Upcoding:
Evidence from Medicare on Squishy Risk Adjustment

Michael Geruso & Timothy Layton

Trend toward Regulated Private Markets

- Reliance on private insurers to deliver public healthcare subsidies
  - Subsidized individual markets
  - Private provision of public benefits in Medicare and Medicaid
- Private markets, even in the bookend case of perfect competition, generate distortions caused by adverse selection
  - Inefficient sorting and market unraveling due to spiraling prices: Akerlof (1970), Einav, Finkelstein, Cullen (2010), Hackmann, Kolstad, Kowalski (2014)
  - Cream skimming and inefficient contracts: Rothschild and Stiglitz (1976), Glazer and McGuire (2000), Azevedo and Gottlieb (2016), Veiga and Weyl (2016)
- Risk adjustment is widely implemented solution to both flavors of adverse selection problems: sorting and contract distortions

Diagnosis-Based Risk Adjustment

- Intuition behind risk adjustment is straightforward:
  - Goal to make all enrollees equally profitable to insurer
  - Higher capitation for higher *expected* cost enrollees
  - Weakens insurer cream-skimming incentives
- Requires informative signal of enrollee health status/cost
  - For many years, signal was based on demographics
  - More recently, shift to more data on diagnoses contained in claims
- Used anywhere government attempts to counteract selection in health insurance: Medicare, Medicaid, Exchanges/Marketplaces, managed competition markets around the world.

Risk Adjustment Can Cause New Distortions

- Prior work has taken coding as fixed; diagnoses are characteristics of enrollees

- We relax this, assume a risk score is a function of a person $\times$ plan match
  - Diagnoses assigned by physicians
  - Insurers incentivized to push physicians to code more aggressively
  - Aside from payment incentives, many reasons plans may generate different scores—e.g., more contact because of lower copays

- We study empirical importance of upcoding in Medicare
  - Traditional Fee-for-Service Medicare (FFS)
    - Government pays physicians directly for services, *not diagnoses*
  - Private Medicare Advantage plan (MA)
    - Government pays private plan fixed annual rate based on diagnosis-based risk scores

Research Questions

Seek to answer three questions:

1. Are there coding differences under the FFS and MA regimes?
2. What are the public finance implications of the coding differences (i.e., how much does it cost)?
3. How do coding differences affect consumer choices?

We will not ask/answer welfare questions about the value of intense coding

Preview of Empirical Results

- **Coding differences are empirically important:** Find that risk scores in MA are 6.4% higher than in FFS
  - Directly corresponds to size of overpayment in late 2000s
  - Size of effect is equivalent to 39% of the population becoming diabetic
  - MA coding intensity differential may ratchet up over time: 6.4% first year; 9% by 2nd year; and continuing to grow into 3rd year in MA
- **Public Finance Impacts:** Overpayments of $640 per enrollee in our time period, $10 billion annually. Though CMS has acted to partially counteract overpayments since
- **Choice Distortions:** Counterfactuals correcting for upcoding changes the size of MA market by 17%-33%
- **Vertical Integration:** Coding more intense for plans with more insurer-provider integration

Outline

1. Background on risk adjustment and medical coding
    - Define upcoding precisely
2. The identification problem and solution
3. Setting and empirical framework
4. Results
    - Main findings
    - Alternative identification using Medicare eligibility threshold
    - Insurer-provider integration (principal-agent problem)
5. Public finance and choice implications

Background

Plan Payments in Risk Adjusted Markets

- Goal of RA is to make insurer j's expected profit identical across enrollees i
$$\mathrm{E}[\pi_i] = P - \mathrm{E}[C_i] + R_i$$

- Take case of fully subsidized plan ($P = 0$). Plan j receives only risk-adjusted payments, R_i, based on individual risk scores, r_i, multiplied by some benchmark payment, ϕ.
$$R_i = \phi \cdot r_i$$
$$R_i = \phi \cdot \lambda \mathbf{x}_i$$

- Risk adjusters $\mathbf{x}_i$ are typically indicators for a small set of chronic conditions
- λ captures the incremental impact of a condition x on expected cost
- Importantly: λ are estimated off of FFS Medicare in our setting, so reflect marginal impact of diagnosis on costs in FFS, not in MA:
$$\frac{Cost_i^{FFS}}{\overline{Cost}^{FFS}} = \lambda \mathbf{x}_i + \epsilon_i$$

Numerical Example to Fix Ideas

- Risk score $r_i = \lambda \mathbf{x}_i$
- Consider an 80 year-old female with cirrhosis of the liver
  - λ(80, Female)$= 0.54$
  - λ(cirrhosis)$= 0.41$
  - So her risk score is $= 0.95$ (nearly the national average)
- $R_i = \phi \cdot r_i$
- Payment (ϕ) in county with benchmark (base payment) of \$900 per month yields $0.95 \times \$900 = \$855$

Female	
0-34 Years	0.187
35-44 Years	0.206
45-54 Years	0.275
55-59 Years	0.333
60-64 Years	0.411
65-69 Years	0.299
70-74 Years	0.368
75-79 Years	0.457
80-84 Years	0.544
85-89 Years	0.637
90-94 Years	0.761
95 Years or Over	0.771

Now allow for possibility that diagnoses are endogenous

- We introduce endogenous diagnoses and risk scores:
  - i's conditions and risk score in plan j : $\mathbf{x}_i^j$, r_i^j
- How does endogenous coding affect government spending?
  - Cost (voucher) when choosing FFS: Cost in FFS (c_i^{FFS})
  - Cost (voucher) when choosing MA: Payment to MA plan ($\phi \cdot r_i^{MA}$)

$$\Delta \text{Govt Spending} = \phi \cdot r_i^{MA} \; - \; c_i^{FFS}$$

- As MA risk scores (r_i^{MA}) are juiced, excess spending increases
- E.g., A diagnosis of Diabetes with Acute Complications in MA incrementally increased the payment to the MA insurer by about $3,400 per year. Huge return to coding that condition.

Upcoding Defined

- Definition of upcoding motivated by expression for ΔVoucher
  - Nothing above makes any claim about the cause of coding difference
  - Upcoding $\equiv$ higher coding intensity across plans $(r_i^{MA} - r_i^{FFS})$
- This could be due to any source of coding difference between plans
  - Something consumers don't value: bots scraping medical records, or
  - Something consumers value: continuity of care, lower copays (that generate more visits), higher diagnostic quality
- Coding intensity difference is sufficient statistic for estimating excess public spending and characterizing certain consumer choice distortions. Only coding *differences* matter.

So what is the "right" level of coding?

- Tempting to think: *We should code everything!* But that ignores the cost of diagnosing and recording codes
- Planner would balance costs and benefits of coding:
  - Coding services, δ, that include activities like insurer chart review or training physicians' desk staff
  - A composite healthcare service, γ, includes everything else.
  - Define the units of δ and γ, so that each unit costs \$1.
  - Consumer valuations of δ and γ in dollar-metric utility are $v(\delta)$ and $w(\gamma)$, respectively.
- Simple to show planner would set δ and γ so that

  $v'(\delta^*) = 1$ and
  $w'(\gamma^*) = 1$
- In other words, efficient to level at which marginal value of coding just equals costs of coding

Will the market deliver the "right" level of coding? No

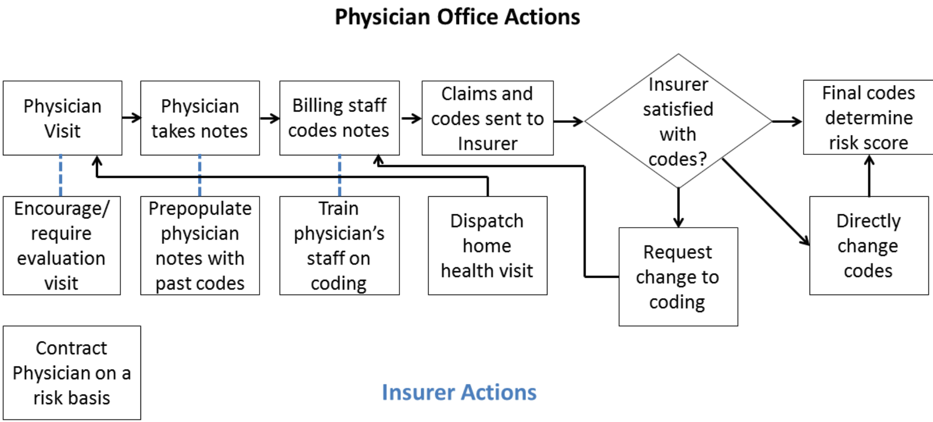
- What will competitive (or imperfectly competitive) market deliver?
    - The subsidy is a function of coding intensity, which is $\rho(\delta, \gamma)$
    - Firms perceive that if they invest in coding, they will not only increase consumer valuation, but also directly increase their subsidy
    - The first-order conditions in a competitive market yield:

      $v'(\tilde{\delta}) = 1 - \phi\frac{\partial\rho}{\partial\delta}$ and

      $w'(\tilde{\gamma}) = 1 - \phi\frac{\partial\rho}{\partial\gamma}$

- Because part of the cost of coding gets reimbursed ($\phi\frac{\partial\rho}{\partial\delta}$), too much coding is provided. That is, the marginal benefit $v'(\delta)$ is too low relative to planner's solution.

How does upcoding happen in practice?



How does upcoding happen in practice?

Upcoding presents principal-agent problem for the insurer

- Pass through incentives to providers via capitation contracts
- Train physicians and coders on revenue-maximizing coding methods

Other tools to directly intervene at patient level

- Encourage enrollees to visit the doctor through prices
- Dispatch home health visit

Why would we expect coding to differ across insurers?

- Asymmetric coding incentives: FFS Medicare vs. MA
- Heterogeneity in cost of coding intensity: More vs. Less Insurer-Provider integration across different MA plans.

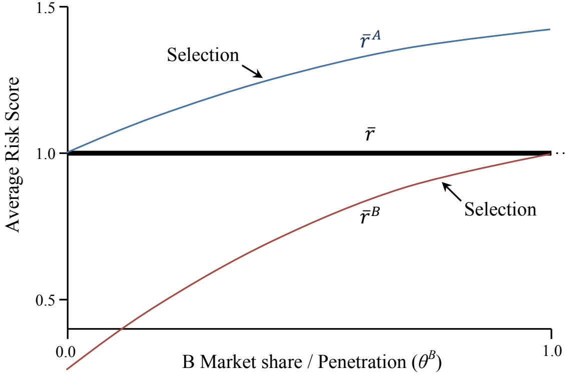
Identifying Differential Coding

Identifying upcoding in presence of selection is difficult

- The basic data on underlying health is contaminated
- Use market-level risk plus variation in plan market share
  - Idea is that if all plans code identically, then switching a fixed distribution of (heterogenous) enrollees across plans in the market will not affect market-level average reported risk
  - But not true if plans code differently
  - In either case, plan-level risk will be a function of which enrollees are in which plans
- We estimate the parameter of interest, without requiring an exogenous change to coding incentives
  - Quantifies the overall public costs of coding in equilibrium
  - Simple strategy can be used by researchers and policymakers in other markets even when data is limited

Selection Only (no differential coding): Risk scores (r)

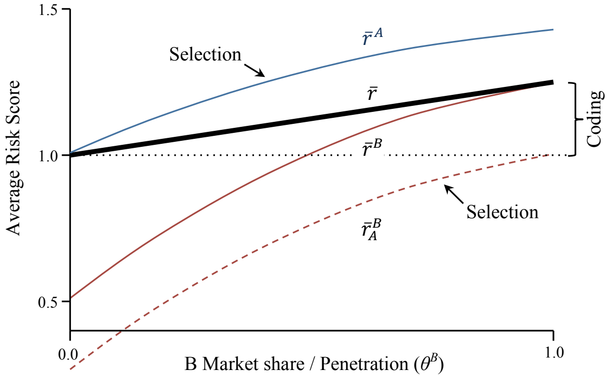
$\bar{r}^A \equiv$ plan A mean; $\bar{r}^B \equiv$ plan B mean; $\bar{r} \equiv$ market mean



The key here is that if both plans code identically, then no impact on market average risk score

Selection with Differential Coding: Risk scores (r)

$\bar{r}^A \equiv$ plan A mean; $\bar{r}^B \equiv$ plan B mean; $\bar{r} \equiv$ market mean



Slope of market average risk score reveals coding differential

Slope Identifies Coding Intensity Difference

- With structural assumptions about form of coding differences, slope $\frac{\partial \overline{r}}{\partial \theta^j}$ reveals average coding difference and average ΔVoucher
- Define a person's risk score had they enrolled in MA as the sum of their potential FFS risk score, a mean MA/FFS difference $\overline{\rho}$ and an arbitrary person-level shifter, ϵ:

$$r_i^{MA} = \hat{r}_i^{FFS} + \overline{\rho} + \epsilon_i$$

- From this, can show that slope of market-level average risk curve is equal to coding difference

$$\frac{\partial \overline{r}}{\partial \theta^{MA}} = \overline{\rho}$$

Under weaker assumptions ($cov(\epsilon_i, \theta^{MA}) \neq 0$), $\frac{\partial \overline{r}}{\partial \theta^{MA}}$ identifies marginal (not mean) coding differences

Setting and Empirical Framework

Data

- Estimating the slope $\frac{\partial \overline{r}}{\partial \theta^{MA}} = \overline{\rho}$ requires observing market-level risk scores at varying levels of MA penetration

- Setting: 3,128 county-level markets in Medicare Advantage
  - Each county is a separate market in terms of menus and prices

- Data obtained from CMS:
  - County-level/market-level average risk scores for 2006-2011
  - County-level MA penetration disaggregated by plan type
  - Demographic variables from Master Beneficiary Summary File

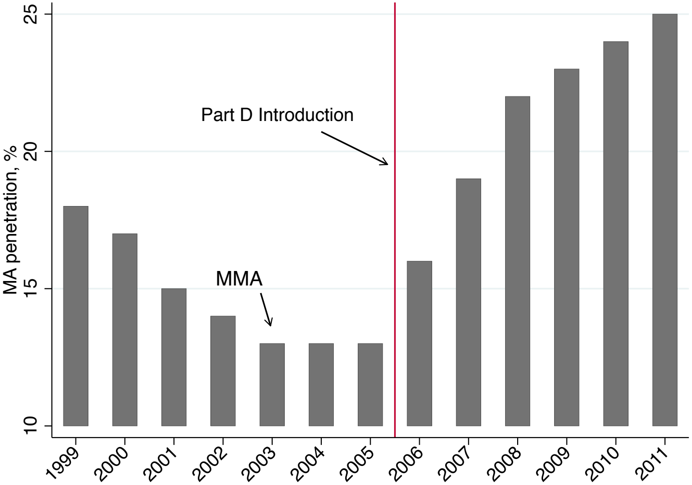
Summary Statistics

Identifying Variation (Strategy 1)

Source 1: Exploit large and geographically heterogeneous increases in within-county variation in MA penetration between 2006-2011

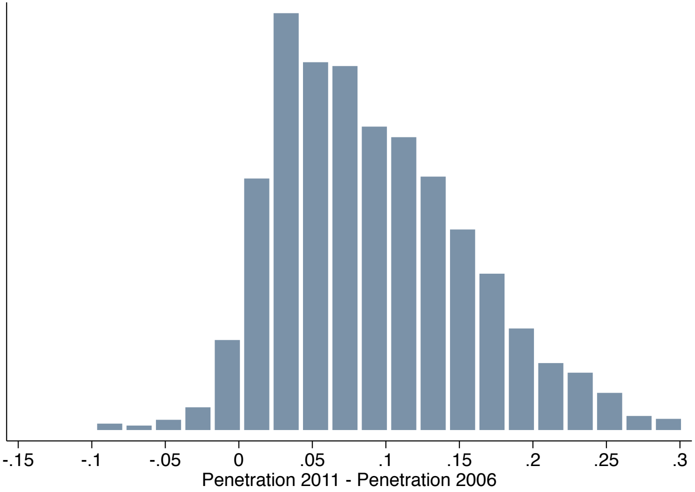
Source 2: Risk score today is based on diagnoses yesterday

Identification Source 1: MA Penetration Variation following MMA

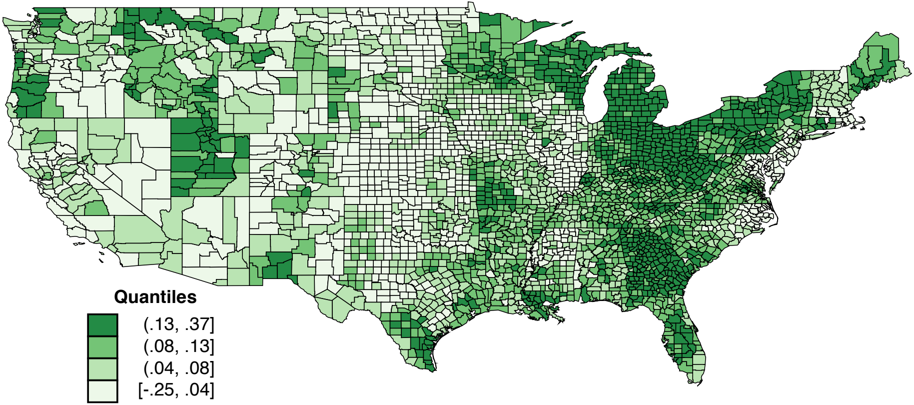


Histogram of MA Penetration Changes, 2006-2011

Observations are counties



Geography of MA Penetration Changes



Identification Source 2: Timing

- Risk scores affected by upcoding only with a lag
- Example case:
  - 2006 enrolled in FFS
  - 2007 switches to MA
  - 2007 risk score in MA reflects last year's FFS diagnoses
  - 2008 stays in MA
  - 2008 risk score finally reflects coding in MA
- Two year lag for new enrollees (more below)
- Yields sharp predictions about timing of effects

Empirical Model

We estimate D-in-D (fixed effects) models of the form:

$$\bar{r}_{sct} = \gamma_c + \gamma_t + \left(\sum_{\tau \in T} \beta_\tau \cdot \theta^{MA}_{sct} \right) + f(X_{sct}) + \epsilon_{sct},$$

where θ^{MA}_{sct} represents the MA penetration rate in county c at time t.

- τ is year relative to t
- Risk scores calculated with lagged diagnoses
- β_{t-1} identifies parameter of interest: $\frac{\partial \bar{r}}{\partial \theta^{MA}_{t-1}} = \bar{\rho}$

Identifying Assumption (Strategy 1)

- Identifying assumption: within-county changes in MA penetration are not correlated with changes in actual underlying population health

- Plausible because risk scores reflect slow-moving chronic conditions such as diabetes and cancer
- In contrast, upcoding would appear as sharp year-to-year changes in *reported* risk

More below on a second strategy that follows diagnoses within-person as beneficiaries age into Medicare

Results

Main Results

	Dependent Variable: County-Level Average Risk Score		
	(1)	(2)	(3)
MA penetration t (placebo)	0.007	0.001	0.001
	(0.015)	(0.019)	(0.019)
MA penetration t-1	0.069**	0.067**	0.064**
	(0.011)	(0.012)	(0.011)
Main Effects			
County FE	X	X	X
Year FE	X	X	X
Additional Controls			
State X Year Trend		X	X
County-Year Demographics			X
Mean of Dep. Var.	1.00	1.00	1.00
Observations	15,640	15,640	15,640

Because $\bar{r} = 1.00$, interpret as a 6.4% difference in risk scores

Falsification Tests: Non-Manipulable Portion of the Score

Age and gender account for 40-50% of typical risk score, but are reported by the SSA, not the insurer

	Dependent Variable: Demographic Portion of County-Level Average Risk Score		
	(1)	(2)	(3)
MA penetration t	0.000	0.001	0.001
	(0.002)	(0.002)	(0.002)
MA penetration t-1	0.001	0.000	-0.001
	(0.002)	(0.002)	(0.002)
Main Effects			
County FE	X	X	X
Year FE	X	X	X
Additional Controls			
State X Year Trend		X	X
County-Year Demographics			X
Mean of Dep. Var.	0.485	0.485	0.485
Observations	15,640	15,640	15,640

Falsification Test: Effects on Morbidity and Mortality

Mortality (SSA records) and morbidity (SEER Database) do *not* come from claims. Plans cannot affect reporting.

	Dependent Variable:					
	Mortality over 65			Cancer Incidence over 65		
	(1)	(2)	(3)	(4)	(5)	(6)
MA penetration t	-0.002	0.002	0.002	-0.005	-0.005	-0.005
	(0.002)	(0.002)	(0.003)	(0.004)	(0.005)	(0.005)
MA penetration t-1	0.002	-0.002	-0.002	0.005	0.001	0.003
	(0.002)	(0.002)	(0.002)	(0.004)	(0.004)	(0.005)
Main Effects						
County FE	X	X	X	X	X	X
Year FE	X	X	X	X	X	X
Additional Controls						
State X Year Trend		X	X		X	X
County-Year Demographics			X			X
Mean of Dep. Var.	0.048	0.048	0.048	0.023	0.023	0.023
Observations	15,408	15,408	15,408	3,050	3,050	3,050

Alternative Identification Strategy

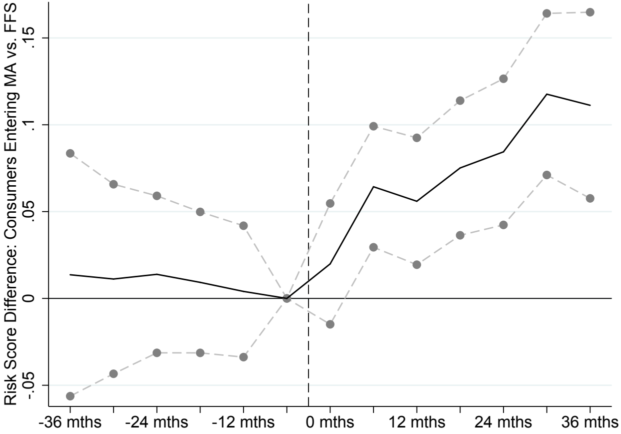
Identification Strategy 2

- Alternative identification scheme using Individual fixed effects in Mass All-Payer Claims Dataset
    - Universe of health insurance claims in Mass from 2011 to 2012
    - Individual identifier allows us to follow people across plans
    - Observe employer/commercial plan claims pre-65 and MA or FFS claims post-65

MAPCD Details

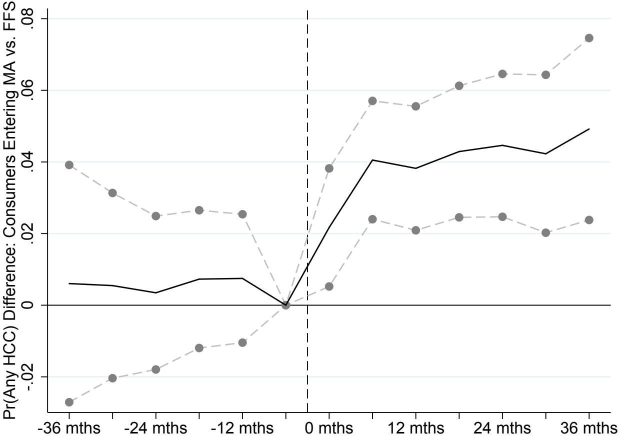
- MA directly observable; FFS more complex
- We identify two groups in the data
    1. All individuals who join an MA plan within one month of their 65th birthday
    2. All individuals who join a Medigap plan within one month of their 65th birthday
- All individuals must have continuous coverage before and after the switch to Medicare
- Limit sample to individuals with at least 6 months of data before and after the switch
- 4,724 Medigap enrollees, 1,347 MA enrollees observed at ages 64/65
- Estimate $r_i = \alpha_i + \beta_1 Post65_i + \beta_2 Post65 \times MA_i$

Difference-in-Differences around age 65 threshold



Only after future MA enrollees join MA do their risk scores shoot up.
This shows something the nat'l analysis couldn't: Risk score gap continues to grow (relative to counterfactual FFS score) as a person's MA enrollment continues.

Difference-in-Differences around age 65 threshold



Same pattern for prob. of being coded with any HCC.

Summary So Far

- Find that MA risk scores are about 6-8% higher than counterfactual TM risk scores
  - Starting at about 6% in first year
  - Climbing to a 12% annual difference by third year

- Timing, Placebos, Falsification tests support identifying assumption that true underlying health was not covarying with MA penetration.

- 7% risk score increase equivalent to
  - 7% of the population becoming paraplegic
  - 12% of the population developing Parkinson's disease
  - 39% of the population becoming diabetic

- Very large if they scores reflected true health, but plausible as coding
  - In 2010, CMS started deflating MA risk scores by 3.4%
  - Increased to 4.91% in 2014; and slated to rise to 5.91% in 2015 (5.16% realized)

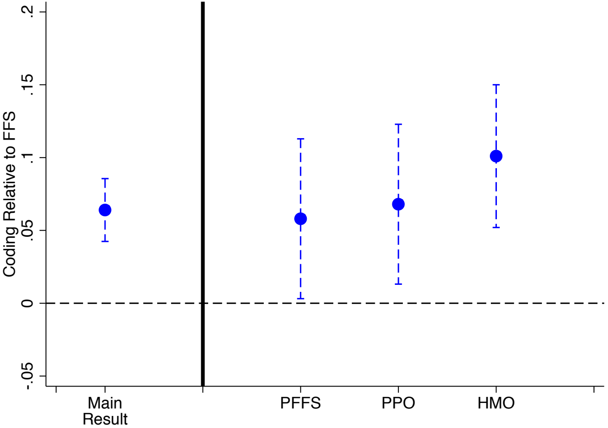
Heterogeneity

The Principal-Agent Problem in Upcoding

- Upcoding in MA is fundamentally a principal-agent problem:
  - Insurers have to convince providers to assign lucrative codes
- Much speculation in health care that vertical integration of insurers and providers can solve principal-agent problem
  - Facilitate pass-through of incentives from insurers to providers
- Econometric evidence is rare relative to policy footprint. Here we have evidence (from a perverse case)
- Return to Identification Strategy 1 to get at this question
  - Decompose effect by contract type

Heterogeneity by Contract Type

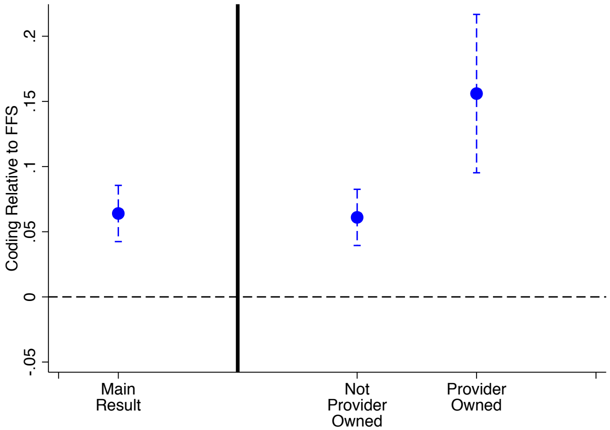
Regression Table



$$\bar{r}_{sct} = \gamma_c + \gamma_t + \sum_{\tau \in T} \beta_\tau^{PFFS} \cdot \theta_{sct}^{MA,\ PFFS} + \sum_{\tau \in T} \beta_\tau^{PPO} \cdot \theta_{sct}^{MA,\ PPO} + \sum_{\tau \in T} \beta_\tau^{HMO} \cdot \theta_{sct}^{MA,\ HMO} + \ldots$$

Heterogeneity by Vertical Integration

Regression Table



Heterogeneity by Plan Type and by Plan Integration

	Heterogeneity by Plan Type				By Plan Ownership
	(1)	(2)	(3)	(4)	(5)
HMO & PPO Share, t-1	0.089**	0.088**			
	(0.026)	(0.026)			
HMO Share, t-1			0.103**	0.101**	
			(0.028)	(0.028)	
PPO Share, t-1			0.068*	0.068*	
			(0.028)	(0.028)	
PFFS Share, t-1	0.057*	0.058*	0.057*	0.058*	
	(0.025)	(0.025)	(0.025)	(0.025)	
Employer MA Share, t-1	0.041**	0.041**	0.041**	0.041**	
	(0.012)	(0.012)	(0.012)	(0.012)	
Non-Provider-Owned Plans Share, t-1					0.061**
					(0.011)
Provider-Owned Plans Share, t-1					0.156**
					(0.031)
Main Effects					

Takeaways

- Significant heterogeneity in coding intensity
  - 5.8% PFFS vs FFS coding
  - 6.8% PPO vs FFS coding
  - 10.1% HMO vs FFS coding
  - 15.6% Provider-owned vs FFS coding (˜$1600 overpayment)
- Implications:
  - Implies choices will be distorted toward more integrated plans
  - Suggests that the cost of aligning physician incentives with insurer objectives may be significantly lower in vertically integrated firms
- Electronic health records appear unimportant: ▸ EHR Results
  - The more important technology may be integration

Public Spending and Consumer Choice Implications

Implications: Public Spending

- MA risk scores are 6.4% higher than counterfactual TM risk in first year. But difference grows to >10% over several years
- Take single year, 6.4%: \$10,000 benchmarks → \$640 per enrollee
- 15 Million enrollees → Implicit subsidy to MA plans of \$10 billion annually if not corrected
- 2010: 3.4% deflation; 2014: 4.9% deflation; 2015 5.1% deflation
  - Even with 2014/2015 deflation, 2007-2011 upcoding implies \$2 billion in overpayments
- Uniform deflation fails to account for coding heterogeneity within MA
  - With 2014 coding deflation, plan-type-specific overpayments are for HMO plans: \$450 per enrollee, and for Provider-owned plans: \$1000 per enrollee

Risk adjustment payments are distortive

- Separate from budgetary impact, upcoding distorts consumer plan choices
- An RA payment is a subsidy that is linked to plan choice. The government pays more when beneficiary chooses a plan with higher coding
- A standard public finance argument says that you want to tax and subsidize in a lump sum way, not tied to consumer/firm choices. If you subsidize intensive coding, too much of it will be provided.
- We show that subsidizing coding is distortive regardless of whether coding generates utility (see paper). But... might be worth it to address selection distortions!
- Some questions about efficiency of the overall level of coding in the market may require additional information about source of coding difference

Upcoding's Impact on Consumer Choices

Our result can be combined with elasticities from the MA literature to shed light on size of choice distortion

How different would MA enrollment be if we didn't overpay plans for upcoding?

- Removing coding subsidy changes the overall monthly payment
- Combine price semi-elasticities: $\left(\epsilon_P \equiv \frac{\partial\theta}{\partial P} \cdot \frac{1}{\theta}\right)$,
- With pass-through rate: $\left(\rho = -\frac{\partial P}{\partial \phi} = 0.5\right)$
  - 50% in Song, Landrum and Chernew (2013), Cabral, Geruso and Mahoney (2014), and Curto et al. (2014)
- To calculate the change in MA marketshare given change in payment

$$\%\Delta\theta = \underbrace{\epsilon_P \cdot \frac{\partial P}{\partial \phi}}_{\text{pay-enroll semi-elast.}} \cdot \underbrace{\Delta\phi}_{\Delta\text{payments}} = (\epsilon_P \cdot -0.50) \cdot (-\$800 \cdot 0.064)$$

Upcoding's Impact on Consumer Choices

$$\%\Delta\text{Market Size} = \underbrace{\epsilon_P \cdot \frac{\partial P}{\partial \phi}}_{\text{pay-enroll semi-elast.}} \cdot \underbrace{\Delta\phi}_{\Delta\text{payments}} = (\epsilon_P \cdot -0.50) \cdot (-\$800 \cdot 0.064)$$

Study	Estimated semi-price elasticity of demand	Implied semi-payment elasticity of demand	removing overpayment due to coding: Relative to counterfactual of no CMS coding adjustment (6.4% reduction in payments)	removing overpayment due to coding: Relative to counterfactual of 3.4% coding deflation by CMS (3% reduction in payments)
Cabral, Geruso, and Mahoney (2014)	-0.0068	-0.0034	-17%	-8%
Atherly, Dowd, and Feldman (2003)	-0.0070	-0.0035	-18%	-8%
Town and Liu (2003)	-0.0090	-0.0045	-23%	-11%
Dunn (2010)	-0.0129	-0.0065	-33%	-15%

Implications: Choice distortions ▸ more

- Coding subsidy to MA plans will distort consumer choices toward MA
  - e.g. in perfect competition, coding subsidy (minus costs of coding) passes-through to consumers ▸ More
- Interacts with imperfect competition: Incidence/distortion tension
  - Perfect competition → Subsidy passed through to enrollees, choices distorted toward MA
  - Imperfect competition → Subsidy distortion actually counteracts imperfect competition distortion
- Exchange risk adjustment is budget neutral
  - enforces transfers from plans with lower average risk scores to plans with higher average risk scores
  - Plans still incentivized to upcode
  - Results suggest Exchange choices will be distorted toward plans with more insurer/provider integration

Conclusions

- Important Public Finance Implications
  - 6.4% upcoding in MA translates to around $10 billion in potential overpayments; $2 Billion excess even with current adjustments
- Rare window into insurers principal-agent problem with physicians
  - Upside: can influence physician behavior with insurer-targeted policies
- Broad applicability to the ACA Exchanges
  - Nearly identical risk adjustment, but budget neutral
  - Results suggest Exchange choices will be distorted toward plans with more insurer/provider integration
- Immediate implications for regulation
  - Deflating payments by upcoding factor simple solution, but rough
  - Deflating only the 60% of the risk score coming from conditions better
  - Longer look back a cheap solution
  - Optimal (second best) payment policy: risk adjustment system that reflects both predictiveness of costs and upcoding susceptibility

APPENDIX

Proof of $\frac{\partial \bar{r}}{\partial \theta} = \Delta\alpha$

Letting $\mathbf{1}[B_i(\theta)]$ represent the indicator function for choosing B,

$$\frac{\partial \bar{r}}{\partial \theta} = \frac{\partial}{\partial \theta}\frac{1}{N}\sum\left(\hat{r}_i + \alpha_A + \mathbf{1}[B_i(\theta)](\alpha_B - \alpha_A)\right) \tag{1}$$

$$= (\alpha_B - \alpha_A) \cdot \frac{\partial}{\partial \theta}\frac{1}{N}\sum \mathbf{1}[B_i(\theta)] \tag{2}$$

$$= (\alpha_B - \alpha_A) \cdot \frac{\partial}{\partial \theta}\theta \tag{3}$$

$$= \alpha_B - \alpha_A \tag{4}$$

- Makes no assumption on the distribution of $\hat{r}_i$ or on joint distribution of risks and preferences that generate the selection curves $\bar{r}^A(\theta)$ and $\bar{r}^B(\theta)$.
- Also holds under the weaker assumption that any heterogeneity in coding at the individual $\times$ plan level is orthogonal to θ^B.

Return

Proof of $\frac{\partial \bar{r}}{\partial \theta} = \Delta\alpha$

Let $\mathbf{1}[B_i(\theta)]$ represent the indicator function for choosing B
Let individual i's risk score in Plan A be equal to $r_i^A = \hat{r}_i + \alpha_A$, and
Let i's risk score in Plan B be equal to $r_i^B = \hat{r}_i + \alpha_B + \epsilon_{iB}$

$$\frac{\partial \bar{r}}{\partial \theta} = \frac{\partial}{\partial \theta}\frac{1}{N}\sum\left(\hat{r}_i + \alpha_A + \mathbf{1}[B_i(\theta)](\alpha_B + \epsilon_{iB} - \alpha_A)\right) \tag{5}$$

$$= \alpha_B - \alpha_A + \frac{\partial}{\partial \theta}\frac{1}{N}\sum\left(\mathbf{1}[B_i(\theta)]\epsilon_{iB}\right) \tag{6}$$

$$= \alpha_B - \alpha_A \tag{7}$$

- Allows for selection between plans on risk $(\hat{r}_i)$ but not ϵ_{iB}
- Selection on ϵ_{iB} implies $\frac{\partial \bar{r}}{\partial \theta}$ identifies the average upcoding factor among the marginal MA enrollees
  - Still identifies average upcoding factor among MA enrollees if marginal MA enrollees are representative of average MA enrollees

Return

Proof of $\frac{\partial \bar{r}}{\partial \theta} = \Delta\alpha$

Let $\mathbf{1}[B_i(\theta)]$ represent the indicator function for choosing B
Let individual i's risk score in Plan A be equal to $r_i^A = \hat{r}_i + \alpha_A$, and
Let i's risk score in Plan B be equal to $r_i^B = \hat{r}_i + \alpha_B + \epsilon_{iB}$

$$\frac{\partial \bar{r}}{\partial \theta} = \frac{\partial}{\partial \theta} \frac{1}{N} \sum (\hat{r}_i + \alpha_A + \mathbf{1}[B_i(\theta)](\alpha_B + \epsilon_{iB} - \alpha_A)) \quad (8)$$

$$= \alpha_B - \alpha_A + \frac{\partial}{\partial \theta} \frac{1}{N} \sum (\mathbf{1}[B_i(\theta)]\epsilon_{iB}) \quad (9)$$

$$= \alpha_B - \alpha_A + E[\epsilon_{iB}|\text{switch from A to B}] - E[\epsilon_{iB}|\text{switch from B to A}] \quad (10)$$

- Allows for selection between plans on ϵ_{iB}
- Selection on ϵ_{iB} implies $\frac{\partial \bar{r}}{\partial \theta}$ identifies the average upcoding factor among the marginal MA enrollees
- Identifies average upcoding factor among MA enrollees if marginal MA enrollees are representative of average MA enrollees

Return

Observe a panel of 3,128 county-level markets 2006-2011

	Analysis Sample: Balanced Panel of Counties, 2006 to 2011				
	2006		2011		
	Mean	Std. Dev.	Mean	Std. Dev.	Obs
MA penetration (all plan types)	7.1%	9.1%	16.2%	12.0%	3128
Risk (HMO/PPO) plans	3.5%	7.3%	10.5%	10.5%	3128
PFFS plans	2.7%	3.2%	2.7%	3.7%	3128
Employer MA plans	0.7%	2.2%	2.8%	4.3%	3128
Other MA plans	0.2%	1.4%	0.0%	0.2%	3128
MA-Part D Only Penetration	6.5%	9.5%	13.1%	10.8%	3128
MA non-Part D Only Penetration	0.6%	1.7%	3.0%	4.0%	3128
Market Risk Score	1.057	0.084	1.054	0.090	3128
Risk Score in TM	1.064	0.087	1.057	0.089	3128
Risk Score in MA	0.949	0.181	1.032	0.155	3124
Ages within Medicare					
<65	19.8%	6.3%	17.2%	6.2%	3128
65-69	23.5%	3.4%	23.7%	3.1%	3128
70-74	19.2%	1.9%	20.2%	2.5%	3128
75-79	15.9%	2.1%	15.4%	1.8%	3128
≥80	21.6%	4.4%	23.5%	5.0%	3128

Return: Data

Heterogeneity by EHR penetration in physician offices

	Dependent Variable: County-Level Average Risk Score		
	(1)	(2)	(3)
MA penetration t	-0.016	-0.024	-0.020
	(0.026)	(0.029)	(0.029)
MA penetration t-1	0.069**	0.069**	0.066**
	(0.016)	(0.017)	(0.016)
High EHR X MA penetration t	0.042	0.051	0.043
	(0.028)	(0.028)	(0.027)
High EHR X MA penetration t-1	-0.002	-0.005	-0.006
	(0.018)	(0.017)	(0.017)
Main Effects			
County FE	X	X	X
Year FE	X	X	X
Additional Controls			
State X Year Trend		X	X
County-Year Demographics			X
Observations	15,640	15,640	15,640