Adjustment Dynamics in the Lab

Silvio Ravaioli (sr3300@columbia.edu)

Economics 4850

December 6, 2019

Two stylized facts about price adjustment

- How do firms and households' adjustment to changes in the economy? For example, do firms adjust prices and wages in response to variation in market condition (interest rate, consumers' demand, ...). How quickly do they react?
- Being able to answer these questions is relevant to understand the effect of nominal changes!
- **Prices are sticky over time** (Bils and Klenow 2004)
- **Chain stores often adopt uniform prices** across different locations (Della Vigna and Gentzkow 2019) and adjust simultaneously (and rarely) several prices at once
- Large macroeconomic literature, classic "benchmarks" include menu cost models (changes occur only when adjustment is large enough, Sheshinski and Weiss 1977) and random timing models (any price is equally likely to be revised, Calvo 1983)

Two stylized facts about price adjustment

- How do firms and households' adjustment to changes in the economy? For example, do firms adjust prices and wages in response to variation in market condition (interest rate, consumers' demand, ...). How quickly do they react?
- Being able to answer these questions is relevant to understand the effect of nominal changes!
- **Prices are sticky over time** (Bils and Klenow 2004)
- **Chain stores often adopt uniform prices** across different locations (Della Vigna and Gentzkow 2019) and adjust simultaneously (and rarely) several prices at once
- Large macroeconomic literature, classic "benchmarks" include menu cost models (changes occur only when adjustment is large enough, Sheshinski and Weiss 1977) and random timing models (any price is equally likely to be revised, Calvo 1983)

Two stylized facts about price adjustment

- How do firms and households' adjustment to changes in the economy? For example, do firms adjust prices and wages in response to variation in market condition (interest rate, consumers' demand, ...). How quickly do they react?
- Being able to answer these questions is relevant to understand the effect of nominal changes!
- **Prices are sticky over time** (Bils and Klenow 2004)
- **Chain stores often adopt uniform prices** across different locations (Della Vigna and Gentzkow 2019) and adjust simultaneously (and rarely) several prices at once
- Large macroeconomic literature, classic "benchmarks" include menu cost models (changes occur only when adjustment is large enough, Sheshinski and Weiss 1977) and random timing models (any price is equally likely to be revised, Calvo 1983)

What can we learn from a laboratory experiment?

- We have a controlled environment, removing several confunding factors that occur in the real world (e.g., correlation between states, technology shock, cost of printing the menu, etc.)
- We remove information barriers (participants know the “rules” of the simplified environment) and know the objective of the agents (participants are incentivized to maximize a well-defined objective function)
- We observe a rich dataset, that includes true states (often unobservable in the real world), participants’ actions, and possible counterfactuals (e.g. Bayesian agent vs Human participant)

Tracking problem

- The second experiment you took part in the lab session was a tracking problem: estimate the probability of a binary event, which changes stochastically (as in Khaw, Stevens, and Woodford 2017)
- The task involved two simultaneous choices (with two independent states)
- Similar to the problem of a store that needs to fix the optimal price of a product in two different markets, with independent fluctuations in the demand (e.g. two different cities)

Tracking problem

- **How often do agents adjust the estimates?**
- H1: changes occur when they are more profitable (larger deviation from the optimal estimate)
- H2: changes occur randomly (no correlation between frequency and magnitude of adjustment)

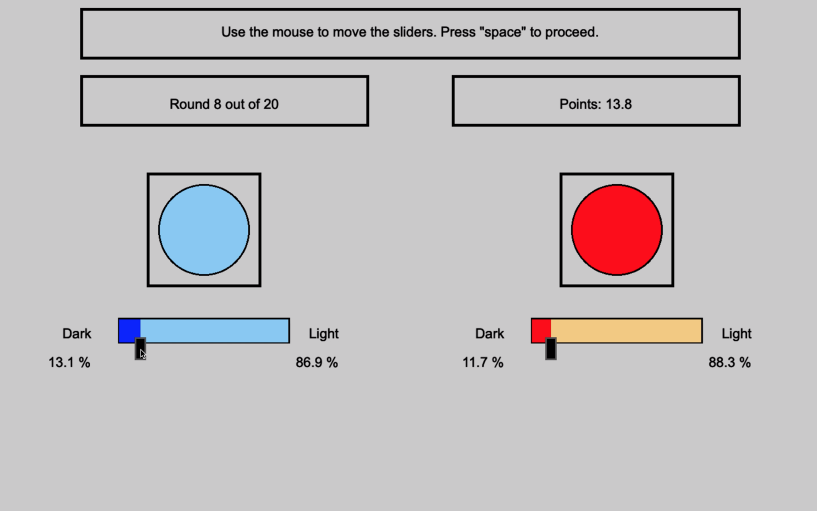
- **What kind of correlation we have across the two parallel tasks?**
- H1: positive correlation. Changes occur more often together than in isolation (decide to change when both the adjustments are profitable enough)
- H2: negative correlation. Changes occur more often in isolation than together (limited attention, focus on one task at the time)

Tracking problem

- **How often do agents adjust the estimates?**
- H1: changes occur when they are more profitable (larger deviation from the optimal estimate)
- H2: changes occur randomly (no correlation between frequency and magnitude of adjustment)

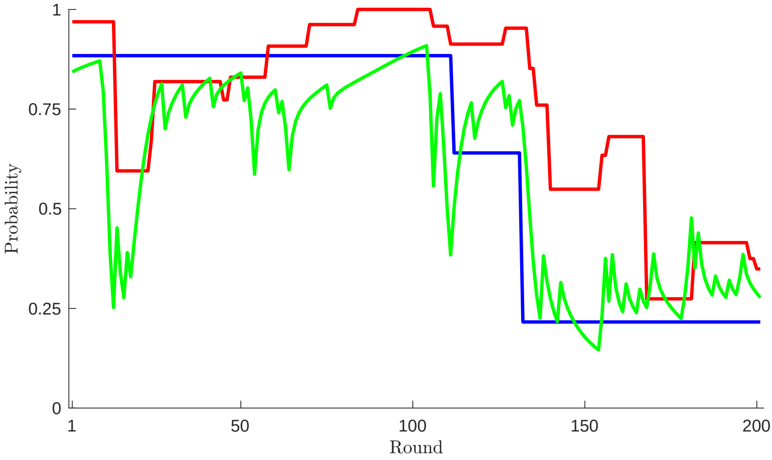
- **What kind of correlation we have across the two parallel tasks?**
- H1: positive correlation. Changes occur more often together than in isolation (decide to change when both the adjustments are profitable enough)
- H2: negative correlation. Changes occur more often in isolation than together (limited attention, focus on one task at the time)

Lab experiment - Interface



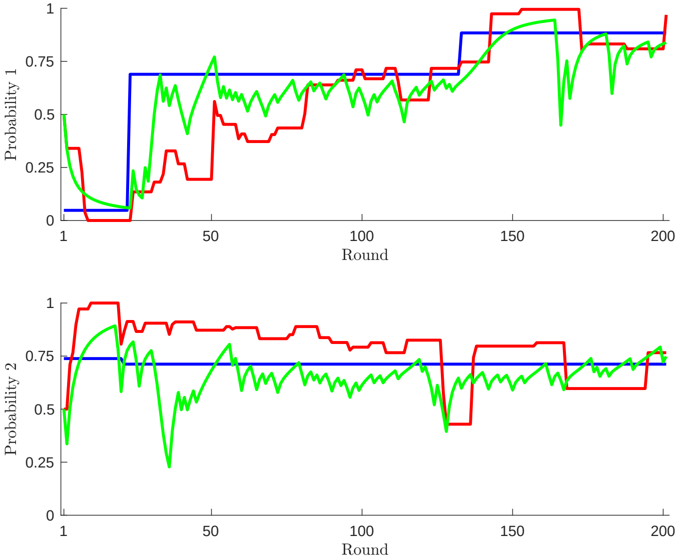
Task adapted from Khaw et al. 2017, we use two independent states

Collected Data - Time Series (one side)



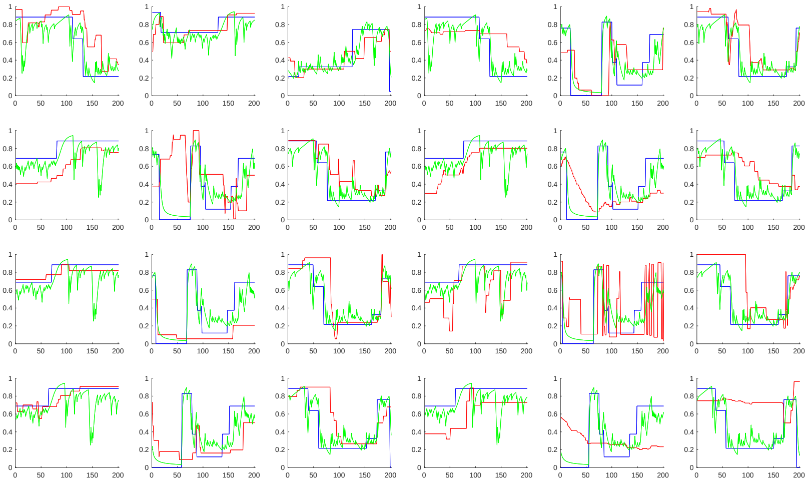
Blue: true probability. Green: Bayesian forecast. Red: subjective estimate.

Collected Data - Time Series (both sides)



Blue: true probability. Green: Bayesian forecast. Red: subjective estimate.

Collected Data - Time Series (24 participants)

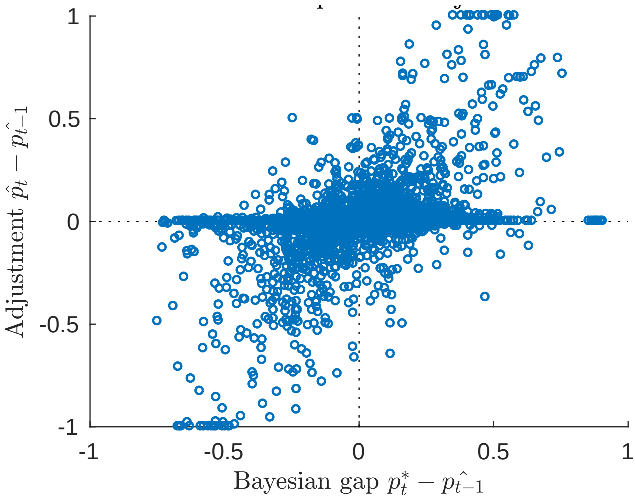


Probabilities for the left box only. Some participants faced the same probabilities (blue) and observed the same sequence of observations (so they have the same Bayesian forecast, green).

Preview of results

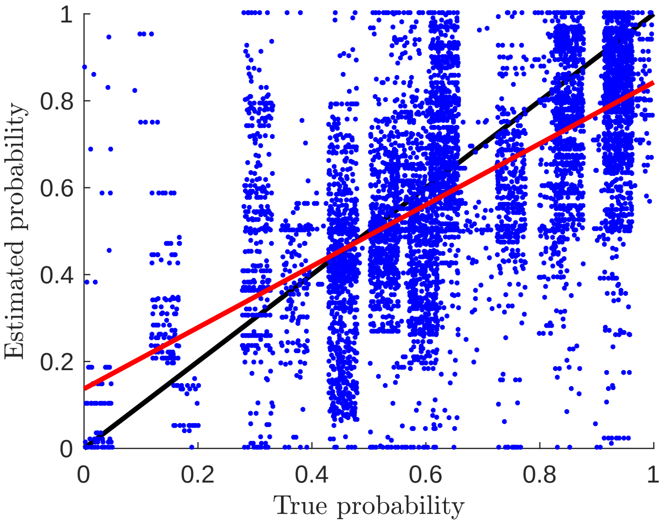
- **Inertia**: adjust the estimates only 32% of the times (the Bayesian agent always adjusts)
- **Stochasticity**: heterogeneity in the response
- **Conservatism**: participants are more conservative than the Bayesian agent
- **Overconfidence**: mass of estimates on extreme events
- **Discrete adjustment:** heterogeneity in wait times between adjustments and size of the adjustment
- **Correlation** in adjustments: adjustment likelihood increases when the other slide is moved

Result 1: Participants display stochasticity



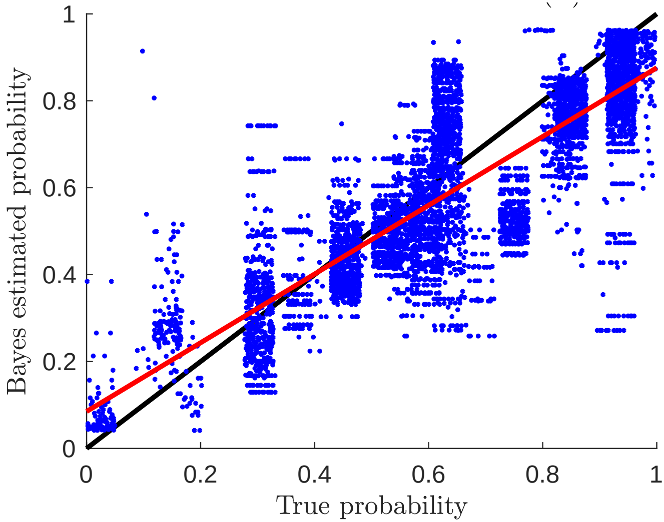
When we consider two rounds with the same Bayesian gap (expected adjustment), we have large variability in the response (adjustment or not, its magnitude), but most of the adjustments are in the predicted direction.

Result 2: Participants display conservatism



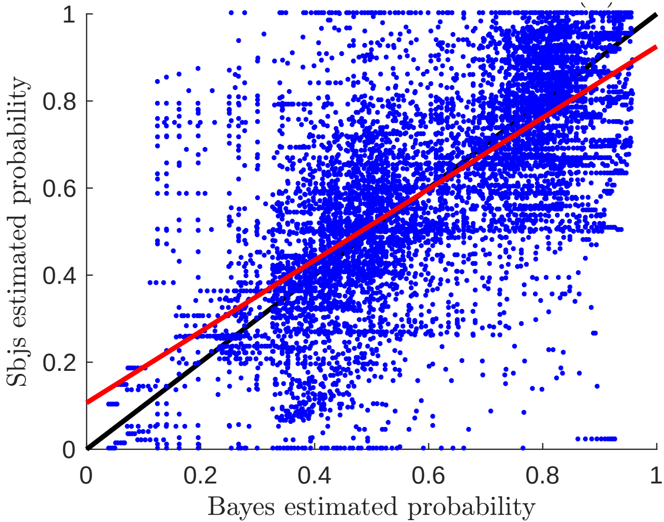
Joint distribution of p (true probability) and $\hat{p}$ (subjective estimates). The red line is the linear fit. We observe conservatism (slope <1).

The Bayesian agent also displays conservatism...



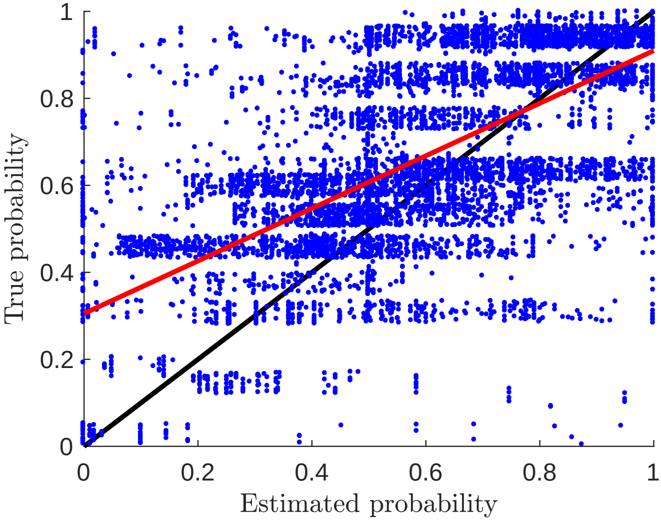
Joint distribution of p (true probability) and $\hat{p}^*$ (Bayesian estimates). The red line is the linear fit. We observe conservatism (slope <1).

...but humans are "extra" conservative!



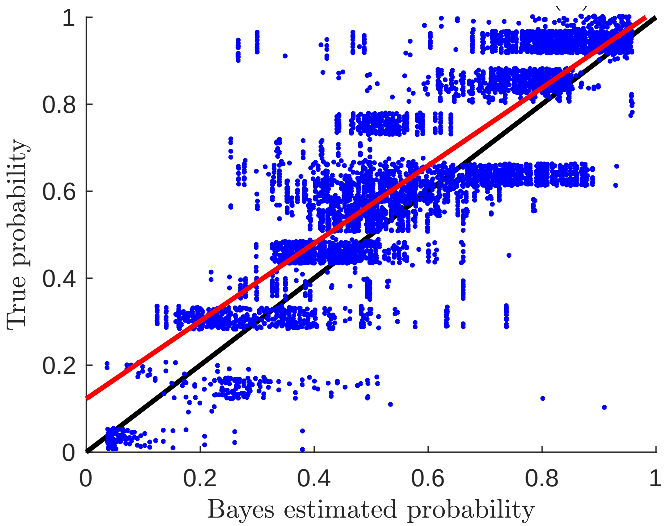
Joint distribution of $\hat{p}^*$ (Bayesian estimates) and $\hat{p}$ (subjective estimates) and . The red line is the linear fit. Humans are more conservative than predicted.

Result 3: Participants display overconfidence



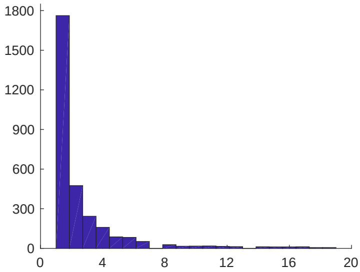
Joint distribution of p (true probability) and $\hat{p}$ (subjective estimates). We observe overconfidence (crossing point between 45° line and linear fit).

The Bayesian agent is NOT overconfident

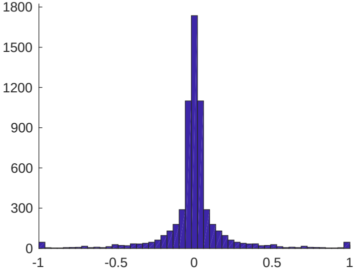


Joint distribution of p (true probability) and $\hat{p}^*$ (Bayesian estimates). No overconfidence (no crossing point but true p are biased towards high p).

Result 4: Discrete adjustment



(a) Samples between adjustments.



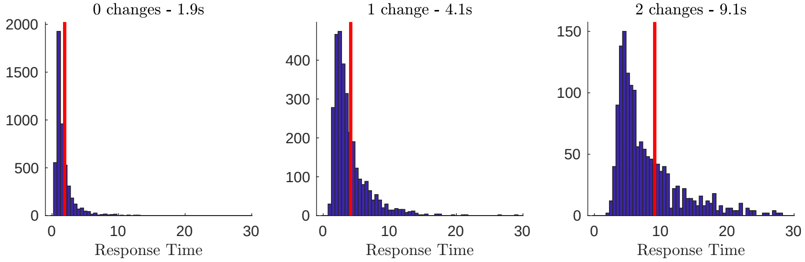
(b) Distribution of the adjustments.

- Heteregeneous timing of adjustment
  (Bayesian benchmark: adjust in every period)
- Both large and small adjustments
  (menu cost models: only large changes should occur)

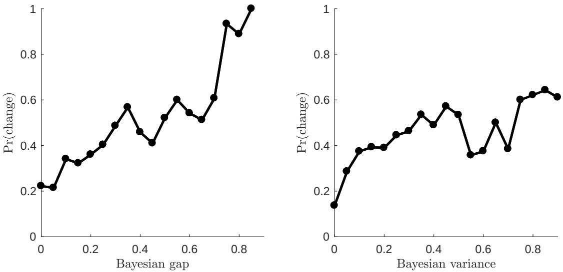
Result 5: Inertia and correlated adjustment

- Inertia: no change (in none of the sliders) in 51% of the rounds
- Correlated changes: a change in p1 increases the likelihood of changing p2 from 1/4 to 1/2

	All	Conditional on p1 changed	Conditional on p1 unchanged
Pr(p2 change)	**32%**	**49%**	**24%**
Avg p2 c (cond.)	10.73%	8.68%	12.71%
Avg p2 change	3.44%	4.25%	3.05%

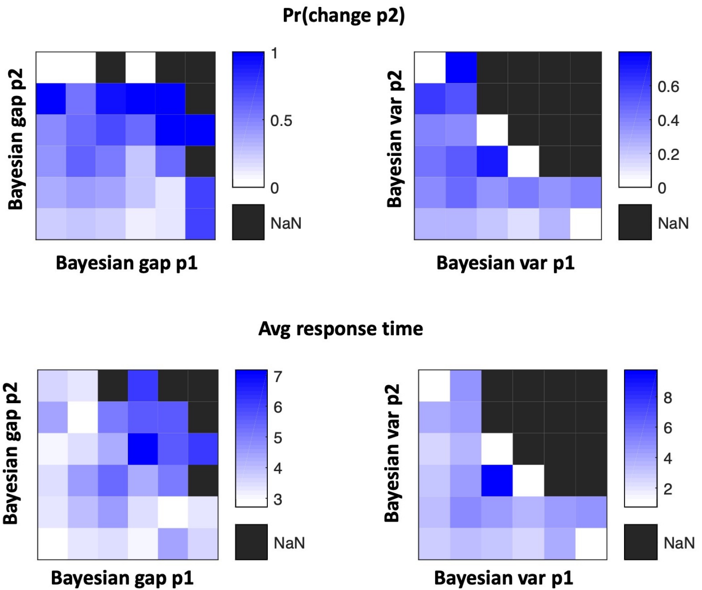


Logit Regression



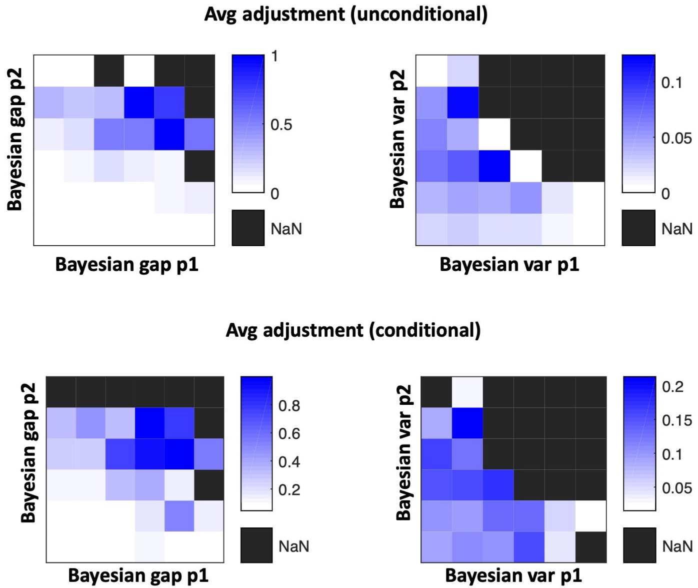
Logit(Change p2)	(1)	(2)	(3)	(4)
Constant	-1.26***	-1.16***	-1.55***	-1.93***
Bayesian gap p2	3.08***		2.64***	4.02***
Bayesian gap p1	0.222		0.265	1.18***
Bayesian var p2		3.01***	2.43***	4.28***
Bayesian var p1		0.334*	0.502***	1.69***
Bg p2 $\times$ Bv p2				-9.14***
Bg p1 $\times$ Bv p1				-6.18***

Heatmaps (1)



Pr(change p2)
Bayesian gap p2
Bayesian gap p1
1
0.5
0
NaN
Bayesian var p2
Bayesian var p1
0.6
0.4
0.2
0
NaN
Avg response time
Bayesian gap p2
Bayesian gap p1
7
6
5
4
3
NaN
Bayesian var p2
Bayesian var p1
8
6
4
2
NaN

Heatmaps (2)


Avg adjustment (unconditional)
Bayesian gap p2
Bayesian gap p1
1
0.5
0
NaN
Bayesian var p2
Bayesian var p1
0.1
0.05
0
NaN
Avg adjustment (conditional)
Bayesian gap p2
Bayesian gap p1
0.8
0.6
0.4
0.2
NaN
Bayesian var p2
Bayesian var p1
0.2
0.15
0.1
0.05
NaN

References

- Khaw, Mel Win, Luminita Stevens, and Michael Woodford. "Discrete adjustment to a changing environment: Experimental evidence." Journal of Monetary Economics 91 (2017): 88-103.
- Gallistel, Charles R., Monika Krishan, Ye Liu, Reilly Miller, and Peter E. Latham. "The perception of probability." Psychological Review 121, no. 1 (2014): 96.
- Magnani, Jacopo, Aspen Gorry, and Ryan Oprea. "Time and state dependence in an Ss decision experiment." American Economic Journal: Macroeconomics 8, no. 1 (2016): 285-310.
- DellaVigna, Stefano, and Matthew Gentzkow. "Uniform pricing in us retail chains." The Quarterly Journal of Economics 134, no. 4 (2019): 2011-2084.
- Woodford, Michael. "Information-constrained state-dependent pricing." Journal of Monetary Economics 56 (2009): S100-S124.