-priced Rx increase with price increase
  - Comparables: Abaluck et al.: $-0.09$; Einav et al.: $-0.50$

- **Complete myopia fits data the best**
  - Enrollees not acting in a dynamically sophisticated way
  - Reasonable for modeling counterfactuals unless pattern changes
Use mix of estimation sample and other enrollees from our data
- Chosen so that 33% hit donut hole (as in 2008 Medicare Part D)
- Use 30% estimation sample, 70% others
- Use middle ACG scores, but results robust to three samples

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 donut hole
### Moral hazard and behavioral hazard

<table>
<thead>
<tr>
<th>Statistic (per week)</th>
<th>Baseline (Case 1)</th>
<th>Geometric discounting (no behavioral hazard) (Case 2)</th>
<th>No insurance (no moral hazard) (Case 3)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of Rxs</td>
<td>0.56</td>
<td>0.55</td>
<td>0.43</td>
</tr>
<tr>
<td>Number of branded Rxs</td>
<td>0.16</td>
<td>0.13</td>
<td>0.12</td>
</tr>
<tr>
<td>Number of generic Rxs</td>
<td>0.33</td>
<td>0.36</td>
<td>0.26</td>
</tr>
<tr>
<td>Expensive Rxs</td>
<td>0.10</td>
<td>0.07</td>
<td>0.06</td>
</tr>
<tr>
<td>Medium Rxs</td>
<td>0.15</td>
<td>0.14</td>
<td>0.12</td>
</tr>
<tr>
<td>Inexpensive Rxs</td>
<td>0.31</td>
<td>0.33</td>
<td>0.25</td>
</tr>
<tr>
<td>Enrollee spending ($)</td>
<td>16.33</td>
<td>11.56</td>
<td>29.47</td>
</tr>
<tr>
<td>Insurer spending ($)</td>
<td>26.44</td>
<td>25.29</td>
<td>0.00</td>
</tr>
<tr>
<td>Total spending ($)</td>
<td>42.78</td>
<td>36.85</td>
<td>29.47</td>
</tr>
<tr>
<td>Consumer welfare</td>
<td>1.10</td>
<td>1.16</td>
<td>0.67</td>
</tr>
</tbody>
</table>

- **Moral hazard**: extra spending from health insurance
  - Without insurance, total spending would decline 31%
- **Behavioral hazard**: extra spending from myopia
  - Forward looking consumers would reduce total spending 14% and own spending 29%
## Closing the donut hole

<table>
<thead>
<tr>
<th>Statistic (per week)</th>
<th>Baseline</th>
<th>No donut hole</th>
<th>No donut hole with constant insurer spend</th>
<th>No donut hole for generics only</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Policy 1</td>
<td>Policy 2</td>
<td>Policy 3</td>
<td>Policy 4</td>
</tr>
<tr>
<td># of Rxs</td>
<td>0.56</td>
<td>0.59</td>
<td>0.58</td>
<td>0.57</td>
</tr>
<tr>
<td># of branded Rxs</td>
<td>0.16</td>
<td>0.17</td>
<td>0.16</td>
<td>0.15</td>
</tr>
<tr>
<td># of generic Rxs</td>
<td>0.33</td>
<td>0.35</td>
<td>0.35</td>
<td>0.36</td>
</tr>
<tr>
<td>Expensive Rxs</td>
<td>0.10</td>
<td>0.11</td>
<td>0.09</td>
<td>0.09</td>
</tr>
<tr>
<td>Medium Rxs</td>
<td>0.15</td>
<td>0.15</td>
<td>0.14</td>
<td>0.15</td>
</tr>
<tr>
<td>Inexpensive Rxs</td>
<td>0.31</td>
<td>0.32</td>
<td>0.35</td>
<td>0.33</td>
</tr>
<tr>
<td>Enrollee spending, $</td>
<td>16.33</td>
<td>12.57</td>
<td>15.11</td>
<td>14.73</td>
</tr>
<tr>
<td>Insurer spending, $</td>
<td>26.44</td>
<td>34.54</td>
<td>26.44</td>
<td>28.01</td>
</tr>
<tr>
<td>Total spending, $</td>
<td>42.78</td>
<td>47.10</td>
<td>41.56</td>
<td>42.74</td>
</tr>
<tr>
<td>Consumer welfare</td>
<td>1.10</td>
<td>1.22</td>
<td>1.18</td>
<td>1.16</td>
</tr>
<tr>
<td>Coinsurance rate</td>
<td>from data</td>
<td>from data</td>
<td>36%</td>
<td>from data</td>
</tr>
</tbody>
</table>

- **No donut hole**: total spending ↑ 10%, insurer spending ↑ 31%
- **36% coinsurance** to close donut hole with same insurer spending
- **Generic-only coverage**: welfare ↑ 5%, total spending ↓ .1%
Conclusions

- We develop a modeling framework to understand the extent of forward-looking behavior under complex insurance contracts
  - Biggest limitations:
    - No dynamic progression of diseases from drug purchases
    - No measurement of substitute therapies to drugs or medical benefits
    - No imperfect physician agency model
- Discontinuity-based test for myopia:
  - Based on sample of enrollees who expect to end up in donut hole
  - People lower consumption *only* upon reaching coverage gap
  - \(\Rightarrow\) Supports myopia, but not geometric discounting
- Develop structural estimation with quasi-hyperbolic discounting
  - First dynamic drug model with I.O.-style multinomial choices
- Findings:
  - Complete myopia, \(\beta = 0\). Why?
  - Behavioral hazard important: rational agents spend 14% less
  - Closing coverage gap implies:
    - Increase of 31% in insurer spending with same coinsurance; or
    - 36% coinsurance for budget neutrality
    - Generic-only gap coverage much cheaper
Dynamics: definitions

- State space:
  - \( m \) – dollars till donut hole
  - Recall that donut hole is an absorbing state in our model
  - \( n \) – number of health shocks in week

- Gross value: \( V^\delta(m, n) \) is future payoffs gross of quasi-hyperbolic \( \beta \) term

- Net value: \( V(m, n, \vec{e}, h) \) is value at the time of realization of a health shock net of quasi-hyperbolic term

- Define “effective price”

\[
p_{ef}(m, p_{hj}, oop_{hj}) = \begin{cases} 
  p_{hj}, & \text{if } 0 \leq m < oop_{hj} \\
  oop_{hj} + p_{hj} - m, & \text{if } oop_{hj} < m \leq p_{hj} \\
  oop_{hj}, & \text{if } m > p_{hj}.
\end{cases}
\]
Dynamics: Bellman equations

- Net value depends on future gross value:
  \[
  V(m, n, h, \tilde{\epsilon}) = \max_{j=0, \ldots, J_h} \{ \gamma_{hj} - \alpha(p^e(m, p_{hj}, oop_{hj})) + \beta V^\delta(\max\{m - p_{hj}, 0\}, n + 1) + \epsilon_{hj} \}
  \]

- Actions depend on net value:
  \[
  s(m, n, h, j) = \frac{\exp(\gamma_{hj} - \alpha(p^e(m, p_{hj}, oop_{hj})) + \beta V^\delta(\max\{m - p_{hj}, 0\}, n + 1))}{\sum_{k=0}^{J_h} \exp(\gamma_{hk} - \alpha(p^e(m, p_{hk}, oop_{hk})) + \beta V^\delta(\max\{m - p_{hk}, 0\}, n + 1))}
  \]

- Gross value depends on future gross value and actions:
  \[
  V^\delta(m, n) = (1 - Q_n)\delta V^\delta(m, 0) + Q_n \sum_{h=1}^{H} \sum_{j=0}^{J_h} s(m, n, h, j) \times \\
  \left[ \gamma_{hj} - \alpha(p^e(m, p_{hj}, oop_{hj})) + V^\delta(\max\{m - p_{hj}, 0\}, n + 1) - \ln s(m, n, h, j) \right]
  \]

- Choices are essentially made with “wrong” Bellman \( V \)
  - \( - \ln s(m, n, h, j) \) captures expected value of \( \tilde{\epsilon} \)
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 \( g \): \( Q_{gn}, \bar{N}_g, P_{gh}, \) 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, $\bar{N}_{g(i)} = 4$
  - 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

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

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

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

- 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