Information Asymmetry in Profit-generating Graduate Education Markets: A Structural Approach to Law Schools

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Introduction

Difficulties in market for training lawyers

- High (and increasing) tuition
- Few job openings (EMSI, BLS)
- Stable, but not growing, real wages
- More schools opening

Questions

- Too many law schools?
- Too many law students? Mismatch problem?
- Tuition too high?

Approach

- Dynamic game (Ericson and Pakes ('95)), schools compete for students
- Asymmetric information between schools and students - use exogenous shock

Contributions

- Add to information asymmetry/market failure literature
  - Asymmetric information leads to matching problem: wrong students pay wrong price for product (not worth expenditure for current students, crowding out potentials)
  - Information helps consumers/producers self-correct
- Market-specific empirical results
  - Schools are affected differentially by information change
  - Producer (Consumer) surplus negatively (positively) affected
  - Total welfare increases by $363 million
- Application of EP model to education market
- Integration of asymmetric information effect with EP

Literature

- **Market-specific empirical results** [Rosen('92), Spur('87), Ehrenberg('88), Oyer and Schaefer('10, '10), MacIntyre and Simkovic('13)]
- **Application of Ericson Pakes ('95) framework to higher education** [Hickman('09), Azevedo('12), Fu('14), Fillmore('15)]
- **Integration of asymmetric information effect with EP**
- **Add to information asymmetry/market failure literature** [Manski('04), Arcidiacono, Hotz, Kang('11), Dranove, Kessler, McClellan, Satterthwaite('03), Jin and Sorenson('06)]

Information Structure

- Information governed by ABA, published in “ABA-LSAC Official Guide”
- Pre-2010 primary ROI statistics:
  - % Placed in a job 9-months after graduation
  - % In Law, Business, Government, public interest, clerk, academia
- Wages guessed from BLS or NALP - not school conditional and low reporting

Information Structure

- Post-2010 ROI statistics
  - 144 placement types
  - Example: # Employed in a law firm with 11-25 employees, full-time, short-term
- Informative:

Firm Size	2-10	11-25	26-50	51-100	101-250	251 or More
Salary	73,000	73,000	86,00	91,000	110,000	130,000

Table: Median Lawyer Starting Salary per Firm Size (2011)

Data

School-level: ABA-LSAC Report and US News and World Report

- Unit of analysis: one school per year
- Academic years beginning 1998-2013
- Variables
  - Quality of program: US News rank, placement, student/faculty ratio, Bar passage rate
  - Quality of students: undergrad GPA, LSAT
  - Revenue: class size, tuition
  - Cost to students: median grant, percent grants, room/board expenses, cost of books
  - Selectivity: accepted, acceptance rate
  - Private-info ROI: %25/%75 private sector starting salary, % reporting

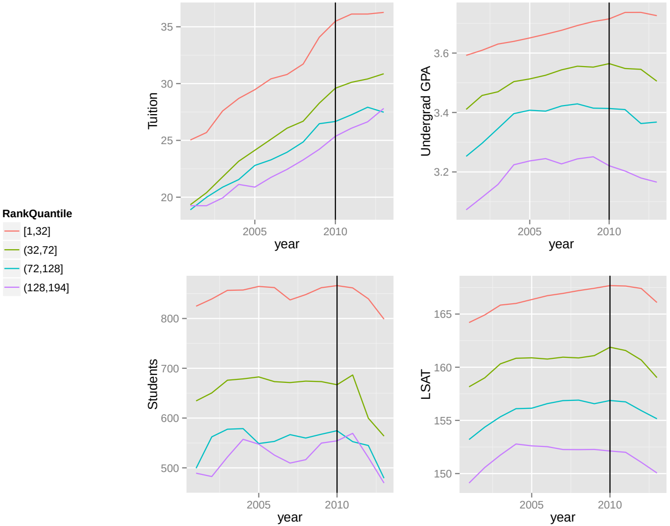
Student-level: LawSchoolNumbers.com

- Unit of analysis: possible student-school match
- Includes applicant profile, name of school, match outcome

Information Effect

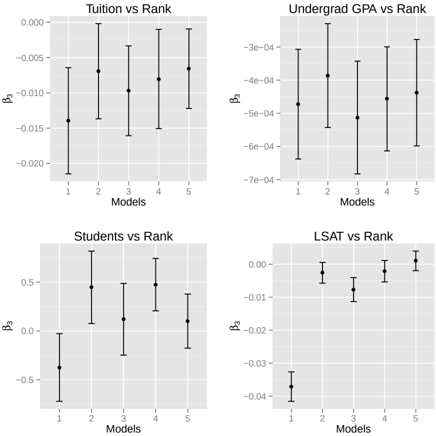
- Based off reporting change in 2010
- Expected: Schools with new lower reports should have to adjust combination of tuition, quality thresholds, class size
- How information is internalized:
  - Direct report
  - US News Rank (information aggregation)
- Both highly correlated

Evidence of Information Effects



Evidence of Information Effects

$$y_{it} = \beta_0 + \beta_1 Rank_{it} + \beta_2 Post2010_t + \beta_3 (Rank_{it} * Post2010_t) + \gamma X_{it} + \varepsilon_{it}$$



Ratio

Reduced Form Takeaways

- Tuition and GPA more elastic than class size and LSAT
- Consistent with inelastic supply wrt. demand
- GPA vs. LSAT also consistent with high rank premium
- New information gives some cardinality to rank

Structural Model

- Why do we need structural model?
  - Welfare - rank premium and student problem
  - Entry/Exit
- Dynamic endogenous capacity game (Ericson and Pakes ('95), Doraszelski and Satterthwaite ('10))
- Schools compete with others for student enrollment (Fu ('04))
  - Application, Admission, Enrollment
  - Embed subgame in Ericson and Pakes framework
- Includes entry/exit decisions

Players

Schools

- Differentiated by rank R_j (zero indicates non-participation)
- State vector (R, g), $R_j \in R$
- Demand growth term g
- $\overline{N}$ possible schools, J participants
- Fixed capacity $\overline{Q}_j$, $\sum_{j=1}^{\overline{N}} \overline{Q}_j < 1$

Students

- Unit mass
- Ability endowment A_i
- Observable signal of ability $(LSAT_i, GPA_i)$
- $A \sim N(f_A(LSAT, GPA), \sigma_A^2)$

Stage Game: Timing

1. School announces tuition (Bertrand-type competition)
2. Students make application decisions, schools choose admission policies (endogenous capacity models)
3. Students learn results, make enrollment decisions

Stage Game: Payoffs

Student Payoffs

- School specific:

$$u_{ij} = \overline{u}(A_i, R_j, I) + \epsilon_{ij}$$
$$\epsilon_{ij} \sim N(0, \sigma_u^2)$$

- Total: $U_{ij}(t) = u_{ij} - t_j$

School Payoffs

- Tuition revenue: $\tilde{\pi}_j = \int t_j dF_j(i)$
- Net donations: $D(R_j; \delta) = \delta_1 R_j + \delta_2 R_j^2$
- Entry/exit costs:

$$\Phi(a_j; \kappa_j, \phi_j) = \begin{cases} -\kappa_j, & \text{if the school is a new entrant} \\ \phi_j, & \text{if the school exits} \end{cases}$$

- Total profits: $\pi_j = \tilde{\pi}_j + D(r_j; \delta) + \Phi(a_j; \kappa_j, \phi_j)$

Information

School private information

- School j receives signal for applicant i: $\nu_{ji} \sim N(0, \sigma_\nu^2)$
- Expected ability: $E[A_i | LSAT_i, GPA_i, \nu_{ij}] = f_A(LSAT_i, GPA_i) + \nu_{ij}$

Student private information

- Latent type: Ai
- Preference shock: ε_{ij}

Application, Admission, Enrollment

Define $X_i = (LSAT_i, GPA_i)$, $S \equiv (t, I, (R, g))$, $\varepsilon_i \equiv (\varepsilon_{ij})_{j \in J}$
Value to admitted student

$$w_i(O_i, A_i, \varepsilon_i | S) = \max\{0, \max_{j \in O_i} U_{ij}(t)\} \tag{1}$$

Probability of i being admitted to j

$$p_j(A_i, X_i | S)$$

Value of application portfolio Y

$$W(Y, A_i, X_i | S) \equiv \sum_{O \subseteq Y} \Pr(O | A_i, X_i, S) E[w(O, A_i, \varepsilon_i | S)] - C(|Y|) \tag{2}$$

The probability that set O of colleges admits student i

$$\Pr(O | A_i, X_i, S) = \prod_{j \in O} p_j(A_i, X_i | S) \prod_{j' \in Y \setminus O} (1 - p_{j'}(A_i, X_i | S)). \tag{3}$$

Student application problem

$$\max_{Y \subseteq \{1, \ldots, J\}} \{W(Y, A_i, X_i | S)\} \tag{4}$$

Dynamics and Timing

Rank evolution

$$R_j' = f_R(R, x, \varepsilon_R; \psi) \in [1, \bar{R}] \tag{5}$$

with $x = (x_j)_{j=1,\ldots,\overline{N}}$ and $x_j \equiv (LSAT_{jM}, GPA_{jM}, A_j)$ Dynamic timing:

1. Potential entrants draw fixed entry cost, make entry decision
2. Incumbents draw scrap value, make exit decision
3. Subsequent participants compete in application-admission game
4. Investment matures, entry/exit occurs
5. Rankings update

School Strategies and Value Functions

School strategies

1. $\sigma_{j1} : (R_j, \nu_{ij}, X_i | t_j, I) \to \{0, 1\}$
2. $\sigma_{j2} : ((R_j, g), \xi_j | I) \to a_j$

with a_j tuition, entry/exit decisions, ξ_j school's private information. Define $\sigma_j \equiv (\sigma_{j1}, \sigma_{j2})$

Value Functions (Incumbent/Entrant)

$$V_j((R, g); \sigma_j, I, \theta) \tag{6}$$
$$= \max \left\{ \pi_j + \max \left\{ \phi_j, \beta \int E_{\xi_j} V_j((R', g'); \sigma_j, I, \theta, \xi_j) dP(R'; R, \sigma_j, I) \right\} \right\}$$

and

$$V_J((R, G); \sigma_j, I, \theta) \tag{7}$$
$$= \max \left\{ 0, \beta \int E_{\xi_j} V_j((R', g'); \sigma_j, I, \theta, \xi_j) dP(R'; R, \sigma_j, I) - \kappa_j \right\}.$$

Application-Admission Equilibrium

Definition 1

Given tuition profile t, information regime I and rank vector (R, g), a symmetric, anonymous application-admission equilibrium, denoted $AE(S)$ is the vector $(d(\cdot|\cdot), Y(\cdot|\cdot), \sigma_{j1}(\cdot|\cdot), p(\cdot|\cdot))$ such that

1. $d(\cdot|\cdot)$ is an optimal enrollment decision
2. Given $p(\cdot|\cdot)$, $Y(\cdot|\cdot)$ is an optimal college application portfolio
3. For every j, given $(d(\cdot|\cdot), Y(\cdot|\cdot), p_{-j}(\cdot|\cdot))$, $\sigma^*_{j1}(\cdot|\cdot)$ is an optimal admissions policy, and $\sigma^*_{j1}(\cdot|\cdot) = \sigma^*_{j'1}(\cdot|\cdot)$ if $R_j = R_{j'}$
4. $p_j(\cdot|\cdot) = \int \sigma^*_{j1}(\cdot|\cdot)\Phi(0, \sigma^2_\nu)$

Markov-perfect Equilibrium

Definition 2

A symmetric, anonymous, Markov-perfect equilibrium for the market for training lawyers is the vector $(\sigma_j^*, d(\cdot|\cdot), Y(\cdot|\cdot), \sigma_{j1}(\cdot|\cdot), p(\cdot|\cdot))$ such that

1. For every t, $(d(\cdot|\cdot), Y(\cdot|\cdot), \sigma_{j1}(\cdot|\cdot), p(\cdot|\cdot))$ constitutes an AE(t)
2. For every j, given σ^*_{-j2}, σ^*_{j2} is optimal for college j and $\sigma^*_{j2} = \sigma^*_{j'2}$ if $R_j = R_{j'}$

Empirical Strategy

Estimate entire game using Bajari, Benkard, Levin ('07) (BBL)

- Flexibly estimate first-stage policy functions, take as optimal
- Forward simulate value functions for optimal and perturbed policies
- Construct minimum-distance estimator based on equilibrium definition

Identifying Assumptions

Assumption 0.1

All schools play the same Markov-perfect equilibrium.

Restricting to symmetric, anonymous equilibria. Proof of existence from Doraszelski and Satterthwaite ('10).

Assumption 0.2

Schools assume that information structure is permanent.

Assumption 0.3

Let $\underline{R}$ be the least profitable ranking for a school. The mean and variance of the distribution of scrap values are such that

1. $\mu_\phi = \{\mu_\phi : \Pr(a = \text{exit} | R_j = \underline{R}, \text{No info}) < 0.01\}$
2. $\sigma^2_\phi = \sigma^2_\kappa$

Gives upper-bound identification

Application-Admission Game

Estimates for stage $k \in 1, 2, 3$ and a student i and school j using gradient boosted classification trees:

$$f_k(LSAT_i, GPA_i, R_j, t_j, I_{\{0,1\}}, year) \rightarrow (0, 1) \quad (8)$$

- Could use brute force approach (simulate market per period)
- Computationally intractable
- Instead, use flexible estimates in (8) to simulate outcome functions

  $$\tilde{f}(R_j, t_j, I_{\{0,1\}}, year) \rightarrow ([120, 180], [0, 1], \mathbb{R}^+)'$$

  for *LSAT*, *GPA*, and class size.
- Estimate with boosted regression trees based on simulated outcomes
- Flavor of Hotz and Miller ('93) and 2SLS

Tuition and State

Tuition

- Estimate with gradient boosted regression tree
- Use to fit the mapping

$$f_T(R_j, I_{\{0,1\}}, year) \to \mathbb{R}$$

Rank

- First, estimate using simple tobit model

$$\tilde{R}_j' = f(\psi_0 + \psi_1 R_j + \psi_x x_j + \varepsilon_R)$$

- After standard expected value, normalize to discrete ranks (similar to US News process)

BBL Estimator

$$V_j((R,g);\sigma,I,\theta) = \mathbb{E}\left[\sum_{t=0}^{\infty} \beta^t \Psi_j(\sigma,(R_t,g_t),\varepsilon_t|(R_0,g_0)=(R,g))\right]\cdot\theta$$
$$= \mathbf{W}_j((R,g);\sigma)\cdot\tilde{\theta}$$

$$\Psi_j = [\tilde{\pi}_j, r_j, r_j^2]'$$

$$\tilde{\theta} \equiv [1,\delta_1,\delta_2]$$

$$W_j((R,g);\sigma_j^*,\sigma_{-j}^*)\cdot\tilde{\theta} \geq W_j((R,g);\tilde{\sigma}_j,\sigma_{-j}^*)\cdot\tilde{\theta} \tag{9}$$

$$m(\tilde{\sigma}_j;\tilde{\theta}) = [W_j((R,g);\sigma_j^*,\sigma_{-j}^*) - W_j((R,g);\tilde{\sigma}_j,\sigma_{-j}^*)]\cdot\tilde{\theta}. \tag{10}$$

$$\min_{\tilde{\theta}} Q_n(\tilde{\theta}) = \frac{1}{K}\sum_{k=1}^{K} 1(m(\tilde{\sigma}_{j,k};\tilde{\theta})>0)m(\tilde{\sigma}_{j,k};\tilde{\theta})^2, \tag{11}$$

First-stage Estimates: Application-Admission Game

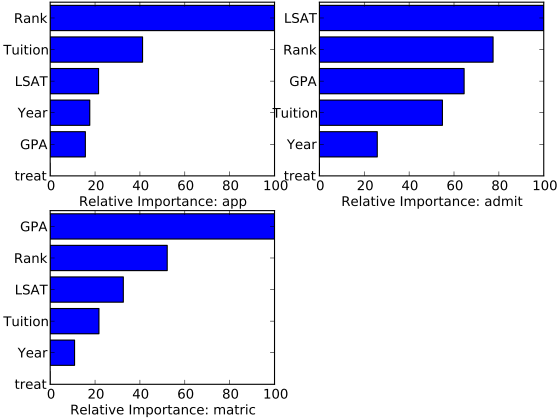
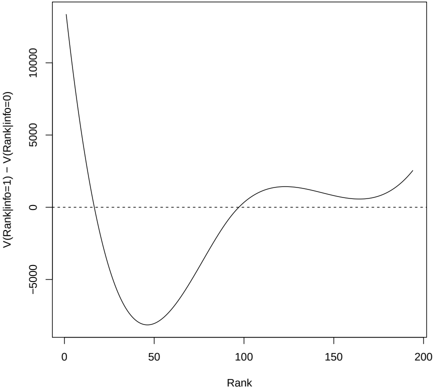


Figure: Application-Admission Game: Variable Importance

Second Stage: Conditional Producer Surplus



Value Functions

Second Stage: Welfare Change

Producer Surplus

- Change calculated with $\Delta V(R) = V(R|info = 1) - V(R|info = 0)$
- Mean estimate:

$$\Delta PS = \sum_{j=1}^{\overline{N}} \Delta V(\hat{R})_j \approx -\$212 \text{ million}$$

Consumer Surplus

- Value for i of attending j given by $U_{ij}(t)$
- Identification given by

$$Pr(U_{ij}(t) > 0) = f_M(LSAT_i, GPA_i, Rank_j, Tuition_j) \equiv f_{Mij}$$

- Value of student i's participation in market previously defined, denoted (with abuse of notation) $W_i(I = \{0, 1\})$
- Change in surplus for i: $\Delta W_i \equiv W_i(I = 1) - W_i(I = 0)$
- Mean estimate:

$$\Delta CS = \int \Delta W_i dG(i) \approx \$575 \text{ million}$$

Total Surplus

$$\Delta TS = \Delta SS + \Delta PS = \$363 \text{ million}$$

Conclusion

- Not necessarily too many students being produced, but uninformed students were attending suboptimal programs and willing students were being driven out
- Policy can improve match, slow rate of entrance, and increase probability of school shut-down
- General application: Information can strictly improve welfare by (partially) mitigating mismatch problem

Direct Report vs Aggregation

Direct Report

- Key indicator: ratio of full-information expected wages to partial-information expected wages:

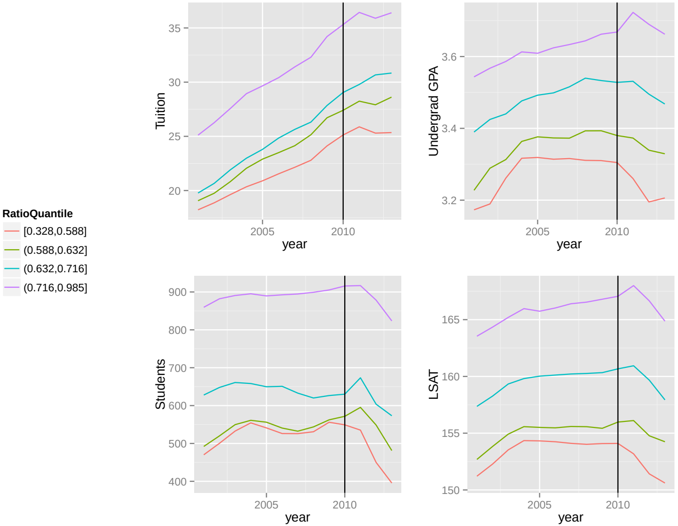
$$Ratio_i = \sum \omega_i placement_i / \sum placement_i$$

- Weights ω_i determined by expected wages in placement type
- Transparency ratio highly persistent
- Impute over schools in time period for placement "types"

Aggregation

- Included in rank calculation
- Used in conjunction with direct report
- Ranks now both ordinal and cardinal!

Evidence of Information Effects: Ratio



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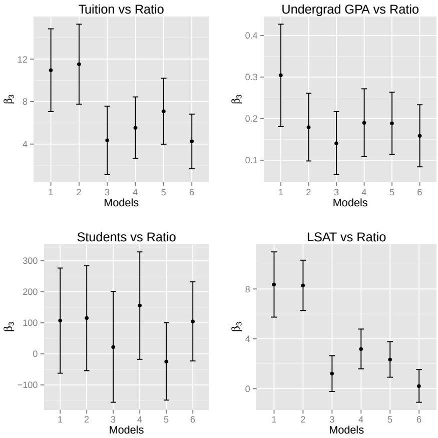

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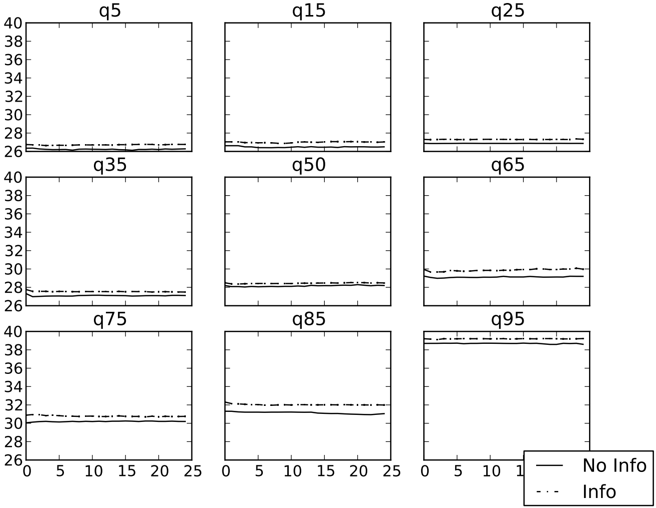
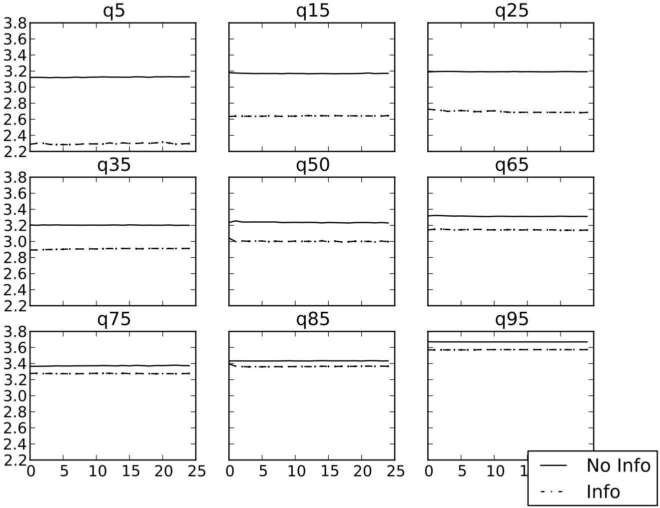
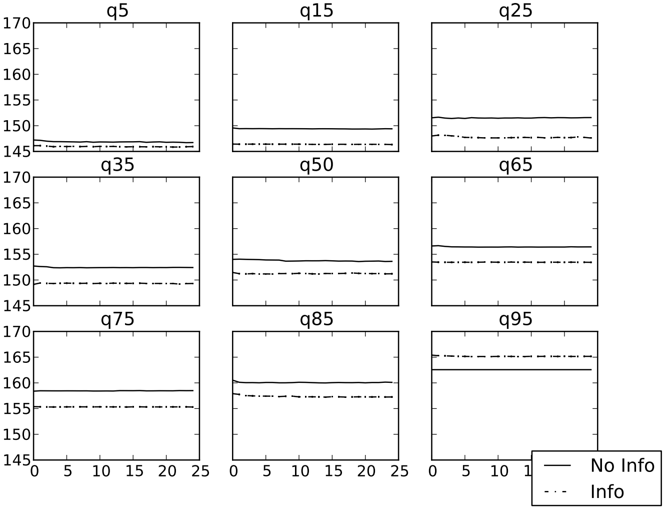
Market Dynamics - Tuition



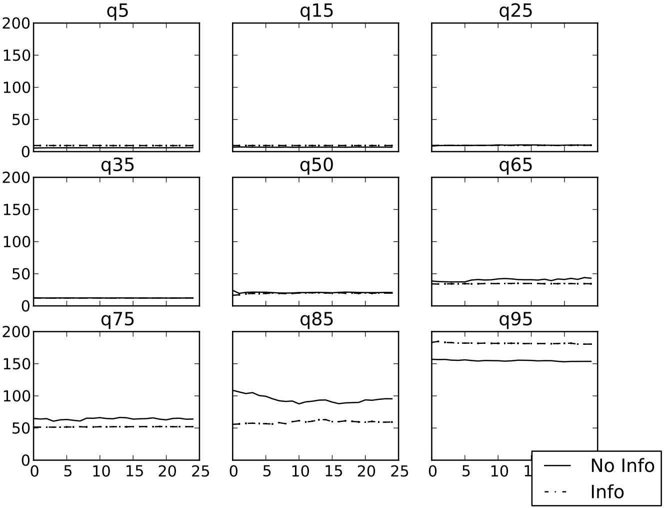
Market Dynamics - GPA



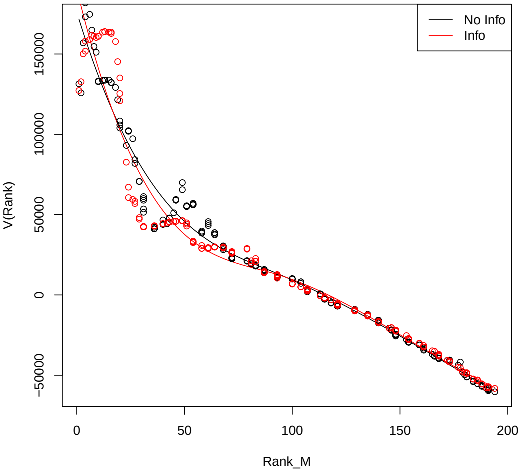
Market Dynamics - LSAT



Market Dynamics - Demand



Market Dynamics - Tuition



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