

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” $\{1,2,\dots,10\}$
- Discloses N numbers that sum up to the secret number ($N=1,2,\dots, 20$)

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

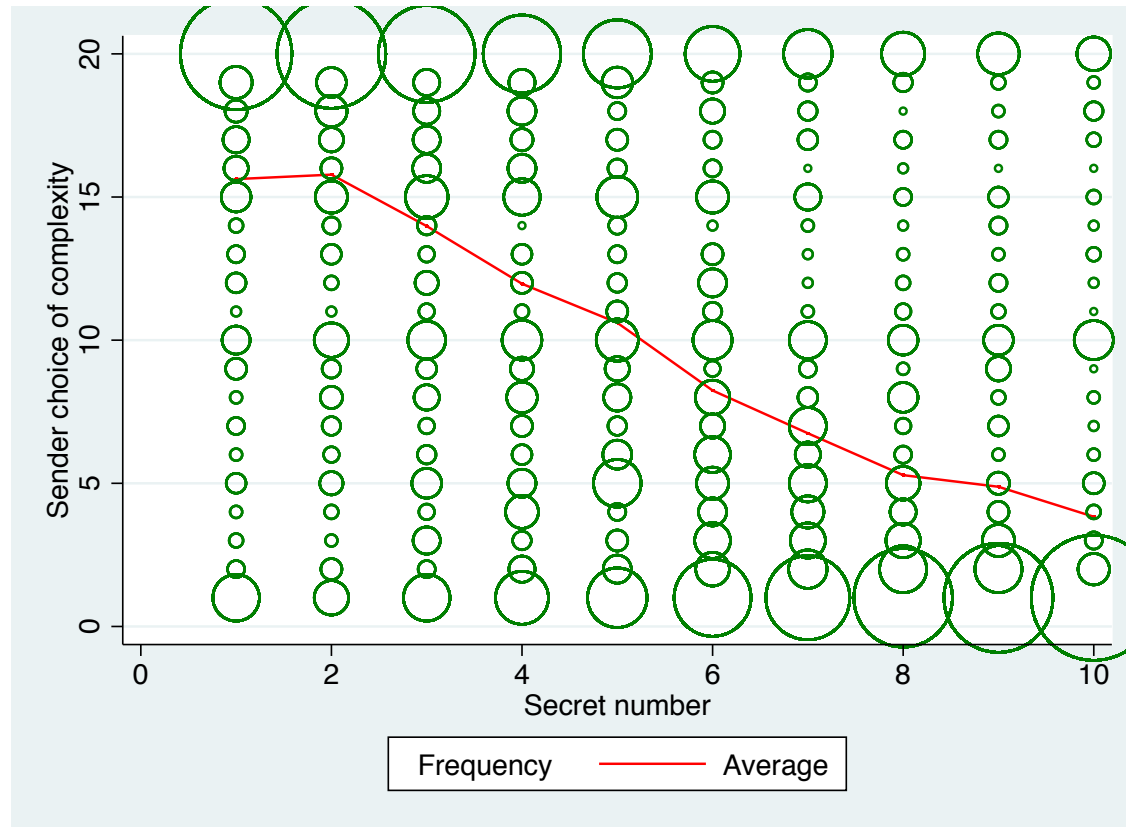
Truth = sum of all numbers = 2

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

Design Details

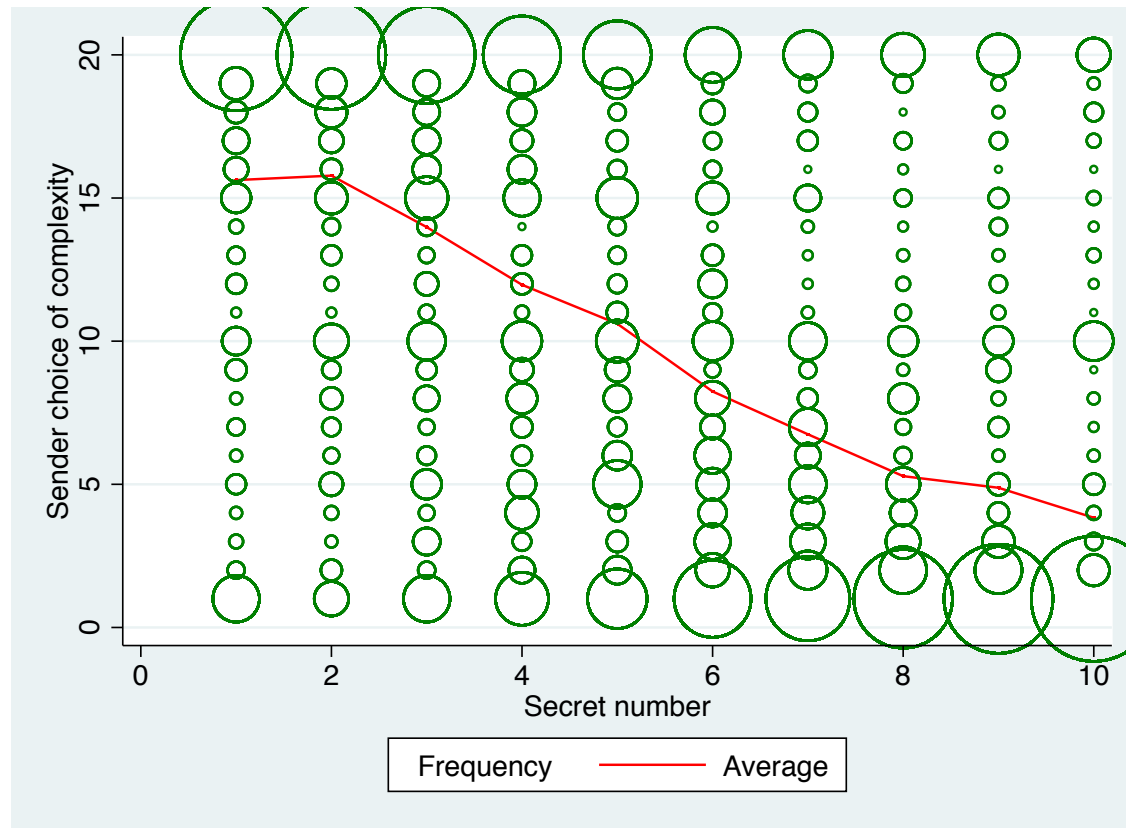
- 304 subjects at HBS CLER Lab
 - 170 subjects completed math test after experiment
- 30 rounds per subject (9,120 decisions)
- Anonymous rematching & random roles
 - Why both roles? So know sender cannot lie
- Feedback: Guess + secret number after round
- Guesses are integers, so [payoffs](#) shown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

Was Complexity Used?



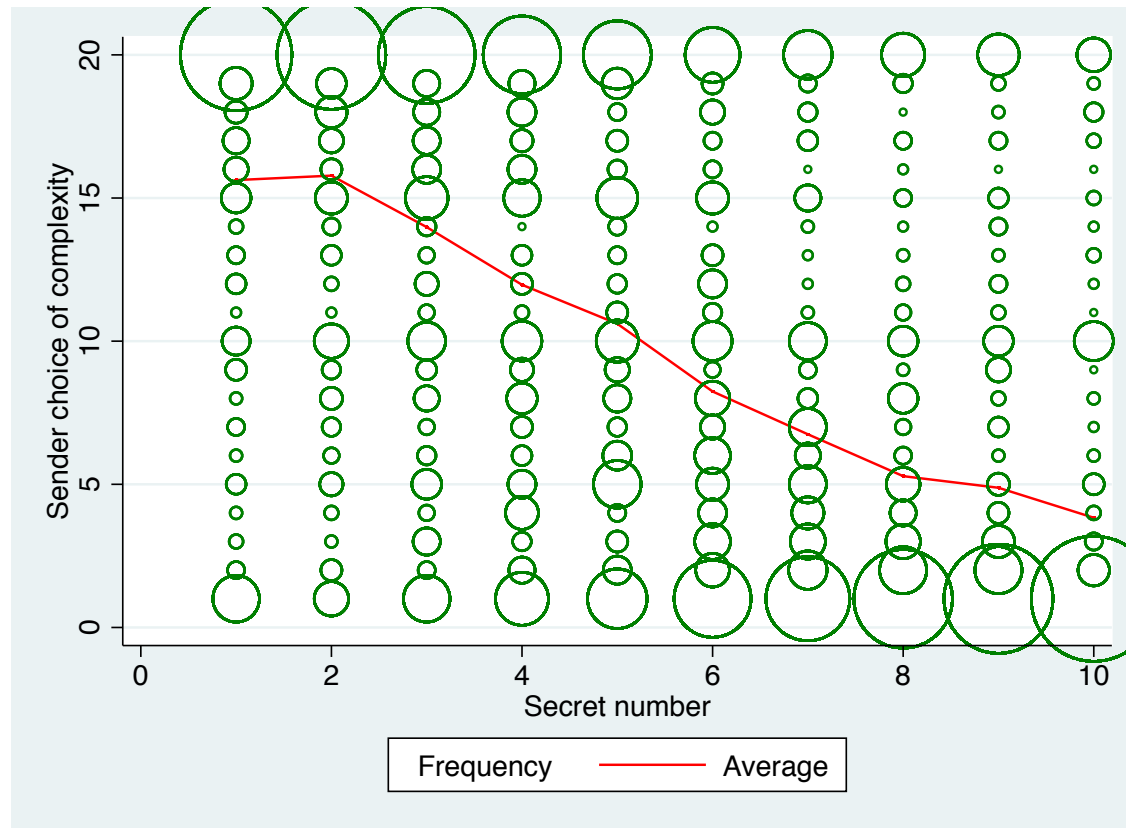
Takeaway #1: Senders used complexity often

Was Complexity Used?



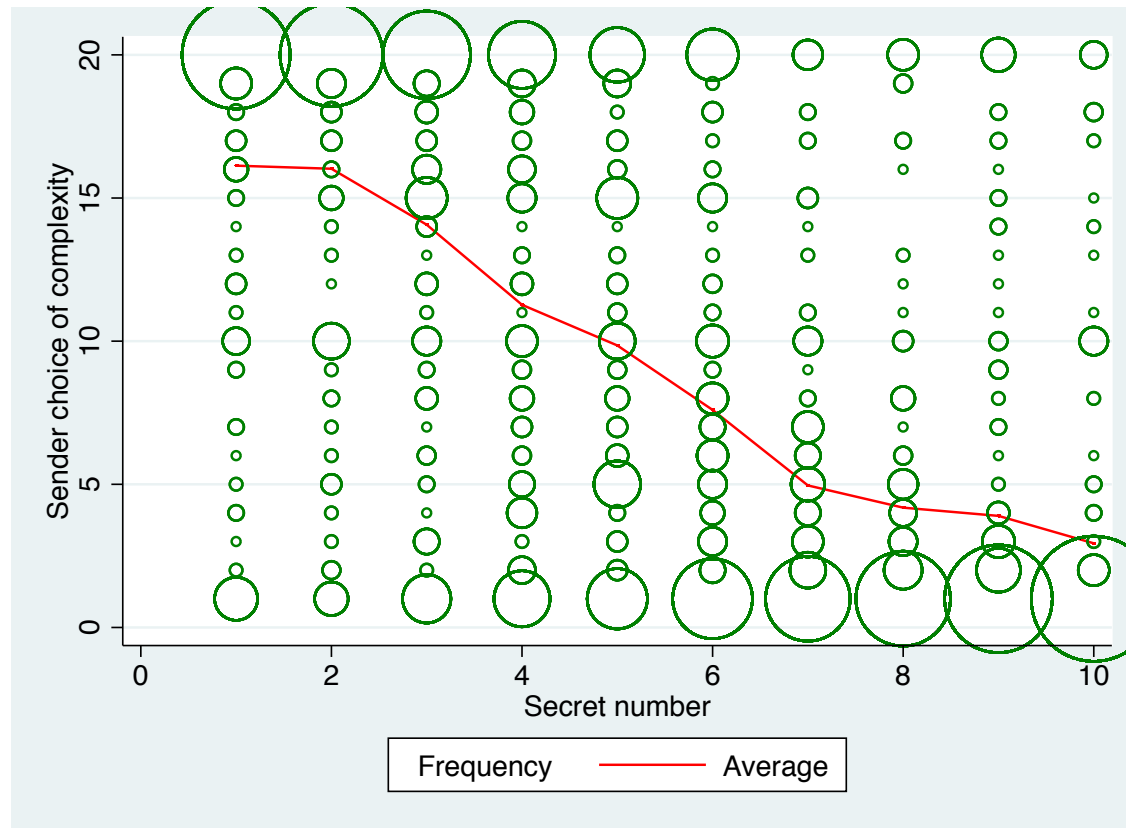
Takeaway #2: Senders used complexity to hide “bad” states

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 $N \geq 15$ (All rounds)	High complexity $N \geq 15$ (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 \geq 15 (All rounds)	High complexity N \geq 15 (Before 60s)
1-3	1.039	0.772
4-7	0.101	0.096
8-10	-1.126	-0.891

Optimal even for guesses before time limit

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 both 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

Structural Model

1. Receiver holds prior beliefs of secret number
 - Correct given complexity (baseline) or naïve
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**

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 $\{1, \dots, 10\}$
 - 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:
 $\{-9, -8, \dots, 0, \dots, 8, 9\}$
 - 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
		<i>lnL=-1.553</i>
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)
 - $\alpha=0$ is risk neutral for CRRA

Secret number	Actual mistakes	Baseline predictions	+ Risk preferences ($\alpha=0.010,0.129$)
		<i>lnL=-1.553</i>	<i>lnL=-1.553</i>
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
		$\ln L = -1.553$	$\ln L = -1.541$
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
		<i>lnL=-1.553</i>	<i>lnL=-1.519</i>
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 overconfident 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
		$\ln L = -1.553$	$\ln L = -1.272$
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 ($\beta=16.9-21.9$)
		<i>lnL=-1.272</i>	<i>lnL=-1.261</i>
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.

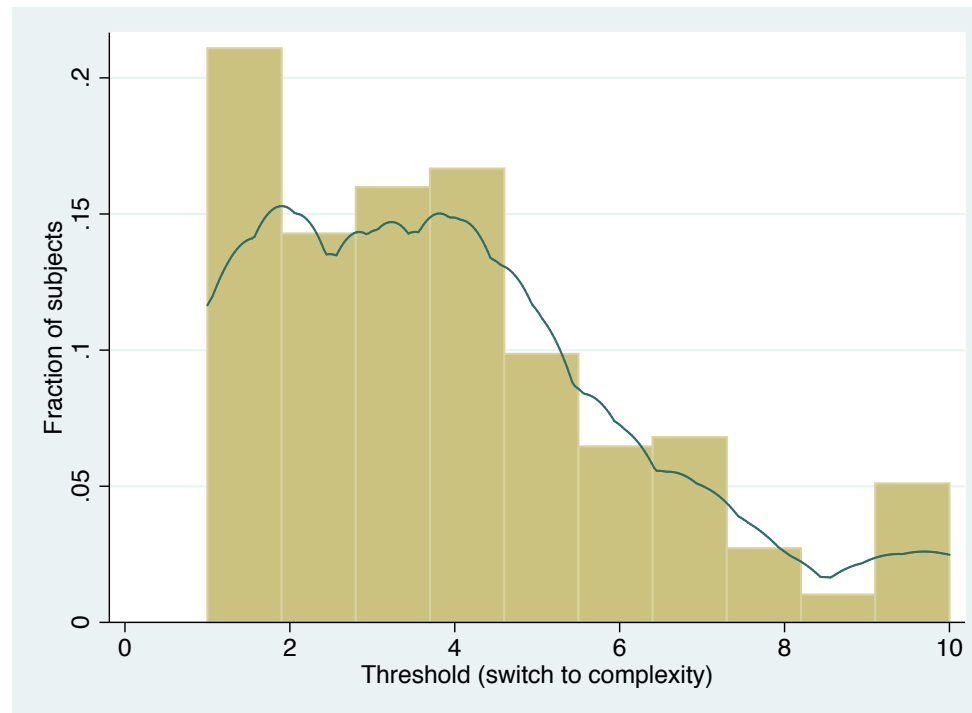
Mistakes as Logit Errors

- 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
		$\lambda_S = 0.111$ (0.221) $\ln L = -0.932$		$\lambda_R = 0.048$ (0.066) $\ln L = -1.733$
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

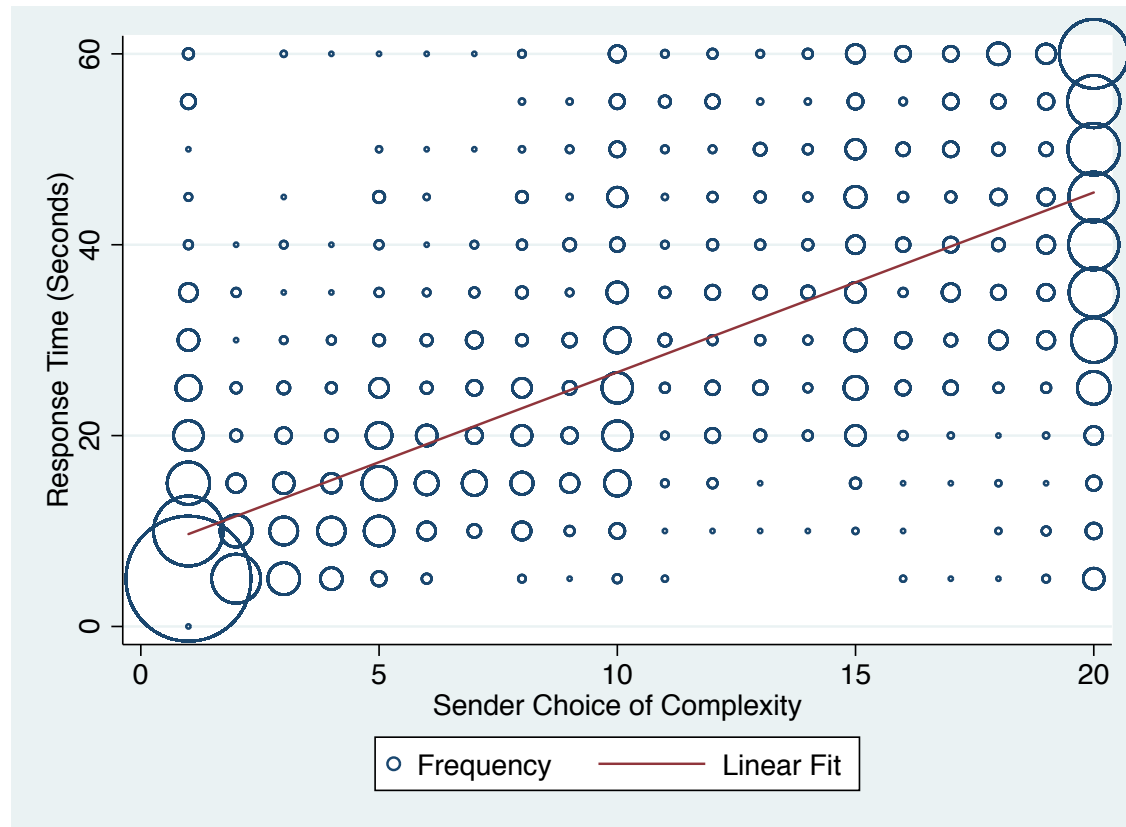
- Estimate individual complexity threshold
 - Use high complexity (≥ 15) at/below draw & not above
- 87% of reports consistent with threshold



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!

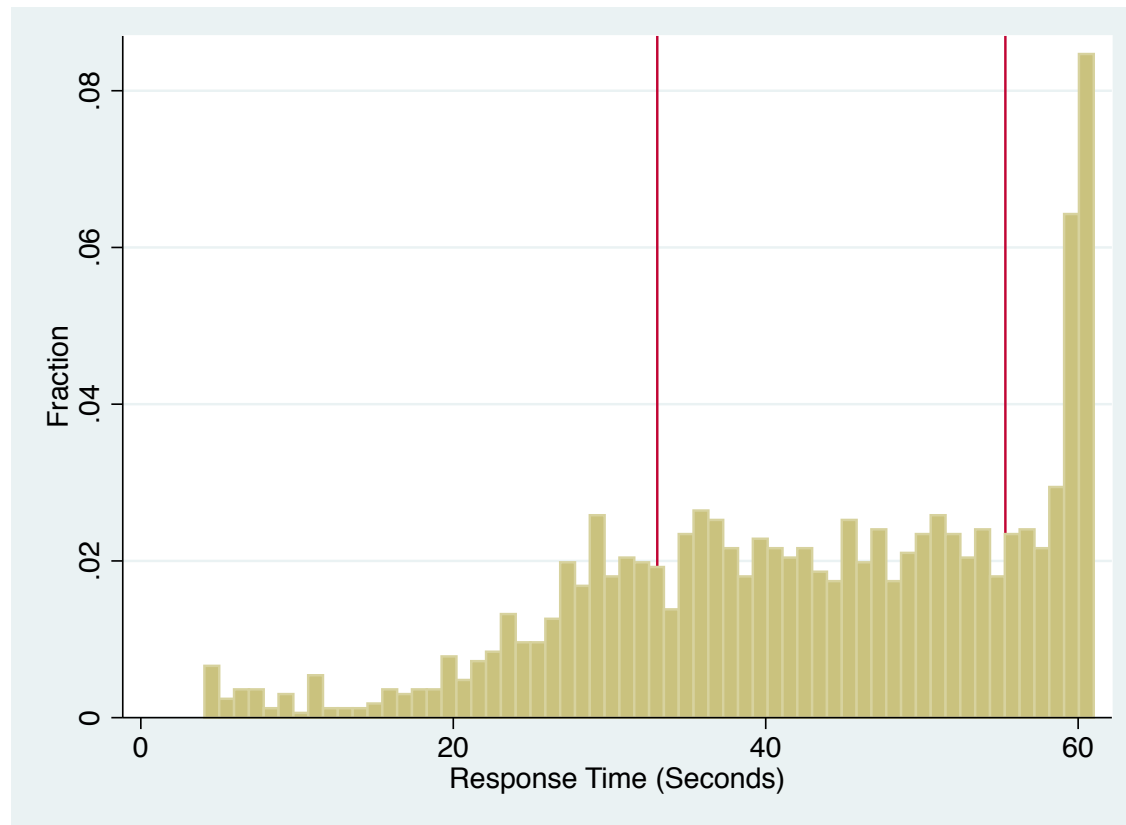
Receiver Response Times



Response times respond to report complexity

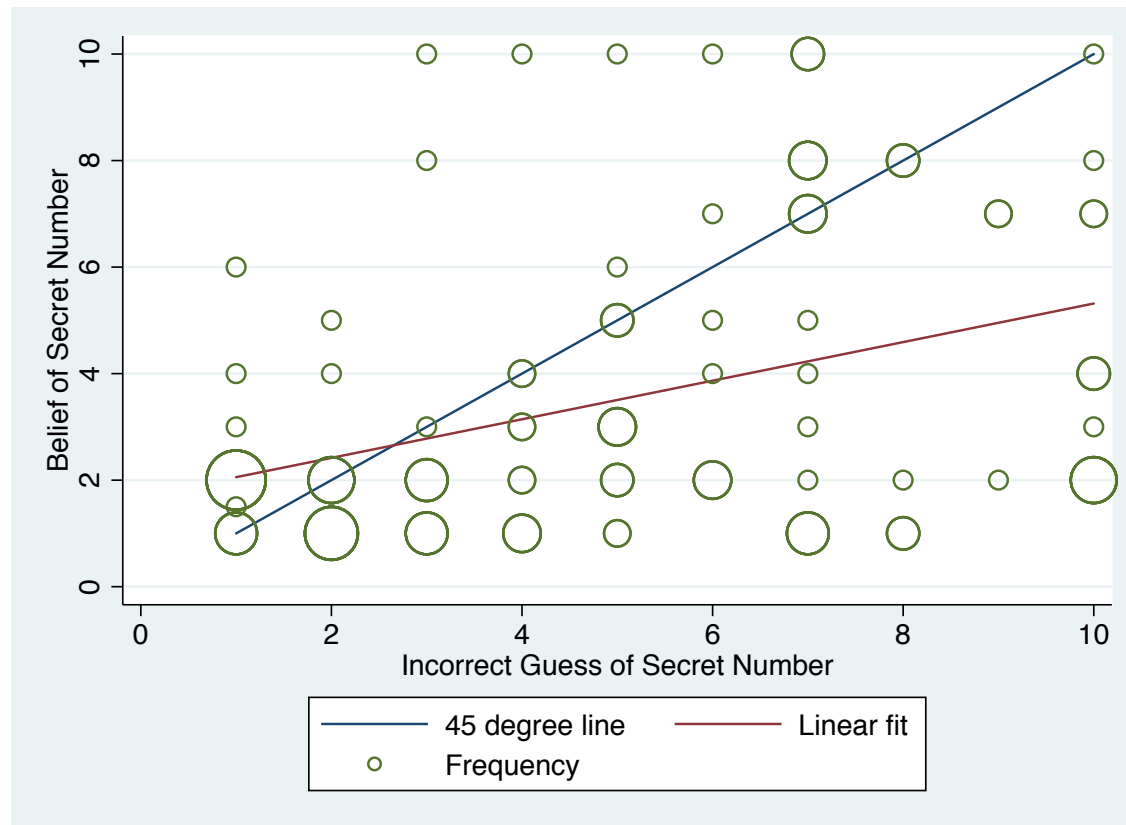
Response Times

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



Beliefs & Guesses

- Strong relationship when “quick” (1st quartile)



Another Behavioral Explanation

- Alternative explanation: Base rate neglect
- Model as underweighting likely states: $\text{Pr}(s)^\alpha$
 - 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 ($\alpha=0.566$)
		$\ln L = -1.272$	$\ln L = -1.280$
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