Complex Disclosure

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Mandated But Complex

In some situations, exemplified by the abstruse legalistic disclosures accompanying securities transactions, the language or underlying information is far too complex for a layperson to digest.

Loewenstein, Sunstein, and Golman (2014)

Strategic Use of Complexity

- Economics
  – Gabaix and Laibson (2006) : Shrouded attributes
  – Spiegler (2006): Competitive obfuscation
  – Armstrong and Vickers (2012): Hidden fees
  – Ellison and Wolitzky (2012): Impact on price search
- Finance
  – Carlin (2009): Complex prices
- Accounting
  – Hirshleifer and Teoh (2003): Financial disclosures

Our Paper

- We use lab experiments to study the use of complexity in mandated disclosure
- Focus on strategic incentives for information senders to use complexity
  - Eliminate legal or technical reasons for complexity
- Questions: Do senders actively choose to use complexity? Is it profitable to obfuscate?

Our Results

- We find senders use complexity often
  - Use it to hide worse than average states
  - This is optimal given receiver actions
- Receivers make systematic mistakes
  - Just a natural consequence of random errors in reading complex information?
  - Or are mistakes exacerbated by naivete or other biases?

Our Experiment

Sender:

- Observes "secret number" {1,2,...,10}
- Discloses N numbers that sum up to the secret number (N=1,2,…, 20)

Receiver:

- Observes message from the sender
  - A table of N numbers
- Guesses the secret number
- Conflict: Receiver wants accurate guesses, sender wants high ones

Design related to:
- Cai & Wang (2006)
- Jin, Luca, & Martin (2015)

Key differences:
- Senders cannot lie
- Can use complexity

Complex Report (N=20) Example

7	3	4	-8	-2	1	5	-2	8	-4
1	9	-4	-7	-2	3	-2	-9	6	-5

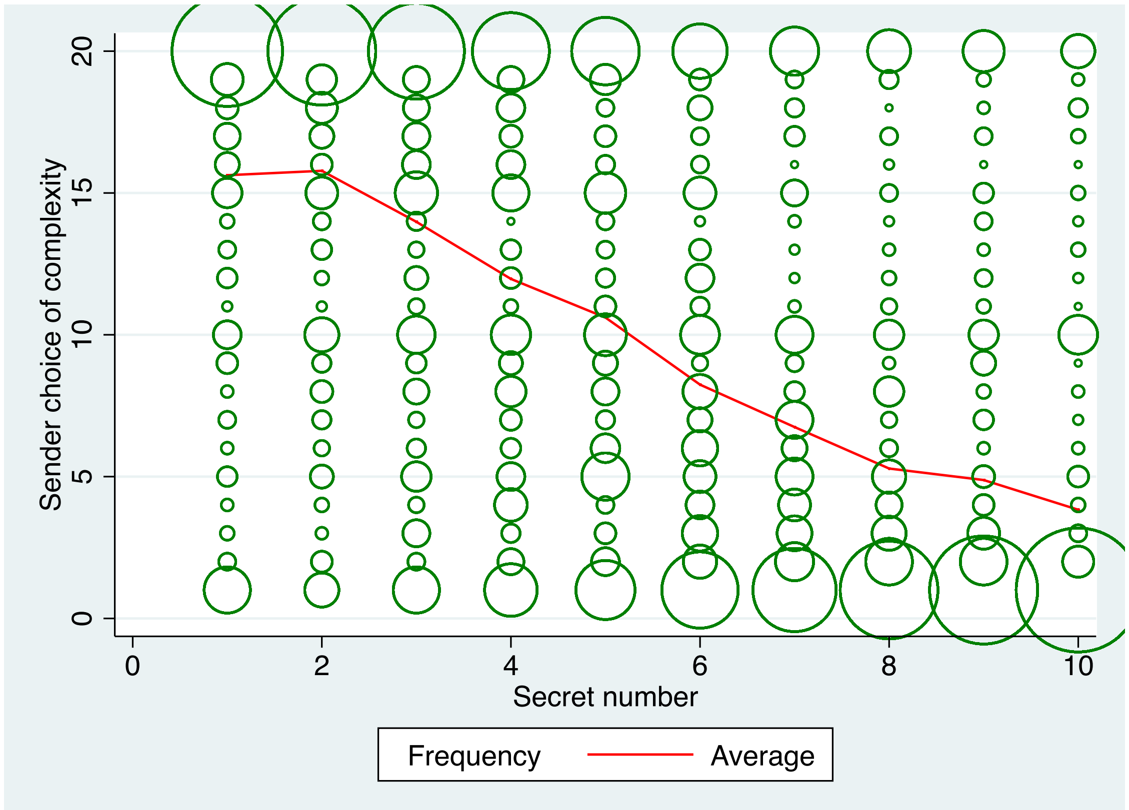
Truth = sum of all numbers = 2

- Numbers not chosen by sender
  - Just choose N
- Both senders and receivers know how numbers are chosen
  - All randomly drawn from {-10,…,10} until they sum to truth
- Time limit for receivers: 60 seconds (random choice if hit)
  - 3.6% of subjects hit time limit

Design Details

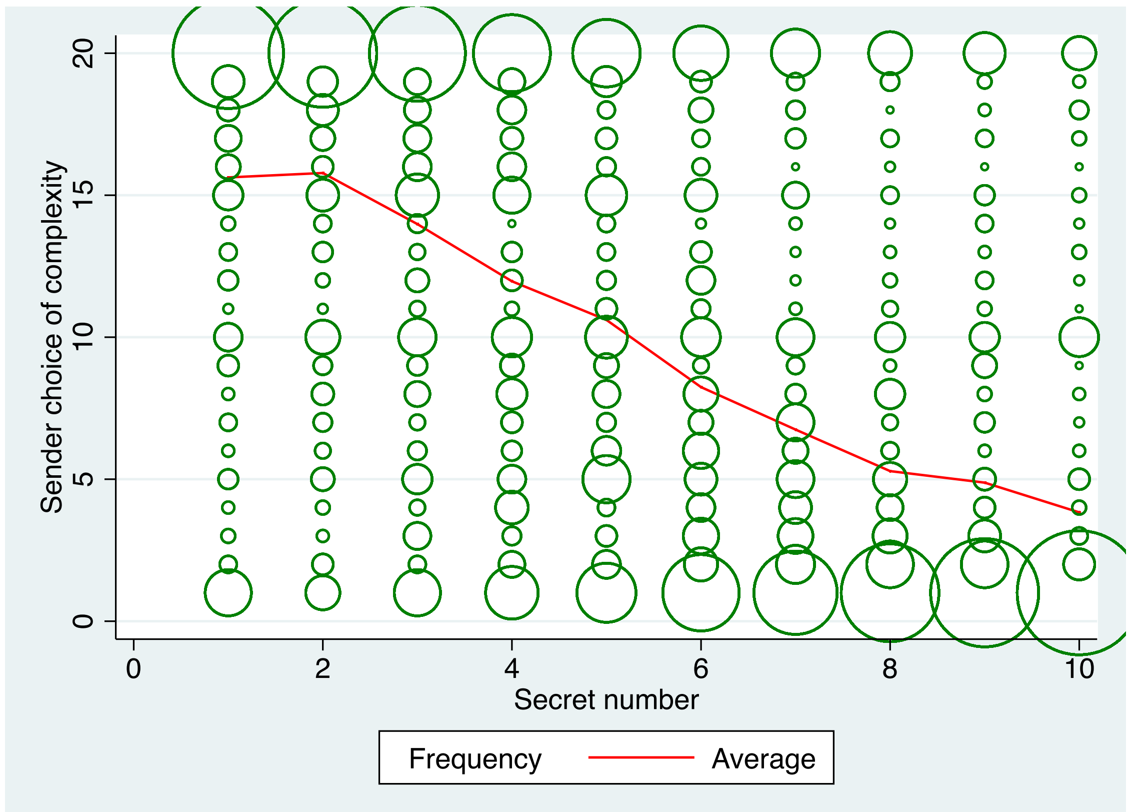
- 304 subjects at HBS CLER Lab
  - 170 subjects completed math test after experiment
- 30 rounds per subject (9,120 decisions)
- Anonymous rematching & random roles
  - Why both roles? So know sender cannot lie
- Feedback: Guess + secret number after round
- Guesses are integers, so payoffs shown in a table
  - Sender: Payoffs increasing in guess
  - Receiver: Payoffs decreasing as guess moves away from true secret number

Was Complexity Used?



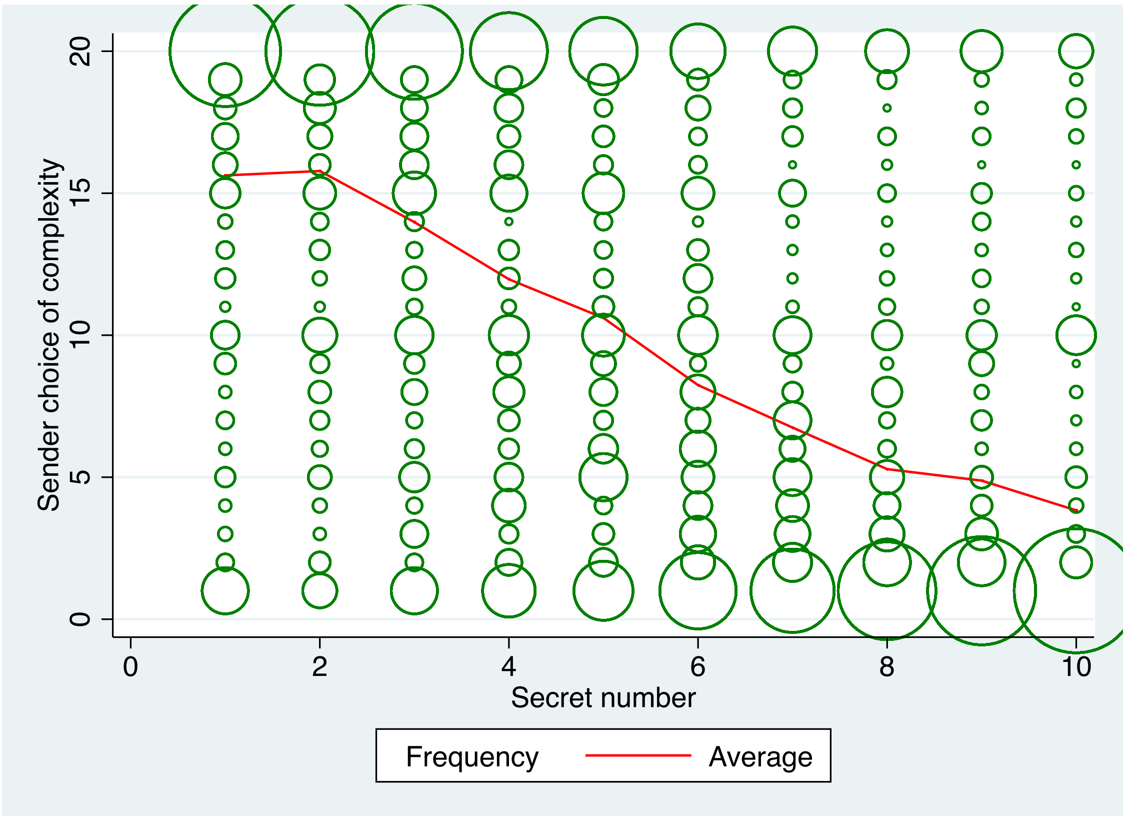
Takeaway #1: Senders used complexity often

Was Complexity Used?



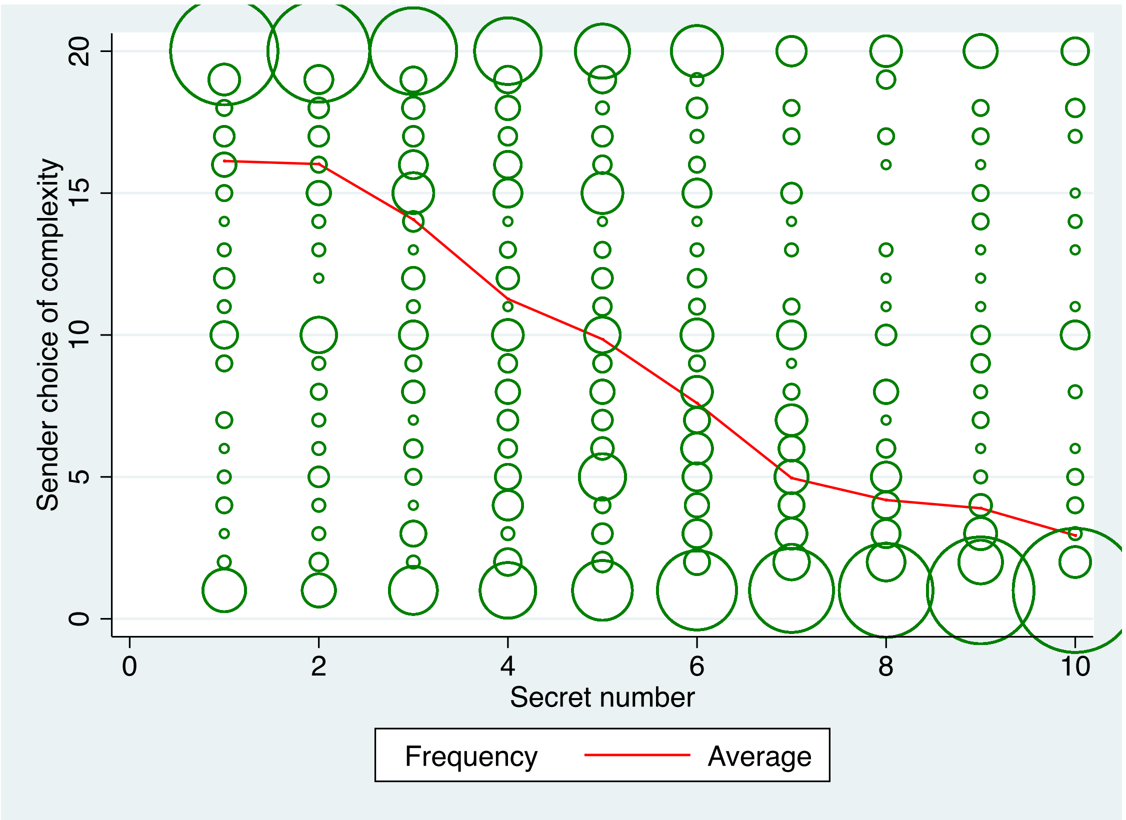
Takeaway #2: Senders used complexity to hide “bad” states

Was Complexity Used?



Takeaway #3: Mostly used high (≥15) or low complexity (≤5)

Was Complexity Used?



Especially in the last 15 rounds

Should Senders Use Complexity?

	Receiver over-guessing (guess – secret number)	
Secret number	High complexity N>=15 (All rounds)	High complexity N>=15 (Last 15 rounds)
1-3	1.039	0.923
4-7	0.101	0.128
8-10	-1.126	-1.066

Optimal even in last 15 rounds

Should Senders Use Complexity?

	Receiver over-guessing (guess – secret number)	
Secret number	High complexity N>=15 (All rounds)	High complexity N>=15 (Before 60s)
1-3	1.039	0.772
4-7	0.101	0.096
8-10	-1.126	-0.891

Optimal even for <u>guesses before time limit</u>

What Causes Over-Guessing?

- Key for policy and theory
  - Justifies use of complexity
- What are some possible explanations?
  - Random errors (from reading of complex reports) leads to over-guessing at lower numbers
- Does not explain over-guessing of 4-7
  - When secret number is actually 5, average guess of complex messages should not be above 5
  - If receiver unsure, should guess low number

Behavioral Explanations

- Naive about the strategic use of complexity?
  - Leading behavioral explanation in literature
- What about overconfidence about the ability to internalize complex information?
  - Observe overconfidence in many settings and forms (Moore and Healy 2008; Grubb 2015)
- How could this lead to over-guessing?
  - If I add up numbers to 8, must be right, even if a complex report of 8 is very, very unlikely

Elicited Beliefs

- To help separate explanations, we elicit:

1. Beliefs about implications of complexity
   - Guess the average secret number for high complexity reports
   - 12.6% guess *higher* than actual rate (naive)
2. Beliefs about math ability
   - Guess the number correct on a math test
   - 33.8% guess *higher* than actual (overestimation)

Receiver Over-Guessing

- Do these beliefs relate to receiver over-guessing of complex reports?
- Start with regressions
  - Regress over-guessing onto size of naivete and overconfidence (how much higher than actual)
- Find evidence that receiver over-guessing is significantly related to <u>both</u> factors
  - Naivete: 0.236** & Overconfidence: 0.245***

Receiver Over-Guessing

- Use a “structural” model to investigate if these factors can explain the choices we observe
  - Model the decision-making process of receivers
  - Estimate the parameters of model and evaluate its fit to the data (its ability to explain choices)
- Find that either “full” naivete or observed overconfidence explain guessing very well

Structural Model

1. Receiver holds prior beliefs of secret number
   – Correct given complexity (baseline) or naive
2. Sees secret number with noise: math errors
3. Forms posterior beliefs of secret number
   – Correctly updates (baseline) or overconfident
4. Makes guesses based on posterior
   – Risk neutral (baseline) or risk/social preferences
5. Guesses with noise: strategic errors

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Estimate Model

- Rely on out-of-sample estimates of key model parameters:
  1. Use math test to estimate math errors free of strategic errors
  2. Use guesses when reports are simple to estimate strategic errors free of math errors
- Then use these estimates to make predictions for over-guessing with baseline model

1. Estimate Math Errors

- To estimate additive math errors out of sample, use math test (160 subjects)
  - 4 summations
  - Uniform distribution on truth {1,...,10}
  - Complete after all 30 rounds
- Same difficulty as highest complexity (N=20)
- Offer high incentives to maximize effort
  - $4 if get a random summation correct

1. Estimate Math Errors

- Use non-parametric approach:
  - Additive error drawn from distribution over:

    {-9,-8,…,0,… 8,9}
  - Assume distribution is symmetric
- Count errors of each type
  - Example: Guess of 1 when number is 10
  - Implies additive error of -9

2. Estimate Strategic Errors

- For strategic errors (and social preferences), use guesses of simple reports
  - Assume strategic error leads to random guessing
  - Assume social preferences take the form of Fehr-Schmidt (1999)
- Estimate: Just 7.4% of choices exhibit strategic error and 2.3% social preferences

Baseline Model

- Assume correct beliefs and belief updating
  - But allow for math errors and strategic errors
  - Zero degrees of freedom within sample!
- Fails to capture over-guessing of middle numbers
  - Why? Skeptical beliefs push down guesses

Secret number	Actual mistakes	Baseline predictions
		lnL=-1.553
1-3	0.772	0.712
4-7	0.096	-0.181
8-10	-0.891	-1.662

Add Risk Preferences

- Benchmark assumes risk neutral preferences
- But face uncertainty about secret number
  - So risk aversion might matter
- Assume CRRA utility (adds free parameter)
  - α=0 is risk neutral for CRRA

Secret number	Actual mistakes	Baseline predictions	+ Risk preferences (**α=0.010,0.129**)
		lnL=-1.553	*lnL=-1.553*
1-3	0.772	0.712	0.712
4-7	0.096	-0.181	-0.181
8-10	-0.891	-1.662	-1.662

Add Social Preferences

- Benchmark assumes no social preferences
- But low guesses hurt senders
  - So social preferences might matter
- Use out-of-sample estimates from simple reports
  - Though this is likely to be an overestimate

Secret number	Actual mistakes	Baseline predictions	+ Social preferences
		lnL=-1.553	*lnL=-1.541*
1-3	0.772	0.712	0.782
4-7	0.096	-0.181	-0.146
8-10	-0.891	-1.662	-1.644

Leading Behavioral Explanation

- In theory and policy, leading explanation is receivers naive about use of complexity
- Assume 12.6% of subjects are (fully) naive
  – Outperforms model with correct beliefs

Secret number	Actual mistakes	Baseline predictions	+ Naive beliefs
		lnL=-1.553	*lnL=-1.519*
1-3	0.772	0.712	0.733
4-7	0.096	-0.181	-0.146
8-10	-0.891	-1.662	-1.554

New Behavioral Explanation

- Could subjects be <u>overconfident</u> in their ability to read complex reports?
- Evidence of overconfidence in many domains
  - Possible reason: ego utility related to ability
  - Can limit usefulness of feedback (Eil and Rao 2011)
- Based on beliefs about math test performance:
  - 33.8% believe performance better than actual
  - Average size: 19.2% of actual performance

New Behavioral Explanation

- Assume receivers think they have a 72.5% chance of performing well at math (in line with beliefs)
  - Estimate math errors non-parametrically for receivers who did well at math task
  - Outperforms baseline (and even naivete)

Secret number	Actual mistakes	Baseline predictions	+ Overconfidence
		lnL=-1.553	*lnL=-1.272*
1-3	0.772	0.712	0.749
4-7	0.096	-0.181	0.018
8-10	-0.891	-1.662	-0.904

New Behavioral Explanation

- Can also model overconfidence as overweighting of signal in updating: $Pr(s|\#)^{\beta}$
  - $\beta>1$: more likely is $Pr(s|\#)$, more likely is $Pr(\#|s)$
- Inspired by approach in Grether (1980) and Holt and Smith (2009)

Secret number	Actual mistakes	+ Overconfidence	+ Overweighting **(β=16.9-21.9)**
		lnL=-1.272	*lnL*=-1.261
1-3	0.772	0.749	0.776
4-7	0.096	0.018	0.050
8-10	-0.891	-0.904	-0.800

Recap

- Obfuscation is used frequently and is optimal given receiver mistakes
- But only a small number of receivers are naive
  - Unlike theory literature on complexity
  - Unlike experiments on information transmission
- Most mistakes come from skeptical receivers
  - Many appear to be overconfident about ability to read complex reports
  - Could explain why feedback is not effective

New Behavioral Explanation

- Overconfidence about ability is missing from literature on strategic use of complexity!
- Generalizable from our experiment?
  - Insurance, credit card, and investment choices involve math calculations
  - More overestimation in hard tasks (Larrick, Burson, and Soll, 2007)
  - Might expect more overconfidence in some populations

Possible Follow-ups

- Overconfidence not well established here
  - Small math test (only 4 questions)
  - Only measured number thought got correct
- Ways to get at it better?
  - Exogenous variation in overconfidence (feedback, task difficulty, population, selection into task)
  - Measure beliefs about distribution of mistake sizes, subjective probability of number correct, and performance in game

Thank you!

Comments welcome.

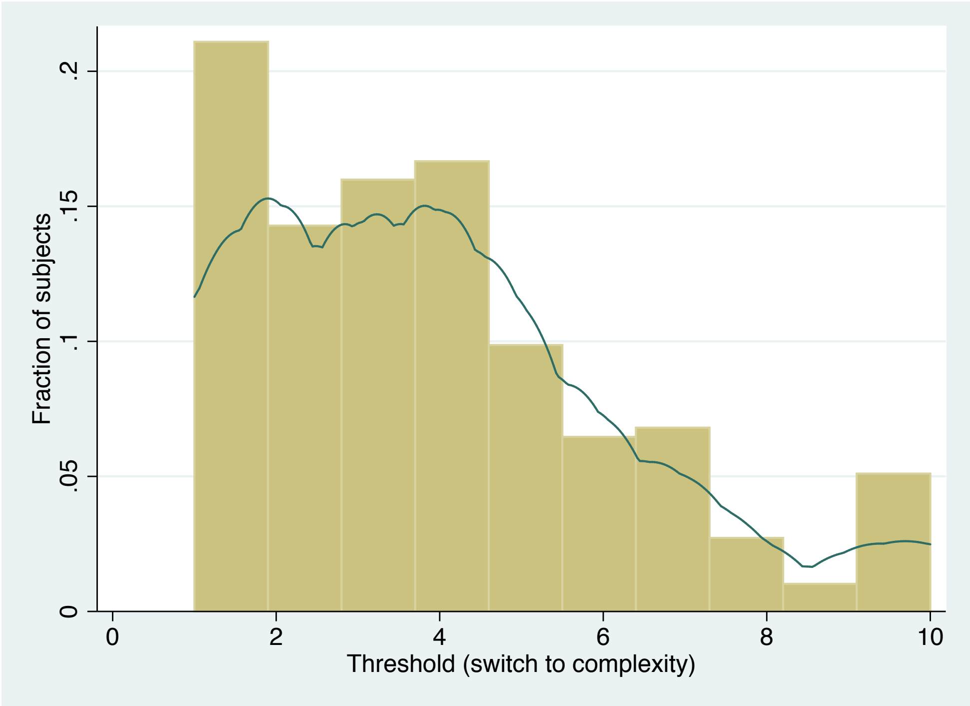
Mistakes as Logit Errors

- Observe mistake for both senders and receivers
  - Logit errors (QRE) can "explain" mistakes
  - But does not explain source of these mistakes

	Sender complexity choice		Receiver guess (N>=15)	
Secret number	Mistakes (N-N*)	Logit error predictions	Mistakes (guess-draw)	Logit error predictions
		λ_S = 0.111 (0.221) *lnL=-0.932*		λ_R = 0.048 (0.066) *lnL=-1.733*
1-3	-3.471	-4.030	0.772	0.707
4-7	-2.494	-2.746	0.096	0.038
8-10	2.810	3.598	-0.891	-0.641

Sender Mistakes

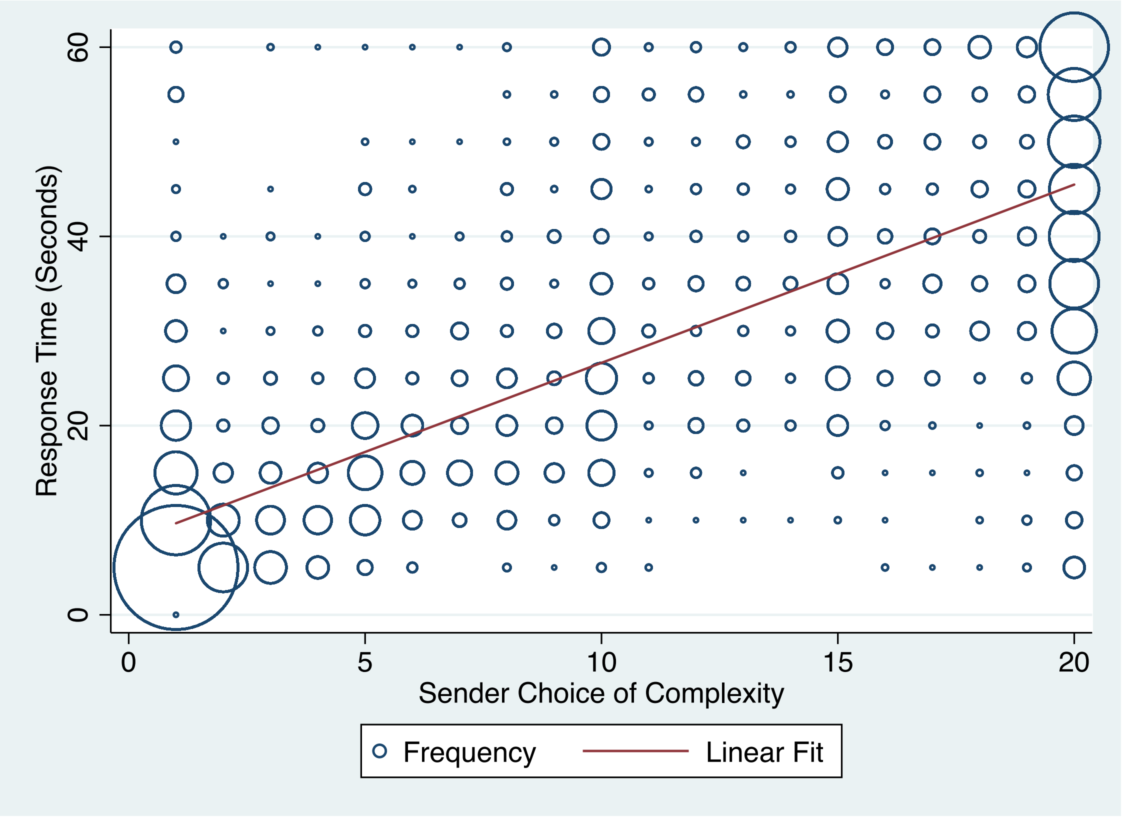
- Estimate individual complexity threshold
  - Use high complexity (>=15) at/below draw & not above
- 87% of reports consistent with threshold



Sender Mistakes

- 7.5% of subjects have thresholds >7 (n=22)
  - If draw >7, complex in 74.9% rounds (vs. 6.3%)
- Best responding to self?
  - If draw >7, less under-guessing
    - -0.88 vs. -1.13 (for others)
  - Especially if guess before time limit
    - -0.40 vs. -0.95 (for others)
  - Also more naïve about complexity
    - But direction of causality not clear!

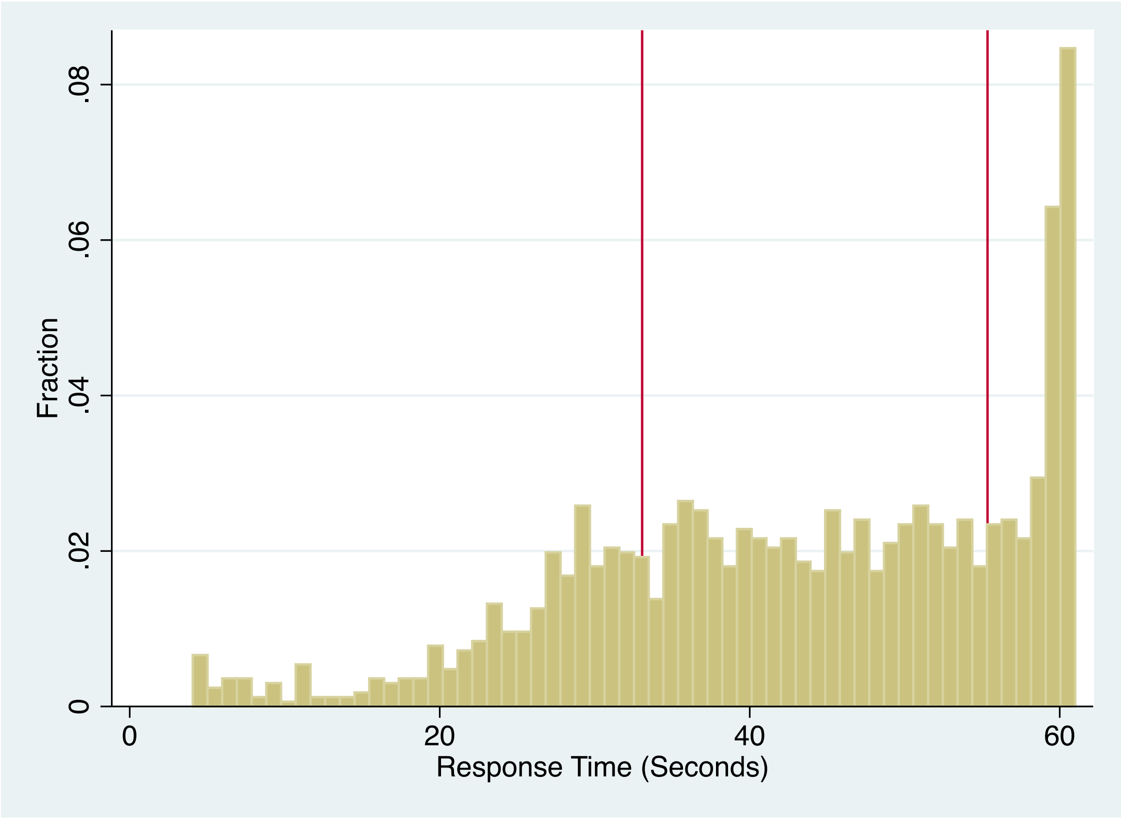
Receiver Response Times



Response times respond to report complexity

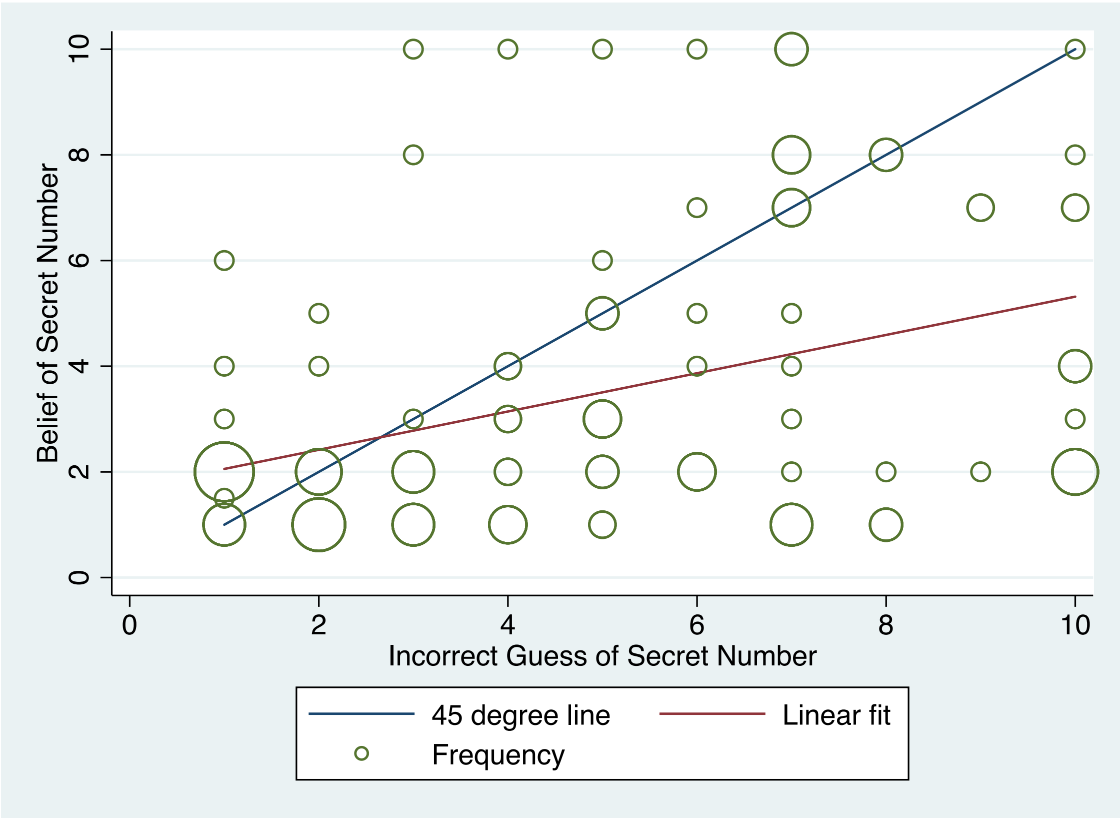
Response Times

- For high complexity: “quick”, “slow”, “at limit”



Beliefs & Guesses

- Strong relationship when "quick" (1^{st} quartile)



Another Behavioral Explanation

- Alternative explanation: Base rate neglect
- Model as underweighting likely states: $Pr(s)^{\alpha}$
  - Adds free parameter to the model
- Slightly worse fit than overconfidence
  - Both in terms of likelihood and in over-guessing rates

Secret number	Actual mistakes	+ Overconfidence	+ Base rate neglect (**α**=0.566)
		lnL=-1.272	*lnL=-1.280*
1-3	0.772	0.748	0.840
4-7	0.096	0.017	0.060
8-10	-0.891	-0.906	-0.869

Method: Signals v. Additions

- Alternative: Senders explicitly choose variance and receivers explicitly receiver signal
- Potential issues:
  - Biases at work in processing signals may be different when signal process is explicit
    - Example: Ambuehl and Li (2017) find *underweighting* of signals in setting with explicit signal process
  - Interested in how people respond to complexity
    - Example: Would not want to test model of lying aversion using an individual decision task with explicit costs