The Promise and Limits of Machine Learning and Big Data in Macrofinance

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Outline

1. Machine learning and big data comments
   a) Prediction versus causation
   b) Virtues of agnostic black-box modeling?
   c) Big Data
   d) Lucas Critique
2. Brief comments on presentations
   a) Giesecke, Sirignano, Sadhwani
   b) Wallace
3. Big data in action: transmission of QE

Why Machine Learning?

- Kleinberg, Ludwig, Mullinaithan, Obermeyer (2015 AER P&P) answer:
- Prediction vs causation
  - Umbrella (FICO) vs. rain dance (monetary policy)
  - Risk management vs. regulation?
  - Variance vs. bias
  - Can prediction inform causation?
- As academics, need a lot of help to care about predictions instead of "how the world works"
  - Not content with a kitchen sink regression, we want to understand mechanisms

Value of Models

- Kay's answer on value of machine learning:
  1. To handle big data
  2. To handle "true" model's unknown nonlinearities
- "All models are wrong, some models are useful." –George Box
- "The art of modeling is what you leave out." –Bengt Holmstrom
- Promise of machine learning is that we won't need our woefully simplistic models.
- But w/o models, we also don't really gain any understanding.
- If we're lucky, we'll gain enhanced predictive power.
- This is no substitute for modeling—it is just for a different purpose than prediction.

Lucas Critique

- Key worry, inspired by "The Failure of Models that Predict Failure," Rajan, Seru, Vig (2015 JFE)
- When we are interested in prediction instead of causation, we always have to be concerned with the stability of that model.
- Teaching to the test ⇔ Lending to the test
- Given the data requirements of machine learning, hard to assess model drift over time.

Big Data: No Substitute for Identification

- Helps with: power, weak instruments, local effects, etc.
- **Not** selection bias, measurement error, endogeneity
- Worry can be thought of as external validity:
- Yes, can get significant coefficients with $R^2 < .0001$ if sample large enough…
- But if pattern only really applies to a very small subset of a very large dataset, have we really learned anything general?
- Estimated treatment effects start to look like very very local treatment effects.

“Deep Learning for Mortgage Risk” Giesecke, Sirignano, and Sadhwani

- Goal: Improve risk management by leveraging machine learning and big data.
- Real goal: Demonstrate proof-of-concept handling breadth and depth of loan-level data for perfect applications yet unspecified.
- Research Question: Can machine learning techniques outperform logit predictions of defaults?
  - *NOT* does X cause default, will macropru foster robust loans, is a crisis coming, etc.
- Method: Compare predictions out of sample for both methods.

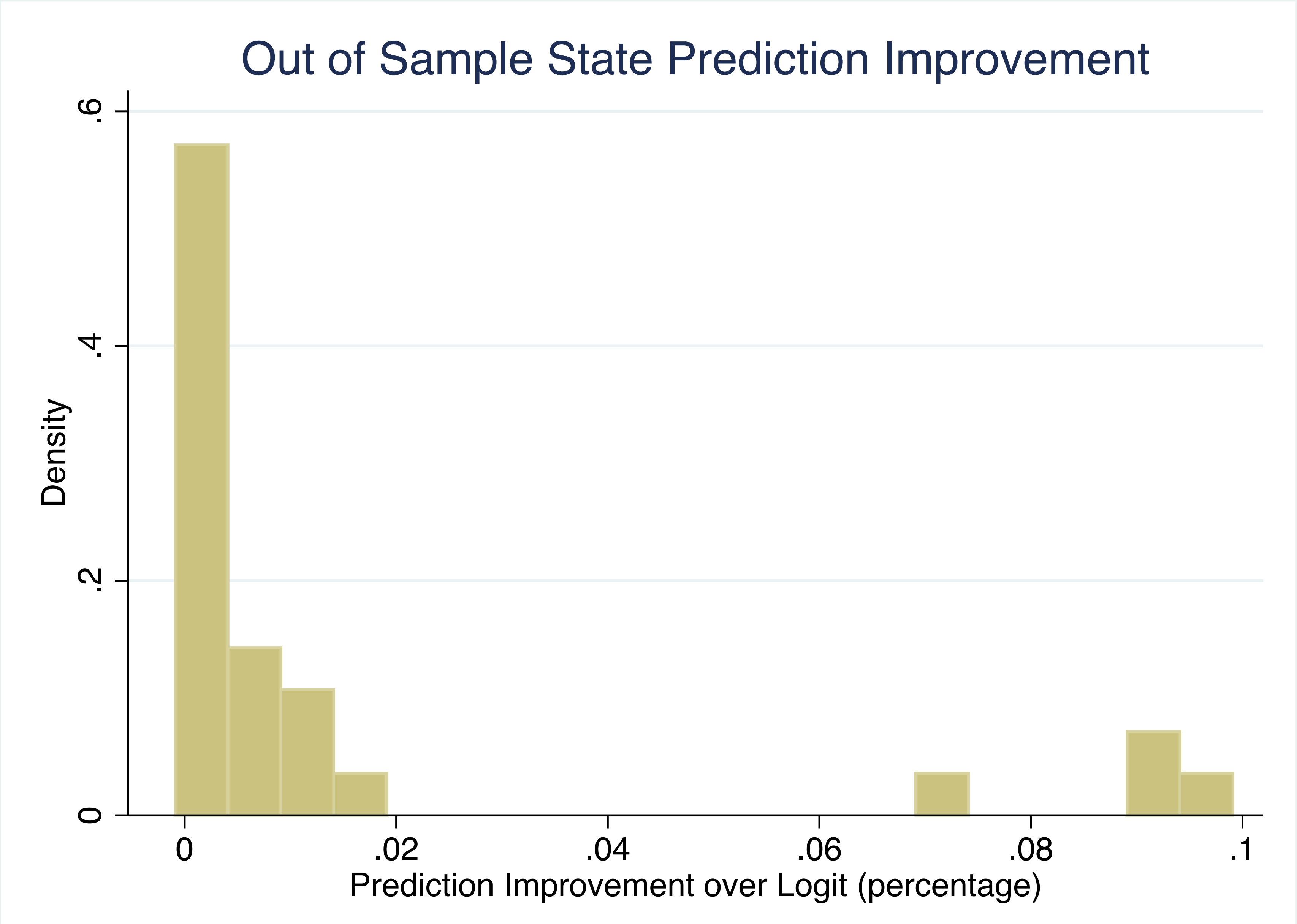
Why Machine Learning Here?

1. To handle big data. Why not a sample?
   - Once you look within zip codes, 120m nationwide becomes small.
   - Nonparametric methods are data hogs: Whitney Newey's "Curse of Dimensionality"
   - For rare events especially, need sufficient failures
2. To improve predictions via neural networks modeling

Prediction Improvements

- Even regularized multinomial logit can predict default state with high degree of accuracy (99%).
- Hardest: predict voluntary prepayment. (Logit 65%)
  - Fundamental problem for risk management, pricing of RMBS…
- Successfully predict voluntary prepayment 9 percentage points better (74% of time) than multinomial logit
  - All other performance states: 0-1 p.p. improvement
- Not done yet. Can do one-month predictions. What horizon is most important for risk management? Stress testing?
- Improvement in false positives or false negatives?

Value Added Predicting Prepayment



ICYMI, Nancy's 5 Points

1. High stakes in this arena: Poterba quote
2. Mortgage contract features jointly endogenous => proceed at your own risk
3. Observing whole "contract space" requires non-trivial merges/assembling, but can be done
4. Systemic risk picture different when you observe lending networks
5. Repeat-sales indices mask volatility and are biased in the presence of frequent renovations.

Importance of Entire Contract Space

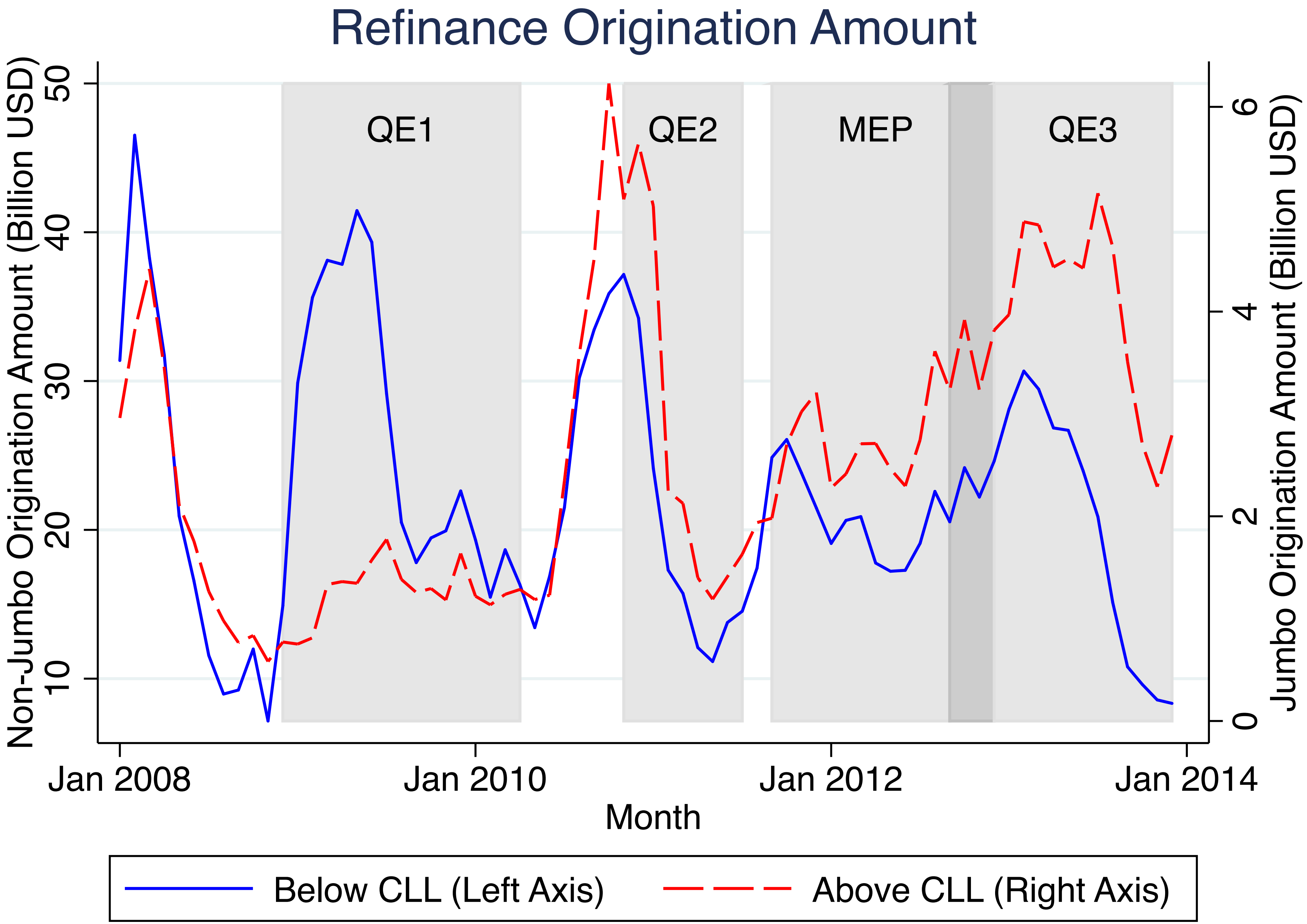
- "Mortgage origination is a high-dimensional contracting problem so most contract elements are jointly endogenous."
- => why we can't "fix" things by having outlawing particular contract features that seems to be most predictive of bad outcomes.
- Dodd-Frank does things like outlaw/restrict long mortgage maturity, prepayment penalties, low-documentation, high DTI, etc.
- If selection (not treatment effect of that contract feature)
  - <u>Best-case scenario</u>: restricting it doesn't change aggregate outcomes it just buries/pools those outcomes with others
  - <u>Worst-case</u>: it restricts access to credit markets based on faulty empirics.

Integrated Data in Action

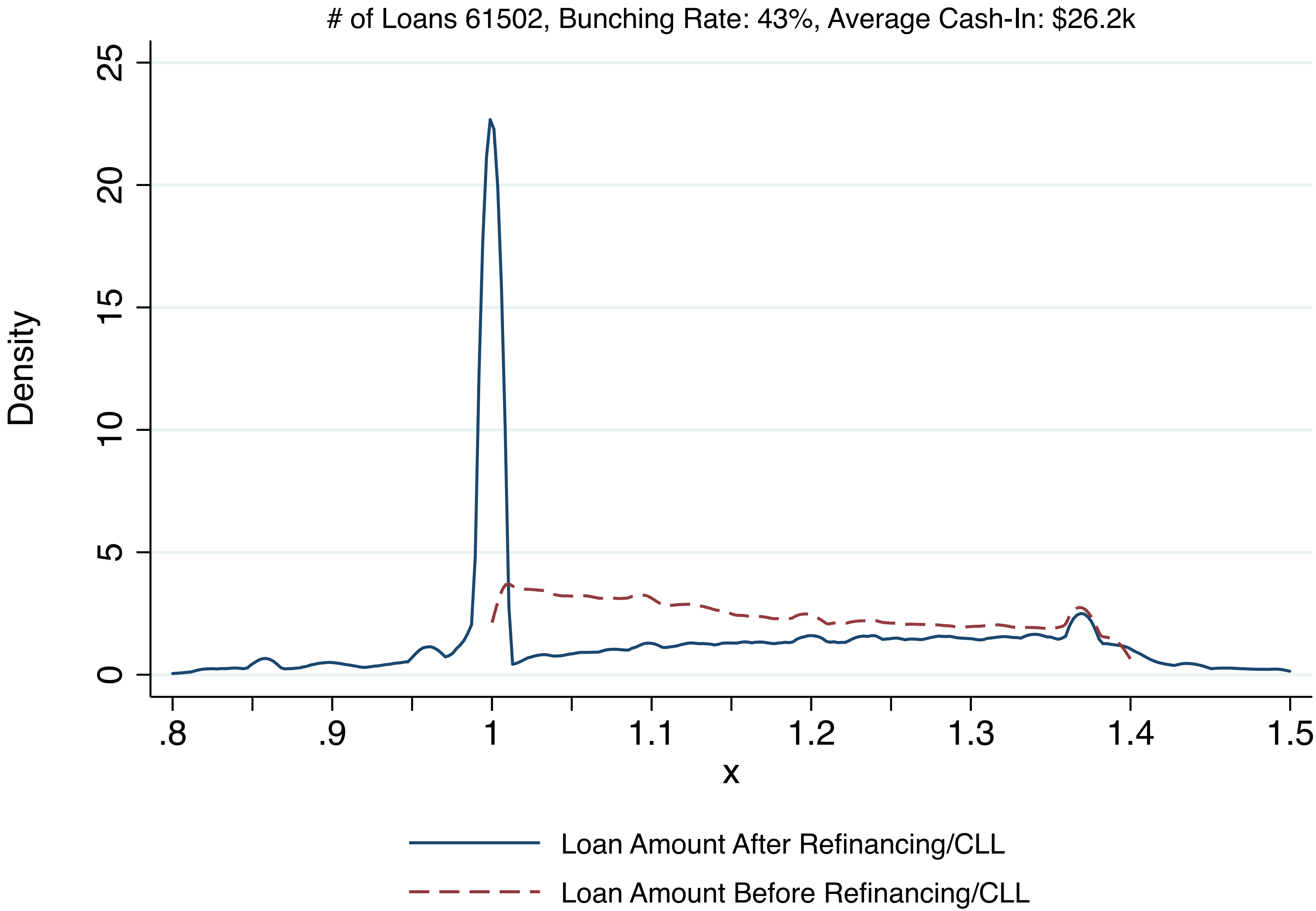
- Disclaimer: Self-promoting discussants
- "Unconventional Monetary Policy and the Allocation of Credit" (with Marco Di Maggio and Amir Kermani)
- Goal: Understand transmission of unconventional monetary policy and its heterogeneous beneficiaries
- Focus: How RMBS purchases affect lending

Why Integrated Database Necessary?

- First-order effect of Fed TBA purchases was to lower GSE mortgage rates.
- How did mortgage volumes change?
  - Identification requires rich microdata for strategy that exploits mortgage market segmentation (CLL, LTV) and controls for borrower and mortgage note heterogeneity
- Who were the borrowers that benefitted?
  - Requires linking mortgage spells within a borrower
- Who were the banks that benefitted?
  - Requires understanding banks' balance sheets, lending networks, RMBS holdings


Refinance Origination Amount
QE1
QE2
MEP
QE3
Non-Jumbo Origination Amount (Billion USD)
Jumbo Origination Amount (Billion USD)
10
20
30
40
50
0
2
4
6
Jan 2008
Jan 2010
Jan 2012
Jan 2014
Month
Below CLL (Left Axis)
Above CLL (Right Axis)

CLL Bunching to "Take-up" QE



Unconventional MP Transmission

- Direct lending channel – during QE1, Fed essentially bypassing banks to inject liquidity directly into household sector.
- How do we know this? Other segments of the market clamored to crowd into GSE segment that was the direct beneficiary of QE purchases.
- Integrated data allows us to view entire mortgage ecosystem.

Conclusion

- We've seen mostly proof-of-concept papers in machine learning + macrofinance.
- Not their fault; should be eye opening. Nontrivial next step is to demonstrate the golden application that teaches us something new about the macroeconomy.
- To facilitate adoption of these methods, hold our hands to help us see what research questions can uniquely be answered with these methods, as opposed to their use in predictive analytics.
  - See Varian (2014) for some of this hand holding.