Credit Constraints and the Distributional Effects of the Refinancing Channel

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Motivation

- Central topic in macro: What monetary policy channels are available to support aggregate demand
  - Post-08 literature moves beyond standard theory: **Refinancing Channel**
  - Monetary Policy \(\Rightarrow\) Aggregate Refinancing \(\Rightarrow\) Aggregate Consumption

- Factors can inhibit the strength of this channel:
  - Behavioral factors: households do not refinance when it is optimal for them to do so
  - Access to credit: households are unable to refinance, even if they want to do so
  - These factors will vary by household based on its characteristics

- This paper: distributional impact of credit constraints on the transmission of monetary policy in the U.S. economy through the mortgage refinancing channel
Paper Overview

1. Empirical Facts
   ▶ Heterogeneity in refinancing originations in the U.S. for different groups of households

2. Model
   ▶ Household-level probabilities of refinancing approval considered independently from the refinancing application probabilities
   ▶ IV for financial condition of borrowers in refinancing approval probability

3. Effects of Credit Constraints on Monetary Policy Transmission
   ▶ Aggregate refinancing response to rate shock under different economic conditions
   ▶ Refinancing response to rate shock for different household groups
     ▶ Decomposing effect of credit constraints
Related literature

- Monetary policy transmission to households and its distributional effects

- Refinancing as a channel of monetary policy transmission
  Andersen et al. (2020), Beraja et al. (2018), Di Maggio et al. (2020), Berger et al. (2020) and Wong (2019)

- Effect of credit constraints on refinancing

- Policies and programs targeting mortgage refinancing

- Slow or sub-optimal refinancing behavior of households
Data

Aggregate Data

- Federal Reserve Financial Accounts (FA)
  - Aggregate data for residential mortgage liabilities, home equity loans and construction loans

Micro data

- Home Mortgage Disclosure Act (HMDA)
  - Covers over 90% of total U.S. mortgage originations (Dietrich et. al., 2019)
  - Data is filtered to match the FA account used, following Greenspan & Kennedy (2005)

- American Housing Survey
  - Distribution of total residential mortgage liabilities by race or ethnicity and gender

- Survey of Consumer Finances
  - Distribution of total residential mortgage liabilities by loan amount and income

- American Community Survey
  - Median home value by census tract or county for 2009 to 2018

- Federal Housing Finance Agency Home Price Index
  - HPI by census tract or county for 1999 to 2008
Aggregate refinancing

- **Aggregate refinancing rate**: fraction of regular mortgage outstanding amount being refinanced

- **Aggregate refinancing incentive**: the average interest rate on outstanding mortgages minus the market mortgage rate

![Graph showing aggregate refinancing rate and incentive over time]
Refinancing cross-section

Refinancing rate by loan amount

Refinancing rate for selected loan amount deciles

Refinancing rate by income

Refinancing rate for selected income deciles
Refinancing cross-section

Refinancing rate by home value

Refinancing rate for selected home value deciles

Refinancing rate by race or ethnicity

Refinancing rate by gender
Setup

Household $i$ in period $t$

- Applies to Refinance
  - Application Approved
  - Application Denied
- Doesn’t Apply to Refinance
A model of refinancing

Household $i$ in period $t$:

- Is defined by the vector of its characteristics $X_{i,t}$ of size $K$ and its taste shock to refinancing $\epsilon_{i,t}$

- The value-cost of refinancing for the household:

$$y_{i,t} = \alpha_i + \beta_i R_t + \epsilon_{i,t}$$

- Cost of refinancing and marginal value of the aggregate refinancing incentive is household-specific:

$$\alpha_i = \alpha_1 + \alpha_2' X_{i,t} \quad \quad \beta_i = \beta_1 + \beta_2' X_{i,t}$$

- Control for relative change in house prices and unemployment

$$\Rightarrow y_{i,t} = \alpha_1 + \alpha_2' X_{i,t} + \beta_1 R_t + \beta_2' X_{i,t} R_t + \gamma_1 \Delta \text{HPI}_t R_t + \gamma_2 U_t R_t + \epsilon_{i,t}$$

- By assuming $\epsilon_{i,t} \sim \text{iid type E.V. 1}$, the household applies to refinance with probability:

$$\Pr(y_{i,t} \geq 0|R_t, \Delta \text{HPI}_t, U_t, \alpha_i, \beta_i, \gamma_1, \gamma_2) = \frac{\exp\left(\alpha_1 + \alpha_2' X_{i,t} + \beta_1 R_t + \beta_2' X_{i,t} R_t + \gamma_1 \Delta \text{HPI}_t R_t + \gamma_2 U_t R_t\right)}{1 + \exp\left(\alpha_1 + \alpha_2' X_{i,t} + \beta_1 R_t + \beta_2' X_{i,t} R_t + \gamma_1 \Delta \text{HPI}_t R_t + \gamma_2 U_t R_t\right)}$$
A model of refinancing

• $D_{i,t}$ is a subset of $X_{i,t}$

• A refinancing application is approved based on:

$$\text{approval}_{i,t} = \omega_1 + \omega_2 D_{i,t} + \eta_{i,t}$$

• By assuming $\eta_{i,t} \sim \text{iid type E.V. 1}$, a household’s application is approved with probability:

$$\Pr(\text{approval}_{i,t} \geq 0 | \omega_1, \omega_2, y_{i,t} \geq 0) = \frac{\exp(\text{approval}_{i,t} = \omega_1 + \omega_2 D_{i,t} + \eta_{i,t})}{1 + \exp(\text{approval}_{i,t} = \omega_1 + \omega_2 D_{i,t} + \eta_{i,t})}$$

• The probability that a household $i$ applies to refinance at $t$ and the application is approved:

$$\rho_{i,t} = \Pr(y_{i,t} \geq 0 | R_t, \Delta HPI_t, U_t, \alpha_i, \beta_i, \gamma_1, \gamma_2) \times \Pr(\text{approval}_{i,t} \geq 0 | \omega_1, \omega_2, y_{i,t} \geq 0) = \Pr(i \text{ applies to refinance in } t) \times \Pr(\text{application from } i \text{ in } t \text{ is approved})$$
A model of refinancing

For the Aggregate Refinancing Rate in period $t$

- The households that choose and are able to refinance at $t$ are defined by the set of their characteristics:

$$A_t(R_t, \Delta \text{HPI}_t, U_t, \alpha_i, \beta_i, \gamma_1, \gamma_2, \omega_1, \omega_2) = \{ (X_{i,t}, \epsilon_{i,t}, \eta_{i,t}) | y_{i,t} \geq 0, \text{approval}_{i,t} \geq 0 \}$$

- To aggregate, integrate over the mass of refinancers (households in $A_t$):

$$\rho_t = \int_{A_t} dP(X, \epsilon, \eta) = \int_{A_t} \rho_{i,t} dP(X)$$

where $P(\cdot)$ population distribution function

$$\rho_t = \int_{A_t} \Pr(y_{i,t} \geq 0 | R_t, \Delta \text{HPI}_t, U_t, \alpha_i, \beta_i, \gamma_1, \gamma_2) \times \Pr(\text{approval}_{i,t} \geq 0 | R_t, \Delta \text{HPI}_t, U_t, \omega_1, \omega_2, y_{i,t} \geq 0) dP(X)$$

- For $\text{Corr}[\epsilon_{i,t}, \eta_{i,t}] = 0$ the household refinancing parameters can be estimated separately from the refinancing approval parameters
Addressing the independence assumption

- Liquidity as an instrument for the Loan-to-Income ratio of applicants in the probability of approval
- Strong correlation between a bank’s liquidity and the LTI of the mortgages it originates (Loutskina (2011), Loutskina & Strahan (2009), Ouazad & Ranciere (2016) and Ouazad & Ranciere (2019))
- Using instrument: Variation in the households that are approved to refinance by their bank, while the household decision to refinance will remain unaffected

\[
\text{approval}_{i,t} = \omega_1 + \omega_{2,1} \hat{LTI}_{i,t} + \omega_{2,2} (\text{LTI} \times \text{Income Dummy})_{i,t} + \\
\omega_{2,3} \text{LTV}_{i,t} + \omega_{2,4} \text{White, Asian or Other}_{i,t} + \omega_{2,5} \text{Female}_{i,t} + \eta_{i,t}
\]

\[
\hat{LTI}_{i,t} = \nu_1 + \nu_{2,1} \text{Liquidity}_{j,t} + \nu_{2,2} (\text{Liquidity} \times \text{Income Dummy})_{j,t} + \nu_{2,3} \text{LTV}_{i,t} + \\
\nu_{2,4} \text{White, Asian or Other}_{i,t} + \nu_{2,5} \text{Female}_{i,t} + e_{i,t}
\]

\[
(\text{LTI} \times \text{Income Dummy})_{i,t} = \nu_1 + \nu_{2,1} \text{Liquidity}_{j,t} + \nu_{2,2} (\text{Liquidity} \times \text{Income Dummy})_{j,t} + \nu_{2,3} \text{LTV}_{i,t} + \\
\nu_{2,4} \text{White, Asian or Other}_{i,t} + \nu_{2,5} \text{Female}_{i,t} + e_{i,t}
\]

where Liquidity_{j,t} the mean liquidity of the bank receiving application \{i, t\} and its 2 closest branches
## Estimation Results

### Approval Parameters

<table>
<thead>
<tr>
<th>Variable</th>
<th>Logit Coefficients</th>
<th>Marginal Probabilities</th>
<th>IV Probit Model</th>
<th>Marginal Probabilities</th>
</tr>
</thead>
<tbody>
<tr>
<td>LTI</td>
<td>-0.224***</td>
<td>-0.046***</td>
<td>-0.387***</td>
<td>-0.133***</td>
</tr>
<tr>
<td></td>
<td>(0.001)</td>
<td>(0.000)</td>
<td>(0.018)</td>
<td>(0.006)</td>
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<tr>
<td>LTI × Income Dummy</td>
<td>-0.226***</td>
<td>-0.047***</td>
<td>2.376***</td>
<td>0.814***</td>
</tr>
<tr>
<td></td>
<td>(0.003)</td>
<td>(0.001)</td>
<td>(0.131)</td>
<td>(0.045)</td>
</tr>
<tr>
<td>LTV</td>
<td>-0.080***</td>
<td>-0.017***</td>
<td>0.014***</td>
<td>0.005***</td>
</tr>
<tr>
<td></td>
<td>(0.001)</td>
<td>(0.000)</td>
<td>(0.003)</td>
<td>(0.001)</td>
</tr>
<tr>
<td>White, Asian or Other</td>
<td>0.672***</td>
<td>0.139***</td>
<td>0.460***</td>
<td>0.157***</td>
</tr>
<tr>
<td></td>
<td>(0.002)</td>
<td>(0.000)</td>
<td>(0.008)</td>
<td>(0.003)</td>
</tr>
<tr>
<td>Female</td>
<td>-0.235***</td>
<td>-0.048***</td>
<td>-0.170***</td>
<td>-0.058***</td>
</tr>
<tr>
<td></td>
<td>(0.001)</td>
<td>(0.000)</td>
<td>(0.006)</td>
<td>(0.002)</td>
</tr>
</tbody>
</table>

### Application Parameters

<table>
<thead>
<tr>
<th>Variable</th>
<th>Means</th>
<th>Interactions with Household Characteristics</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Loan Amount</td>
<td>Income</td>
</tr>
<tr>
<td>Refinancing Cost</td>
<td>-3.795***</td>
<td>2.428***</td>
</tr>
<tr>
<td></td>
<td>(0.056)</td>
<td>(0.035)</td>
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<tr>
<td>Marginal Value of Refinancing Incentive</td>
<td>1.381***</td>
<td>-0.909***</td>
</tr>
<tr>
<td></td>
<td>(0.133)</td>
<td>(0.044)</td>
</tr>
<tr>
<td>Relative House Price Growth</td>
<td>-0.031**</td>
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</tr>
<tr>
<td></td>
<td>(0.014)</td>
<td></td>
</tr>
<tr>
<td>Relative Unemployment</td>
<td>-0.362***</td>
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</tr>
<tr>
<td></td>
<td>(0.026)</td>
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</tbody>
</table>
Estimation Results

Aggregate refinancing

By loan amount

By income

By home value

By race or ethnicity

By gender

Imperial College Business School
Mortgage rate shock in different economic conditions

Monthly refinancing
Cumulative refinancing
Aggregate refinancing incentive

Δ House Price Index
Unemployment
Distributional effects of a mortgage rate shock

By loan amount

By income

By home value

By race or ethnicity

By gender
Decomposing effect of credit constraints: Cumulative refinancing

By loan amount

By income

By home value

By race or ethnicity

By gender
Conclusion

- Empirical analysis of mortgage refinancing shows large heterogeneity in originations
- My model separately identifies credit constraints to refinancing from refinancing behavior
- Main Results:
  - **Aggregate and Cross-Sectional Refinancing**: The model can match aggregate refinancing and refinancing in the cross-section closely for the 20-year period considered
  - **Access to Credit**: Households with high loan amounts, low incomes, as well as Black, Hispanic and Female households are most negatively affected by credit constraints
  - **After a Monetary Policy Shock**: Differences in likelihood to secure refinancing are amplified over time, as specific household groups consistently fail to take advantage of lower mortgage rates. Credit constraints play a significant role in this
  - **Targeted Streamlined Refinancing Programs**: Differential impact of credit constraints highlights need for refinancing programs that are targeted to specific household groups
Credit standards tightening over time

- Some insight into supply-side factors affecting refinancing: Senior Loan Officer Opinion Survey on Bank Lending Practices

![Net % of Banks Tightening Standards for Mortgage Loans](image-url)
Effects of credit tightening

When banks tighten their credit standards, are all households affected equally?

- During 2014, banks tightened their credit standards for mortgage originations (SLOOS)
- Quantify impact of event for different households

<table>
<thead>
<tr>
<th>Variable</th>
<th>Logit Model</th>
<th>IV Probit Model</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Baseline</td>
<td>Δ Tight Constraint Period</td>
</tr>
<tr>
<td>LTI</td>
<td>-0.225***</td>
<td>0.047***</td>
</tr>
<tr>
<td></td>
<td>(0.001)</td>
<td>(0.005)</td>
</tr>
<tr>
<td>LTI × Income Dummy</td>
<td>-0.223***</td>
<td>-0.091***</td>
</tr>
<tr>
<td></td>
<td>(0.003)</td>
<td>(0.020)</td>
</tr>
<tr>
<td>LTV</td>
<td>-0.079***</td>
<td>-0.050***</td>
</tr>
<tr>
<td></td>
<td>(0.001)</td>
<td>(0.005)</td>
</tr>
<tr>
<td>White, Asian or Other</td>
<td>0.676***</td>
<td>-0.187***</td>
</tr>
<tr>
<td></td>
<td>(0.002)</td>
<td>(0.013)</td>
</tr>
<tr>
<td>Female</td>
<td>-0.238***</td>
<td>0.129***</td>
</tr>
<tr>
<td></td>
<td>(0.001)</td>
<td>(0.010)</td>
</tr>
</tbody>
</table>
Effects of credit tightening

By loan amount

By income

By home value

By race or ethnicity

By gender
Data filtering I

- HMDA, following Greenspan & Kennedy (2008) and Greenspan & Kennedy (2005)
  - Manufactured homes
    - Manufactured homes are mostly financed by personal property loans
    - Before 2004, HUD provides a list of lenders that mainly originate loans backed by manufactured homes. I exclude all mortgages originated by those lenders
    - After 2004, manufactured home loans are identified, and I retain a random sample of 30% of these originations
  - Home Equity Loans
    - Home equity loans are not included in the aggregate liability level used. Home equity loans include home improvement and piggyback loans
    - Home improvement loans are identified in the data and excluded
    - Piggyback loans are home purchase or refinance loans that are second lien. They are only identified after 2004 and only for sold loans. These are taken out. For before 2004, we assume piggyback loans are all home purchase or refinance loans under $25,000. For purchased second lien loans originated after 2004, I exclude all purchased loans under $25,000.
Data filtering II

- **Survey of Consumer Finances**
  - Following the Distributional Financial Accounts published by the Federal Reserve, the SCF tracks the Financial Accounts by 90% on average (Batty et al., 2019)
  - I exclude home equity lines of credit and junior liens
  - I normalize all categorical variables so that the codes match the HMDA classification

- **American Housing Survey**
  - I filter the data to exclude secondary loans and loans for manufactured homes
  - I normalize all categorical variables so that the codes match the HMDA classification

* All dollar amounts are adjusted for inflation, so that I use 2019 dollars in the model
Preliminary calculations

- Regular mortgage liabilities level, \( d_t \)
- New originations, \( l_t \)
- 30yr fixed rate mortgage market rate, \( r_t^M \)
- Refinancing rate, \( \rho_t = \frac{\text{HMDA refinancing originations}_t}{d_{t+1}} \)
- Average outstanding mortgage rate, \( \hat{r}_t \): weighted average of rate of new originations \( l_t \) and existing mortgages. For the averaging weight \( \phi_t \):

\[
l_t = \text{HMDA purchase originations} + \text{HMDA refinancing originations} \\
\phi_t = \frac{l_t}{d_{t+1}} \\
\Rightarrow \hat{r}_t = (1 - \phi_t)\hat{r}_{t-1} + \phi_t r_t^M
\]
Model Derivations

Defining the set of characteristics for households that refinance and by integrating over $A_t$, I create a synthetic panel of households.

Refinancing and not refinancing are exclusive choices. Therefore:

$$\rho_t = \int_{A_t} dP(X, \epsilon, \eta)$$

$$= \int_{A_t} dP(\epsilon|X, \eta)dP(\eta|X)dP(X)$$

$$= \int_{A_t} dP(\epsilon)dP(\eta)dP(X)$$

$$= \int_{A_t} \rho_{i,t}dP(X)$$

by Bayes' rule

by $\epsilon_{i,t} \sim iid$, $\eta_{i,t} \sim iid$ and Corr[$i,t,\eta_{i,t}$]

where $P(\cdot)$ population distribution function
Estimation Methodology

Household Refinancing Parameters

- I use the Generalized Method of Moments (Hansen, 1982) for estimating these parameters
  - \( \theta_1 \) is the vector of household refinancing parameters
  - \( g(R_t, \Delta HPI_t, U_t, X_t, \theta_1) = M - m(R_t, \Delta HPI_t, U_t, X_t, \theta_1) \) where \( M \) vector of data moments, \( m(\cdot) \) vector of model moments
  - \( \Xi \) a positive definite matrix
- The GMM estimator \( \hat{\theta} \) minimizes the form:
  \[
  Q_T(\theta) = \left[ T^{-1} \sum_{t=1}^{T} g(R_t, \Delta HPI_t, U_t, X_t, \theta_1) \right]' \hat{\Xi} \left[ T^{-1} \sum_{t=1}^{T} g(R_t, \Delta HPI_t, U_t, X_t, \theta_1) \right]
  \]

Refinancing Approval Parameters

- I use Maximum Likelihood Estimation for the logistic function
  - \( \theta_2 \) is the vector of refinancing approval parameters
  - \( L_{i,t}(R_t, \Delta HPI_t, U_t, X_t, \theta_2) = \Lambda(\psi_1 + \psi_2'X_{i,t} + \omega_1 R_t + \omega_2'X_{i,t}R_t + \chi_1 \Delta HPI_t R_t + \chi_2 U_t R_t) \) from \( i \) in \( t \)
- The log likelihood function is then
  \[
  \mathcal{L}(R_t, \Delta HPI_t, U_t, X_t, \theta_2) = \sum_{t=1}^{T} \sum_{i=1}^{R} \ln(L_{i,t}(R_t, \Delta HPI_t, U_t, X_t, \theta_2))
  \]
GMM Estimation Moments

- I use $L = 30$ moments to estimate the $P = 18$ household refinancing parameters.
- For parameters common for all households $\alpha_1, \beta_1, \gamma_1, \gamma_2$, I take moments with respect to $\rho_t$ and $R_t$, $\Delta HPI_t R_t$ and $U_t R_t$ respectively.
- For household-specific parameters $\alpha_2$ and $\beta_2$, I take moments with respect to a subset of cross-sectional refinancing rates, as shown in the Empirical Facts section of the paper.
- Test of overidentifying restrictions
  - As the number of moments used in the estimation is larger than the number of parameters, the model is overidentified.
  - To test that the model is not misspecified, I use Hansen’s J-Test:
    \[
    T \left( \frac{1}{T} \sum_{t=1}^{T} g(R_t, \Delta HPI_t, U_t, \mathbf{X}_t, \theta_1) \right) \hat{\Xi} \left( \frac{1}{T} \sum_{t=1}^{T} g(R_t, \Delta HPI_t, U_t, \mathbf{X}_t, \theta_1) \right) \]
    converges to a $\chi^2_{L-P}$ statistic under the null that the overidentifying restrictions hold (Whited, 2019).
  - For this model, the J-Test gives 2246.888, hence the model is not misspecified.