Credit Constraints and the Distributional Effects of the Refinancing Channel*

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Abstract

This paper investigates the distributional impact of credit constraints on the transmission of monetary policy in the U.S. economy through the mortgage refinancing channel. In order to shed light on the effect of credit constraints for the refinancing rate of different household groups, I develop a model that considers the household-level probability of refinancing approval separately from the refinancing application probability. I find that households with high loan amounts, low incomes, as well as Black, Hispanic and Female households are most negatively affected by credit constraints. Additionally, approvals decrease with increasing Loan-to-Income for applicants with lower incomes, whereas the opposite is true for higher incomes. By applying the model to compare a period of tighter credit constraints to the average findings, I find that households with high loan amounts, low to middle income levels, Hispanic and Asian or Pacific Islander and Female households experience the largest decrease in refinancing approvals. Through different monetary policy experiments, I find that refinancing heterogeneity is amplified over time, as specific groups are consistently unable to take advantage of lower mortgage rates. Using an experiment to model the extreme case of no credit constraints, I show that borrowers who have the lowest refinancing rates are missing out on refinancing opportunities primarily due to the credit constraints they face. These findings can help us understand which households are most often unable to refinance and thus in most need for streamlined refinancing programs.

Keywords: mortgage, refinance, credit constraints, monetary policy, distributional effects

JEL Codes: G51, G21, E52

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1 Introduction

One of the central topics in macroeconomics is what channels are available to policymakers for supporting aggregate demand. Over and above standard macroeconomic theory, which focuses on how interest rate changes can drive household consumption directly through intertemporal substitution, the literature after the Global Financial Crisis has discussed alternative monetary policy transmission channels, including that of mortgage refinancing. The degree by which monetary policy changes result in changes in aggregate demand through refinancing depends on behavioral factors and households’ access to credit. On the one hand, on the demand side, even though it may be advantageous for a household to refinance, its perceived cost and value of refinancing may lead it to choose to forego the option. On the other hand, on the supply side, the odds that an application to refinance is accepted by the lender will influence the refinancing channel. The probability a household applies for refinancing and the probability its application gets approved will vary based on the household’s characteristics.

This paper studies the transmission of monetary policy in the U.S. economy through the refinancing channel in the presence of credit constraints, by incorporating heterogeneity in refinancing behavior and approval. First, data on refinancing originations is examined to identify empirical patterns of refinancing rates in time and in the cross-section of households. Combining aggregate with micro data, I begin by presenting the heterogeneity in the mortgage refinancing rate in the U.S. for different groups of households in the 2004-2019 period. However, as these empirical patterns are based on refinancing originations, they show the net impact of demand and supply side factors to refinancing. To make a preliminary assessment of the importance of supply side factors that may affect refinancing, I present data from the Federal Reserve Senior Loan Officer Opinion Survey on Bank Lending Practices on bank credit standards for the period considered. The data show that there are large changes in credit standards during the 2004-2019 period. This variation in the tightness of credit standards in time points to the importance of modelling refinancing applications apart from refinancing approvals.

I develop a model that isolates the effects of credit constraints from demand side factors to refinancing, which considers the household-level probability of refinancing approval separately from the refinancing application probability. As it is expected that borrowers who believe they are less likely to be approved will likely choose not apply, it is important that the model eliminates any latent correlation between the application and approval probabilities. To achieve identification in
the model, Instrumental Variable analysis is used, where the Loan-to-Income (LTI) ratio of households applying for refinancing is instrumented using banks’ liquidity. I estimate the model using the empirical refinancing patterns and highlight new results on the heterogeneity of household groups’ willingness to refinance, as well as their access to refinancing due to credit constraints. In the model, monetary policy changes drive refinancing through the aggregate refinancing incentive, defined as the difference between the average interest rate on outstanding mortgages and the market mortgage rate. This aims to approximate the lever available to a central bank, that can change the aggregate refinancing incentive through monetary policy. I find that there is significant heterogeneity in refinancing demand among households and that households with a high loan amount, low income, as well as Black and Hispanic and Female households are the ones most affected by credit constraints. I also show that the approval rate decreases as the LTI ratio of the applicant increases for households with lower incomes, whereas the opposite is true for higher incomes.

In order to shed light on the effect of credit constraints on monetary policy transmission through the refinancing channel, this paper evaluates the distributional impact of credit standard tightening. I focus on the first half of 2014, during which financial institutions reportedly tightened their credit constraints on aggregate. I then show the distributional effects of this change by comparing the model predicted refinancing originations under baseline credit constraints and tight credit constraints. The difference between the two reveals that the households most impacted from credit constraint tightening are households with high loan amounts, low to middle income levels, high home values, Hispanic and Asian or Pacific Islander households, as well as Women. It is interesting to highlight that under tight credit constraints, credit standards tighten significantly against LTI for lower income households and relax for higher income borrowers, with the two opposite effects having approximately equal magnitudes.

The following section tests two types of policy experiments that are performed to examine the dampening effect credit constraints have over time on monetary policy transmission after a policy shock. First, mortgage rates are shocked under different economic conditions and the model-predicted monthly and cumulative aggregate refinancing responses are compared. Second, the mortgage rate is again shocked and the monthly and cumulative refinancing rates following the shock are tracked for different groups of households, in order to study the distributional effects of the refinancing channel. These experiments emphasize that the impact of the differences in refinancing originations between groups is amplified over time, as specific household groups con-
istently fail to take advantage of lower mortgage rates whereas others systematically refinance when it is in their interest to do so.

Finally, in order to determine whether household groups that refinance less after a monetary policy change do so because of their refinancing behavior or because of supply side constraints from approvals, the model is used to compare how households would refinance after a monetary policy shock in the absence of any credit constraints against the baseline refinancing prediction. The difference between the two predictions reveals the distributional effect of credit constraints on households. I find that when constraints are removed, borrowers at the lower end of the loan amount, income and home value distributions reach the refinancing levels of households at the median and Black and Hispanic households reach the refinancing rate of White and Asian and Pacific Islander households. These results show the significance of streamlined refinancing programs that target households exhibiting lower refinancing rates, as households who are predicted to have the lowest refinancing rate in the distribution are not missing out on opportunities to refinance mostly due to their smaller probability of applying, but rather due to the credit constraints they face.

The paper is organized as follows: Section 2 provides an overview of the related literature and Section 3 details the data used in the analysis. Section 4 presents patterns in refinancing for both the aggregate measure, as well as refinancing conditional on different household characteristics and data on mortgage lending standards. These stylized facts inform the modelling decisions made and parameters identification. Section 5 then outlines the model and Section 6 provides an overview of the estimation methodology and how parameter identification is achieved. The Section also includes the results of the estimation and how the model fits the data. Sections 7 and 8 apply the model to show the effect of credit constraints on the refinancing originations of different household groups, the distributional effects of monetary policy and the effect of credit constraints on separate household groups after a monetary policy shock. Model robustness is discussed in Section 9. Finally, Section 10 concludes.

2 Literature Review

This paper is related to the literature that examines monetary policy transmission to households and its distributional effects. Holm et al. (2020) investigate how monetary policy shocks affect consumption, income and saving for households along the distribution of liquid assets. Coibion et al. (2017) in turn focus on how different monetary policy shocks lead to inequality across households.
in income, labor earnings, expenditures and consumption. Another growing area of the literature that relies on distributional effects in order to inform policy are papers using Heterogeneous Agent New Keynesian models (HANK), such as Kaplan et al. (2018), Gornemann et al. (2016), Luetticke (2018) and Auclert (2019). My paper identifies empirical patterns in the refinancing originations of different households that can be used to inform HANK models, when they incorporate mortgage refinancing. The paper also presents a model that provides insight into heterogeneous refinancing after a monetary policy shock while incorporating credit constraints.

This work joins the literature focusing on refinancing as a channel of monetary policy transmission. Beraja et al. (2018) show how the time-varying regional distribution of housing equity dampens the refinancing and consumption response of households on aggregate, with depressed regions being less responsive to refinancing incentives, particularly in the case of the Great Recession. Although this paper’s model does not explicitly account for differences in refinancing by household location, it incorporates how refinancing varies for different home values. Di Maggio et al. (2020) focus on how unconventional monetary policy transmission affects the real economy through refinancing and show that the strength of the channel depends on the composition of assets purchased by the Federal Reserve and the segmentation of the mortgage market. Another paper that examines monetary policy transmission is Berger et al. (2020), who show that past monetary policy decisions about rates affect the degree to which the economy can be stimulated. Similarly to Berger et al., my model incorporates the history of past mortgage rates, by using the difference between the mortgage rate on the outstanding stock of household debt and the market mortgage rate to capture the incentive to refinance. But in my paper, this measure is used to capture how households deviate from the average refinancing response. Finally, Wong (2019) presents how refinancing differs along the age distribution of households and uses a life-cycle model to highlight that younger people refinance more as they have more outstanding mortgage debt and are more liquidity constrained. The analysis in this paper does not include demographics such as age, because each household is purposefully described by the characteristics that are included in a refinancing application. This choice reflects the fact that the current paper focuses on understanding the transmission of monetary policy through the refinancing channel and the role of the application approval process.

Primarily, this paper relates to the area of the literature that focuses specifically on how credit or credit-related requirements affect refinancing. Because refinancing a mortgage requires underwriting, this typically calls for the review of the household’s income, creditworthiness and value
of underlying collateral. As Amromin et al. (2020) point out, these criteria have a strong cyclical component and therefore constitute cyclical impediments to refinancing. Older work by Archer et al. (1996) and Pavlov (2001) shows that income constraints limit mortgage refinancing. Recent work by DeFusco and Mondragon (2020) examine how documentation requirements and up-front costs can act as frictions in mortgage refinancing. Greenwald (2016) shows the effect LTV and PTI constraints have on the credit channel of monetary policy transmission more broadly. My paper adds to the literature as it identifies which households are most impacted by credit constraints in refinancing by modelling separately the probability of a mortgage refinancing application being approved from the probability that a household applies to refinance their mortgage. Although certain papers have tried to account for credit constraints by exploiting unique features of different mortgage markets, my paper deals with credit constraints by directly incorporating in the model household-specific probabilities of refinancing application approval. Other works in the literature also consider the probabilities of approval and application separately, but do not refer to refinancing (Ouazad and Ranciere 2019) and other works incorporate approval probabilities when looking into the role of mortgage search, such as Agarwal et al. (2020) or Ambokar and Samaee (2019), who explicitly modelling the supply side. This paper does not follow that approach and the additional assumptions that comes with it, so it is able to define refinancing approval probabilities that account for the household characteristics used by banks when assessing an application.

Additionally, my paper is related to other works in the literature that assess and consider different policies that target mortgage refinancing. Parts of the literature focus on the results of refinancing programs that have been implemented in the past, such as Agarwal et al. (2015) and Amromin and Kearns (2014), who consider the Home Affordable Refinancing Program (HARP), or DeFusco and Mondragon (2020) who investigate the effects of a change in the provisions of the Streamlined Refinance Program (SLR) after the Great Recession, where household employment had to be verified and households with negative equity could no longer roll over any upfront refinancing fees with their new mortgage. In turn, Ehrlich and Perry (2015) focus on a later reversal of these requirements and show the effects of the changes. Other papers propose changes to the current requirements to refinance and present the potential effects of these proposals. Lucas et al. (2011) bring forth a proposal for a large-scale mortgage refinancing program for Fannie Mae, Freddie Mac, or the Federal Housing Administration mortgages, which would relax the income and LTV restrictions currently in place for borrowers to refinance. The findings of my paper on the distributional effects of the refinancing channel can inform policymakers on which households are
most often less willing or unable to refinance and thus in most need for streamlined refinancing programs.

This paper also contributes to the evidence on slow or suboptimal refinancing behavior of households that has been highlighted in the household finance literature. Slow refinancing may be a consequence of credit constraints, behavioral factors or both (Gomes et al. forthcoming). Many papers have tried to control for such constraints, like Campbell (2006), Caplin et al. (1997) and Archer et al. (1996). Informed by this literature, the model in this paper controls for aggregate shocks to a household’s ability to refinance as well as weighs the observed refiners to account for households deciding not to apply during periods of tighter credit constraints. With regards to behavioral biases, early papers on the subject such as Stanton (1995) and Green and LaCour-Little (1999) suggest that, when it comes to refinancing, households act as if they face unrealistically high transaction costs or even further, act irrationally as they refinance when it is not optimal to do so and fail to refinance when it is. With the introduction of a closed form solution that provides the rule for optimal refinancing of a mortgage, provided by Agarwal et al. (2013), more recently published literature quantified the cost to households of refinancing suboptimally. Such papers include Keys et al. (2016), Agarwal et al. (2017) and Agarwal et al. (2016). More recent literature has focused on understanding what drives this suboptimal behavior. Andersen et al. (2020) explain failures to refinance through inattention and inertia, where households are less likely to refinance in any period and incur a psychological cost in addition to any financial cost when refinancing. Other papers look into the role of lack of borrower sophistication (Bucks and Pence, 2008) or trust in the financial system (Johnson et al., 2019). My paper confirms relevant findings in this literature, but also moves a step further in separating out credit constraints faced by households.

3 Data

This Section provides an overview of the data used. For a more detailed discussion on the data, refer to Appendix A.

As mentioned previously, this paper combines aggregate with micro data. With regards to aggregate data, the source for the outstanding stock of regular mortgages is the Federal Reserve Financial Accounts (FA). The main series used is Households and Nonprofit Organizations; One-To-Four-Family Residential Mortgages; Liability, Level. Home equity and construction loans are deducted to focus on regular mortgages only. The FA data is also interpolated from their quarterly
frequency to monthly.

In order to allocate the fraction of the total stock of regular mortgages outstanding to households with different characteristics such as loan amount, income, home value, race or ethnicity and gender, the Survey of Consumer Finances (SCF) is used, as well as the American Housing Survey (AHS). The survey data is filtered appropriately, so that it corresponds to the outstanding stock of regular mortgages and interpolated to monthly frequency. Then, the FA data is multiplied by the share of outstanding mortgage balance held by each household group to get the dollar amount of total mortgages held by the different households. This methodology mirrors the approach implemented to produce the Federal Reserve’s Distributional Financial Accounts (Batty et al., 2019).

The Home Mortgage Disclosure Act (HMDA) Loan Application Register Data is used for originated applications of home purchase mortgages and originated as well as denied applications for refinancing mortgages. This data provides the loan amount, income, race, ethnicity, gender and location of each application. An important condition for using this micro data along with the FA aggregates is that the HMDA population covers the U.S. mortgage market to such an extent that it can be used for identifying characteristics for the entire population of U.S. mortgage borrowers. As of 2017, the Consumer Finance Protection Bureau (CFPB) reports the percentage of total mortgage originations that HMDA reports in their Data Point studies. Indicatively, in 2016 HMDA covered 94% of the estimated number of originations in the U.S., in 2017 92% and in 2018 90% (Dietrich et al., 2018) and (Dietrich et al., 2019). In order to ensure that the population of HMDA loans selected corresponds to the FA account, I follow Greenspan and Kennedy (2005) and Greenspan and Kennedy (2008) in order to filter the data appropriately.

I enrich the HMDA data with an estimation of the value of the home corresponding to each mortgage application. Although not in the public HMDA data, the value of the collateral plays an important role in whether a mortgage application is originated. I use the American Community Survey (ACS) for the median home value in each Census Tract in the U.S., and match this data to each loan application, for years 2009 to 2018. For the years before 2009, I use House Price Index information by tract from the Federal Housing Finance Agency (FHFA). Lastly, the county-level equivalent is used for any mortgage applications located in a tract where there is no tract-level home value information.

To perform the Instrumental Variable analysis outlined in Section 6, each mortgage application for each year in the analysis is matched to the liquidity of the financial institution receiving the
application, using data from the Federal Reserve’s Report of Condition and Income. For each application, I also find the two other branches that are geographically closest to the center of the census tract corresponding to the application. So for each application, I take the average of the liquidity of the bank that received the application and the liquidity of the two closest branches. This mean then corresponds to the liquidity measure assigned to that application.

4 Empirical Evidence

I first document stylized facts, by examining both aggregate refinancing as well as how refinancing varies in the cross-section of households. This evidence informs my modelling decisions in Section 5 and helps identify the parameters that need to be pinned down in order to capture monetary policy transmission through mortgage refinancing. Because the Figures included in this Section depict refinancing originations, they inform us about the combined effect of demand side and supply side factors that affect refinancing. Finally, to have a first look into how changes in the supply side of credit may have affected refinancing, I examine relevant data from the Federal Reserve Senior Loan Officer Opinion Survey on Bank Lending Practices.

4.1 Aggregate Refinancing over Time

First, define the aggregate refinancing rate $ρ_t$ as the sum of total refinancing originations in period $t$ over the outstanding mortgage stock in period $t + 1$, where total refinancing originations are taken from the HMDA data and the total outstanding mortgage stock is the total outstanding balance of regular mortgages, as defined in Section 3. The aggregate refinancing incentive $R_t$, is the mean rate incentive for refinancing in the mortgage market in period $t$, defined as the current 30 year market mortgage rate, $r^M_t$ subtracted from the average interest rate on outstanding mortgages, $\hat{r}_t$.

The average interest rate on outstanding mortgages $\hat{r}_t$ is calculated as the weighted average of the market mortgage rate $r^M_t$ and the average outstanding mortgage rate in the previous period $\hat{r}_{t-1}$. The averaging weight $φ_t$ is the proportion of new originations $l_t$ over total mortgage outstanding debt in the next period $d_{t+1}$. Formally:

$$φ_t = \frac{l_t}{d_{t+1}}$$ (1)

$$\hat{r}_t = (1 - φ_t)\hat{r}_{t-1} + φ_tr^M_t$$ (2)
The estimate for the average outstanding mortgage rate is benchmarked to the Bureau of Economic Analysis ‘effective rate of interest rate on mortgage debt outstanding’, following Greenspan and Kennedy (2005). New originations \( l_t \) are defined as the sum of purchase originations and refinancing originations, known from HMDA.

The aggregate refinancing rate and the aggregate refinancing incentive are plotted in Figure 1. From the plot it is evident that there exists a positive relationship between the two variables, however it does appear that this relationship is not constant over the period shown.

Because aggregate refinancing is an equilibrium outcome in the mortgage market, driven by both the demand for refinancing by households as well as the supply of credit, cyclical impediments play an important role in the refinancing channel (Amromin et al., 2020). During recessions, house prices decrease and unemployment increases. Since a refinancing application origination is subject to the value of the underlying collateral, the household’s employment and its available income, the ability of households to refinance during recessions is significantly impaired, as it is expected that these constraints bind more households during periods of economic downturn. Although households can be subject to idiosyncratic shocks to income and localized real estate market shocks to home value, any aggregate income shocks or national house market shocks to all households can be captured by controlling for house price growth and unemployment relative to the aggregate refinancing incentive. Due to this evidence, these controls are used in the model, as described in Section 5.
4.2 Cross-Sectional Refinancing Patterns

In order to examine how the relationship between aggregate refinancing and the aggregate refinancing incentive varies among heterogeneous households, I consider the refinancing rate along the distribution of households, against the aggregate refinancing rate. First, each household is summarized by a vector of its characteristics, namely loan amount, household income, home value, race or ethnicity of the household and gender of the household. Therefore, each household is mapped to the household characteristics space. To determine the refinancing rate along the distribution of each characteristic, the household characteristics space is discretized. Specifically, for the continuous variables loan amount, income and home value, the households are mapped to the space based on the decile their loan amount, income or home value falls in. Similarly for the categorical variables, race or ethnicity and gender, the households are mapped by their attributes. This results in the creation of $10 \times 10 \times 10 \times 4 \times 2 = 8,000$ household groups. Note that the dollar amounts corresponding to the loan amount, income and home value deciles are listed in Table 1.
<table>
<thead>
<tr>
<th>Decile</th>
<th>Loan Amount</th>
<th>Income</th>
<th>Home Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>D1</td>
<td>29,000</td>
<td>37,000</td>
<td>95,000</td>
</tr>
<tr>
<td>D2</td>
<td>57,000</td>
<td>56,000</td>
<td>137,000</td>
</tr>
<tr>
<td>D3</td>
<td>84,000</td>
<td>73,000</td>
<td>177,000</td>
</tr>
<tr>
<td>D4</td>
<td>111,000</td>
<td>92,000</td>
<td>225,000</td>
</tr>
<tr>
<td>D5</td>
<td>143,000</td>
<td>113,000</td>
<td>292,000</td>
</tr>
<tr>
<td>D6</td>
<td>182,000</td>
<td>144,000</td>
<td>383,000</td>
</tr>
<tr>
<td>D7</td>
<td>240,000</td>
<td>196,000</td>
<td>520,000</td>
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<tr>
<td>D8</td>
<td>335,000</td>
<td>321,000</td>
<td>794,000</td>
</tr>
<tr>
<td>D9</td>
<td>574,000</td>
<td>880,000</td>
<td>1,494,000</td>
</tr>
<tr>
<td>D10</td>
<td>&gt;574,000</td>
<td>&gt;880,000</td>
<td>&gt;1,494,000</td>
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</tbody>
</table>

Table 1: Decile Cutoff Values. Notes: The Table reports the cutoffs for the 10 Deciles shown in the following figures, separately for each of the three variables used in the model with dollar units. All dollar values are in 2019 USD, rounded to the nearest thousand.

For each group, the total refinancing amount and outstanding mortgage stock need to be determined in each period. The total refinancing amount can be calculated using the HMDA data, by grouping the data in the aforementioned groups for each period in time. For the outstanding mortgage stock of each group, the fraction of the total mortgage debt that belongs to the households in each group is required. As mentioned in Section 3, the SCF and AHS are used to calculate these fractions in each time period. By multiplying these values by the total outstanding mortgage stock in each period, the regular mortgage debt outstanding for each household group is retrieved. Dividing the total refinancing amount of the group by the outstanding mortgage stock in the next period gives the refinancing rate for the household, conditional on it belonging to the specific group based on its characteristics. Finally, in order to examine the relationship between this refinancing rate and the aggregate refinancing incentive, the monthly incentive values are sorted into 8 bp wide bins and the mean refinancing rate of each group-bin combination is calculated.

For each household characteristic, the conditional refinancing rates are plotted against the aggregate refinancing incentive. By showing the data in this way, I focus on identifying two types of patterns in the data. First, the level of the conditional refinancing rate, irrespective of the level of the incentive and second, the slope of the refinancing rate against the incentive. Note that, for each of these type of patterns, the effect of credit constraints cannot be isolated from the observed rates of refinancing originations using the data alone.

Starting with loan amount at Figure 2, Panel a depicts the conditional refinancing rate by loan amount decile against the aggregate refinancing incentive. As loan amount increases, so does the
refinancing rate at any level of the incentive. Similarly, the slope of the refinancing rate against the incentive also appears to be increasing for larger loan amounts. This pattern implies that the net effect of loan amount on the refinancing of a household can be captured through a linear relationship. Both these observations are highlighted in Panel c of the Figure, that takes 3 cuts from the surface plot of Panel a, for the first, fifth and tenth decile.

With respect to income, from Figure 2 the relationship between the refinancing rate and the incentive is quadratic, with households in the sixth income decile appearing to have the highest level
Figure 3: Cross-Sectional Refinancing Patterns - Home Value, Race or Ethnicity and Gender. Notes: The plots in the current Figure show the relationship between the refinancing rate and the refinancing incentive for the cross-section of households. Panel a depicts the conditional refinancing rate by home value decile against the aggregate refinancing incentive and Panel c of the Figure takes 3 cuts from the surface plot of Panel a, for the first, fifth and tenth decile. Similarly, Panel b depicts the conditional refinancing rate by race or ethnicity and Panel d shows the conditional refinancing rate by gender.

of refinancing rates at any incentive, as well as the highest slope of the refinancing rate against the incentive. For higher or lower household income levels, the level and slope decrease. These patterns inform my decision to include the absolute value of income as a term in the model. Similarly in Figure 3, the slope is again the highest for households with homes values in the sixth decile and decreasing for greater or lower home values. The level is the highest in the sixth decile and it decreases for decreasing or increasing home values. Again, this leads me to include the absolute value of home value as a term in the model. Note that, unlike income, the refinancing rates decrease for higher valued homes is very steep at the right-most end of the distribution. This is due
to the fact that the home value for each refinancing household is approximated using the median house price in the tract or county the mortgage was originated.

Finally, Figure 3 shows the refinancing rate by race or ethnicity and gender against the refinancing incentive. From Panel b, we see that the refinancing rate level for different race or ethnicity households is at similar levels, but the slope of the refinancing incentive is lower for Black and Hispanic households compared to White, Asian or Pacific Islander. This clear differentiation between race or ethnicity refinancing behavior leads to my considering two groups with respect to this characteristic: Black and Hispanic households versus White, Asian or Pacific Islander or Other households. With respect to gender, Female households have a lower level of refinancing and a lower slope of refinancing against the refinancing incentive.

4.3 Credit Tightening over Time

In order to gain insight into how credit constraints varied over the period considered and how they may be driving the patterns shown for refinancing originations, the Senior Loan Officer Opinion Survey on Bank Lending Practices (SLOOS) is used. This survey, run by the Federal Reserve and completed by eighty large domestic banks and twenty-four U.S. branches and agencies of foreign banks, provides information on credit markets and banking developments on a quarterly basis and is leveraged by the Federal Reserve in the formulation of monetary policy. The publicly available data from the survey include an aggregate series on the Net Percentage of Domestic Respondents Tightening Standards for Mortgage Loans, which can be used to show time series trends in mortgage credit constraint tightening. The data for the 2004-2019 period considered is available in different groupings across years, based on mortgage type. The average results across groups is plotted in Figure 4.
Figure 4: Net % of Banks Tightening Standards for Mortgage Loans. Notes: The graph shows the net % of SLOOS respondents who indicated that they tightened their standards for providing mortgage credit in the last quarter. The data is publicly available in aggregate form, or grouped by type of mortgage product. The figure shows the aggregate or average across mortgage groups, depending on data published for each year in the 2004-2019 period.

From Figure 4, according to the SLOOS, banks tightened their standards for mortgage loans in the period leading to and during the Global Financial Crisis and during 2014. The implications of this fact for this paper’s modelling approach is two-fold. First, it does provide further justification for independently modelling the probability of applying for refinancing from the probability of the application being accepted. Second, it indirectly informs us about the demand side factors driving the realized refinancing rate. Specifically, the HMDA data available on all applications received for mortgage refinancing can be used to model the probability of application, but they do not account for households that may have wanted to apply but decided against it because they thought they would have a small chance of being accepted due to some unobserved characteristic in the data. In periods when banks tighten their standards for giving credit, households who might want to refinance will choose not to apply, because in a regime of tighter credit constraints, their probability of being accepted is low. I can leverage the fact that in the period of 2007-2009 and 2014, households that would have otherwise applied did not, as they expected their likelihood of being accepted was too low for them to invest their time and money in applying. This is used in the modelling approach.
Figure 5: Model Setup. Notes: The Figure outlines the steps and possible outcomes involved in the origination of a refinancing mortgage, as modelled in the paper. A household $i$ which holds a mortgage in any period $t$ can decide between applying to refinance its mortgage or taking no action. In the case that the household applies to refinance, there are in turn two possible outcomes: the application may be approved and hence the mortgage will be originated, or the application is denied and the household is unable to refinance its mortgage.

5 Model

The empirical evidence provides insight into the varying relationship between aggregate refinancing and the aggregate refinancing incentive, as well as refinancing differences among households. As mentioned in the previous Section, because this evidence refers to refinancing originations, it informs us only about the combined effect of demand side and supply side factors that affect refinancing. As a result, the empirical evidence cannot uncover the effect of credit constraints in monetary policy transmission through the refinancing channel. Therefore, I develop a model where aggregate refinancing is micro-founded and the probability of applying to refinance and that of being approved are independent.

The general setup of the model in depicted in Figure 5. In each month $t$ consider household $i$ that has a mortgage. The household can choose either to apply to refinance or to not apply. In the case the household does apply to refinance, there are two possible outcomes: that the application is approved or that the application is denied by the financial intermediary that received the application. The aggregate refinancing rate and the cross-sectional refinancing rates shown in Section 4 correspond to the refinancing originations resulting from households deciding to refinance and their application being approved. Therefore, in order to model refinancing, it is necessary to de-
termine the probability of a household applying to refinance and the probability of an application being approved. In this Section I present how each of these probabilities are modelled for every household \( i \) in period \( t \). I then aggregate over these household-specific probabilities to model the aggregate refinancing rate.

Some assumptions are necessary, particularly for modelling the probability of a household applying to refinance due to data availability. To examine the refinancing decision of households with a mortgage, the simplest approach would require the full panel of households with mortgage debt outstanding for the period considered, as well as the history of their refinancing decisions. The available data consists of the stock of outstanding mortgages, flows of new originations for purchase mortgages and refinancings, as well as a set of household characteristics for the mortgage applicants. This data can be leveraged to create a synthetic panel of households, by defining each household using its characteristics and integrating over the repeated cross-section of refinancing households. This implies a model that requires an aggregate measure of refinancing as the dependent variable equal to an integration of repeated cross-sections of households. Household characteristics are defined with respect to their deviation from the ‘average’ household, or the household whose characteristics take the population average. Therefore, a Berry-Levisohn-Pakes type model (examples include Berry et al. (2004b), Berry et al. (2004b) and Nevo (2001)) is adapted, allowing the prediction of aggregate refinancing, while gaining insight in the distributional effects of the refinancing channel.

5.1 Household Decision to Refinance

In each month \( t \), there exist households that hold a mortgage. In each period \( t \) households can choose to refinance their mortgage to the market mortgage rate \( r_{M}^{t} \), or take no action. Each household \( i \) can be represented by a set of \( K \) characteristics \( X_{i,t} \) and a taste shock for refinancing \( \epsilon_{i,t} \). Note that \( X_{i,t} = [\text{loan amount}_{i,t}, \text{income}_{i,t}, |\text{income}|_{i,t}, \text{home value}_{i,t}, |\text{home value}|_{i,t}, \text{race or ethnicity}_{i,t}, \text{gender}_{i,t}] \). For \( i \) there is a cost of refinancing \( \alpha_{i} \) and a benefit of refinancing, which is the product of the marginal value the household assigns to the aggregate refinancing incentive \( \beta_{i} \) and the aggregate refinancing incentive \( R_{i} = \hat{r}_{i} - r_{M}^{t} \). This aggregate refinancing incentive aims to approximate the lever available to a central bank for controlling the refinancing channel of monetary policy, in order to study this channel. Note that Section 9 discusses the implication of not including household-specific mortgage rate spreads to the market mortgage rate.
The cost of refinancing and the marginal value of the aggregate refinancing incentive are household-specific and functions of the characteristics of the household.

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

Households know that they need to meet certain requirements in order for their refinancing application to be approved. The two primary requirements refer to their LTV and PTI ratios. Whether a household meets these constraints will depend on the value of their home and their income. Because both of these criteria have a strong cyclical component, this implies that in an economic downturn, all households will be more vulnerable and subject to an aggregate negative shock to their home value or income (Amromin et al., 2020). Therefore, it is expected that households’ sensitivity to the refinancing incentive will decrease under these economic conditions. The model controls for aggregate shocks to a household’s ability to refinance using the interaction of the refinancing incentive and the year-on-year change in the national house price index \( \Delta HPI_t \), as well as the interaction of the refinancing incentive and the national level of unemployment \( U_t \). Households then refinance according to:

\[ y_{i,t} = \alpha_i + \beta_i R_t + \gamma_1 \Delta HPI_t R_t + \gamma_2 U_t R_t + \epsilon_{i,t} \]

Because \( \epsilon_{i,t} \) are taste shocks and follow a type E.V. 1 distribution, by McFadden et al. (1973), the probability \( i \) applies to refinance their mortgage in period \( t \), conditional on the observables and the parameters is:

\[ \text{Pr}(y_{i,t} \geq 0 | R_t, \Delta HPI_t, U_t, \alpha_i, \beta_i, \gamma_1, \gamma_2) = \frac{\exp \left( \alpha_1 + \alpha_2'X_{i,t} + \beta_1 R_t + \beta_2'X_{i,t} R_t + \gamma_1 \Delta HPI_t R_t + \gamma_2 U_t R_t \right)}{1 + \exp \left( \alpha_1 + \alpha_2'X_{i,t} + \beta_1 R_t + \beta_2'X_{i,t} R_t + \gamma_1 \Delta HPI_t R_t + \gamma_2 U_t R_t \right)} \]

5.2 Refinancing Application Approval

The probability that an application is approved depends on the value of an index approval \( i_{i,t} \), which is a function of the information available to a financial intermediary receiving a refinancing
application, when determining whether to grant refinancing approval to the borrower. The information included in the model is the borrower’s loan-to-income ratio, loan-to-value ratio, their race or ethnicity and their gender. Note that these household characteristics are either equal, as is the case for race or ethnicity and gender, or transformations of the set of characteristics for household $i$ in period $t$, $X_{i,t}$ defined earlier. I define then set $D_{i,t} = [\text{LTI}_{i,t}, \text{LTV}_{i,t}, \text{race or ethnicity}_{i,t}, \text{gender}_{i,t}]$, where $D_{i,t} \in X_{i,t}$. The index for refinancing approval is then:

$$\text{approval}_{i,t} = \omega_1 + \omega_2 D_{i,t} + \eta_{i,t} \quad (7)$$

Because $\eta_{i,t}$ are taste shocks and follow a type E.V. 1 distribution, the probability that the refinancing application made by household $i$ in period $t$ is approved, conditional on the observables and the parameters is:

$$\Pr(\text{approval}_{i,t} \geq 0 | \omega_1, \omega_2, y_{i,t} \geq 0) = \frac{\exp (\omega_1 + \omega_2 D_{i,t})}{1 + \exp (\omega_1 + \omega_2 D_{i,t})} \quad (8)$$

### 5.3 Refinancing Origination

The product of the probability that household $i$ refinances in period $t$ and the probability that the application is approved, as expressed by Equations (6) and (8) respectively, give the probability a refinancing mortgage is originated for household $i$ in period $t$:

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

### 5.4 Aggregate Refinancing Rate

Households that choose to and are able to refinance in month $t$ are defined by the set of their characteristics $A_t$, as in Nevo (2000):

$$A_t(R_t, \Delta \text{HPI}_t, U_t, \alpha_i, \beta_i, \gamma_1, \gamma_2, \omega_1, \omega_2) = \{(X_{i,t}, \epsilon_{i,t}, \eta_{i,t}) | y_{i,t} \geq 0, \text{approval}_{i,t} \geq 0\} \quad (9)$$

For the aggregate refinancing rate in period $t$, I integrate $\rho_{i,t}$ over the mass of refiners, or else the set of their characteristics in that period $A_t$. Because the choice between refinancing and not is
\[
\rho_t = \int_{A_t} dP(X, \epsilon, \eta) \\
= \int_{A_t} dP(\epsilon|X, \eta)dP(\eta|X)dP(X) \quad \text{by Bayes' rule} \\
= \int_{A_t} dP(\epsilon)dP(\eta)dP(X) \quad \text{by } \epsilon_{i,t} \sim \text{iid}, \eta_{i,t} \sim \text{iid and } \text{Corr}[\epsilon_{i,t}, \eta_{i,t}]=0 \\
= \int_{A_t} \rho_{i,t}dP(X)
\]

where \(P(\cdot)\) is the population distribution function. Therefore, the aggregate refinancing rate is the below:

\[
\rho_t = \int_{A_t} \Pr(y_{i,t} \geq 0|R_t, \Delta HPI_t, U_t, \alpha_i, \beta_i, \gamma_1, \gamma_2) \times \Pr(\text{approval}_{i,t} \geq 0|\omega_1, \omega_2, y_{i,t} \geq 0)dP(X) \quad (10)
\]

6 Estimation

This Section outlines how the parameters of the aggregate refinancing model are estimated, defined by Equation (10). Further details on the estimation methodology can be found in Appendix B. As the primary strength in the model lies in modelling the probability of application to refinance separately from the probability of approval to refinance, it is important to ensure that the taste shock to refinancing \(\epsilon_{i,t}\) and the error of the approval index \(\eta_{i,t}\) are independent of one another. This section describes the identification strategy used to ensure that the independence holds, and presents the separately estimated parameters of each probability. Note that the household characteristics used in the model have been standardized, so that the parameters can be directly comparable to one another in terms of importance, despite the different original units of the parameters. The model is estimated for the period between 2004 and 2019.

6.1 Parameter Identification Methodology

The model as defined in Equation (10) faces a challenge in its identification. Namely, there may be parameters not included in the model that drive both the probability of application as well as the probability of approval, resulting to the errors \(\epsilon_{i,t}\) and \(\eta_{i,t}\) not being independent. The primary reason for this is not controlling for the credit quality of the household in the probability of approval. Specifically, along with the state of its financials, a household will consider its credit score.
to judge how likely it is that its application to refinance its mortgage is approved and whether this likelihood is high enough for it to decide to apply for refinancing. At the same time, a financial institution will use an applicant’s credit score as one of the most important criteria based on which it will decide whether to approve the refinancing application. Therefore, when banks tighten their supply of credit and households are aware of this, banks will approve less refinancing applications and less borrowers will apply, because they believe it will be unlikely that their refinancing application is approved. As a result, if this is ignored in the modelling approach and no steps are taken to isolate these effects, the estimates of the refinancing approval probability will be biased upwards and the estimates of the refinancing application probability will be biased downwards. Even more so, it would be expected that these effects may be in different directions for households with lower credit scores and lower income compared to other households, so the model results in the cross-section will also be affected.

This threat to identification can be addressed by implementing an Instrumental Variable approach for the probability of application approval, where an instrument will provide variation in the households that are approved to refinance by their bank, while the household decision to refinance will remain unaffected. Loutskina (2011), Loutskina and Strahan (2009), Ouazad and Ranciere (2016) and Ouazad and Ranciere (2019) have shown that a bank’s liquidity is significantly correlated with the Loan-to-Income of the mortgages they originate, and we can safely expect that a bank’s liquidity will have no effect on the household’s choice about whether to apply for refinancing. Therefore, guided by these findings, I use the bank’s liquidity as an instrument for the LTI of the household when estimating the probability of refinancing approval. Although a local branch’s decisions about who to extend credit to will be a result of the liquidity of the bank, branches will also be influenced by their local competitors in these decisions. Similarly to Ouazad and Ranciere (2019), I use the two geographically closest branches of financial institutions granting mortgages and match them to each mortgage in the data. The liquidity of their institutions is averaged with the liquidity of the bank receiving the application in order to account for local competition, resulting in the final instrument used in the analysis.

An important differentiation from the cited papers is that in this model, the LTI variable is also interacted with a dummy indicating whether the applicant’s income is in the higher 50\textsuperscript{th} percentile. This is informed by the work of Vojtech et al. (2020), who show that the relationship between mortgage origination denial rates and the change in the LTI distribution of applicants is not mono-
tonically increasing at the bank-quarter level. Specifically, they find that denial rates increase when more applicants’ LTI is at the lower end of the distribution, or the pool of applicants includes more low credit quality borrowers, whereas denial rates decrease as more applicants apply with higher LTI ratios. The dummy aims to capture this nonlinear relationship.

A final considerations in parameter identification, which has also been discussed in Section 4, is that households may decide not to apply to refinance even if they think it will be beneficial for them due to tighter credit constraints. As the micro data comprises of a repeated cross-section of refinancers, the households who in a period of tight credit constraints do not submit an application whereas they would during a time of regular credit constraints at the same incentive level will not be included in the analysis. To account for this, I define 2007-2009 and the first half of 2014 as ‘periods of tight constraints’ and the rest of the sample as the ‘regular period’. This stems from Figure 4 where the Net % of banks tightening their lender standards exceeds 10% during these two periods. A logistic regression of an application belonging to the ‘regular period’ against the household characteristics is then estimated. This regression produces weights against which the micro data is weighed, to signify the likelihood of each household being in the set of refinancing applications, while accounting for the households that did not self-select into the applicant pool during the ‘periods of tight constraints’.

6.2 Refinancing Application Approval Results

For ease of notation, let the vector of parameters \( \omega \) to be estimated be defined as \( \theta_2 \). HMDA LAR data include information on all applications to refinance and identify whether each entry was approved or not. Therefore, the desired parameters \( \theta_2 \) can be determined using Maximum Likelihood Estimation (MLE) of the logistic function (8) without the use of an instrument for LTI and then using Newey’s Two-Step Estimation of the Probit model with the instrument.
Table 2: Estimates for Refinancing Approval Parameters. Notes: Estimates for the coefficients of the refinancing approval probability and the corresponding marginal probabilities. The results on the left of the table are estimated using a Logit model that does not leverage any instruments, whereas the results on the right hand side correspond to a Probit model, where LTI is instrumented by the liquidity metric described in the previous Section, corresponding to each application in the sample. Asterisks denote significance levels (***=1%, **=5%, *=10%).

Table 2 shows parameter and marginal probability estimates of the Logit model without the use of an instrument at the left hand side and of the Probit model, using an instrument for the LTI of the borrowers on the right hand side. As discussed when considering parameter identification, the inclusion of the instrument aims to isolate the unobserved credit quality of the borrower in the available data. Therefore, by comparing the two models, we gain insight into the effect that different household characteristics have on the probability of refinancing approval, but are also informed about the effect credit quality has on the approval probability. Focusing first on the LTI ratio of lower and higher income households, with the estimate corresponding to households with income higher than the median level captured through the interaction with the income dummy, the parameter estimates between the two models reveal opposite relationships between credit quality and LTI, as well as approval probability and LTI for different income levels.

For the lower income households, the estimate for LTI becomes more negative when moving from the Logit to the IV Probit model, changing from -0.224 to -0.387, implying a positive relationship between credit score and LTI. In contrast, for households with higher income, the estimate increases for the IV Probit and turns positive, from -0.450 to 1.989, therefore revealing a negative relationship between credit quality and LTI for these borrowers. In other words, as these results focus on mortgage refinancing, for lower income households, it is more likely that original mortgages were originated with higher LTI ratios for borrowers who had higher credit scores, so when applying to refinance, credit quality remains higher for higher LTI applicants. On the other hand, higher income households with higher LTI mortgages will have large loan amounts and their high

<table>
<thead>
<tr>
<th>Variable</th>
<th>Logit Coefficients</th>
<th>Marginal Probabilities</th>
<th>Probit Coefficients</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>
</tr>
<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>
leverage levels appear to be associated with poorer credit quality. Moving on to the relationship between approval rates and LTI as estimated by the IV Probit, approvals fall with increasing LTI for lower income households, but in contrast approvals increase at higher LTI values for higher income households. These results show that for lower income households, financial institutions judge a higher LTI ratio as an indication of a riskier loan, as would be expected, even if credit scores are higher. But for higher income households, banks are more comfortable taking on the additional risk associated with the higher LTI ratio, even if credit scores decrease for higher LTI ratios. This non-linear relationship between the approval rate and the LTI at different levels of income was also indirectly implied by the findings of Vojtech et al. (2020). With respect to the rest of the estimates, the LTV parameter is positive, but very small in magnitude and for race or ethnicity and gender, refinancing approval is less likely for Black or Hispanic households, as well as for women. Note that, comparing the results between models, the relationship between the approval rate and the parameters other than the instrumented LTI become weaker, supporting the case for the use of the instrument.

6.3 Refinancing Decision Parameters

For ease of notation, let the vector of parameters $\alpha_1, \alpha_2, \beta_1, \beta_2, \gamma_1, \gamma_2$ to be estimated be defined as $\theta_1$. The Generalized Method of Moments (GMM) is used, as formalized by Hansen (1982), because it works well with larger samples, nonlinear models and allows for us to remain relatively agnostic with respect to the exact distributional properties of all elements in the model. The insights drawn from the empirical analysis in Section 4 are used to ensure identification.

The vector $g(\cdot)$ is defined as the distance of the data moments from their corresponding model moments. Using GMM, the vector of parameters are estimated by choosing parameters that minimize the distance between the chosen set of data moments from their model moment equivalents. Therefore, the GMM estimator minimizes the form:

$$Q_T(\theta_1) = \left[ T^{-1}\sum_{t=1}^{T} g(R_t, \Delta HPI_t, U_t, X_t, \theta_1) \right]' \Xi \left[ T^{-1}\sum_{t=1}^{T} g(R_t, \Delta HPI_t, U_t, X_t, \theta_1) \right]$$ (11)

where $\Xi$ is the weighting matrix, a positive definite matrix. The empirical moments are used to determine the optimal weighting matrix, by defining influence functions for the GMM estimator, as explained by Whited (2019). By pre-specifying the weights given to each moment, it is ensured that economically important information which may be estimated less accurately is not
under-weighted. An equivalent approach with this reasoning is used by [Chen et al. (2020)] in their estimation. The diagonal terms of the optimal weighting matrix are used in the model estimation, as the moments all refer to refinancing rates.

### 6.3.1 Moments and Parameter Identification

The parameters that need to be estimated can be classified as aggregate parameters and cross-sectional parameters. The aggregate parameters characterize the mean relationships between ag-

<table>
<thead>
<tr>
<th>Moment</th>
<th>Data</th>
<th>Model</th>
<th>s.e.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean of $\rho_t$</td>
<td>0.009</td>
<td>0.008</td>
<td>0.000</td>
</tr>
<tr>
<td>Mean of $\rho_t$ for households with $X_{1,j,t} &gt; Q_{0.4}^X$ and $X_{1,j,t} \leq Q_{0.5}^X$</td>
<td>0.004</td>
<td>0.004</td>
<td>0.000</td>
</tr>
<tr>
<td>Mean of $\rho_t$ for households with $X_{1,j,t} &gt; Q_{0.3}^X$ and $X_{1,j,t} \leq Q_{0.5}^X$</td>
<td>0.005</td>
<td>0.005</td>
<td>0.000</td>
</tr>
<tr>
<td>Mean of $\rho_t$ for households with $X_{1,j,t} &gt; Q_{0.4}^X$ and $X_{1,j,t} \leq Q_{0.6}^X$</td>
<td>0.006</td>
<td>0.005</td>
<td>0.000</td>
</tr>
<tr>
<td>Mean of $\rho_t$ for households with $X_{2,j,t} &gt; Q_{0.4}^X$ and $X_{2,j,t} \leq Q_{0.5}^X$</td>
<td>0.009</td>
<td>0.009</td>
<td>0.000</td>
</tr>
<tr>
<td>Mean of $\rho_t$ for households with $X_{2,j,t} &gt; Q_{0.5}^X$ and $X_{2,j,t} \leq Q_{0.6}^X$</td>
<td>0.009</td>
<td>0.010</td>
<td>0.000</td>
</tr>
<tr>
<td>Mean of $\rho_t$ for households with $X_{2,j,t} &gt; Q_{0.6}^X$ and $X_{2,j,t} \leq Q_{0.7}^X$</td>
<td>0.010</td>
<td>0.010</td>
<td>0.001</td>
</tr>
<tr>
<td>Mean of $\rho_t$ for households with $X_{3,j,t} &gt; Q_{0.4}^X$ and $X_{3,j,t} \leq Q_{0.5}^X$</td>
<td>0.008</td>
<td>0.008</td>
<td>0.000</td>
</tr>
<tr>
<td>Mean of $\rho_t$ for households with $X_{3,j,t} &gt; Q_{0.5}^X$ and $X_{3,j,t} \leq Q_{0.6}^X$</td>
<td>0.009</td>
<td>0.009</td>
<td>0.001</td>
</tr>
<tr>
<td>Mean of $\rho_t$ for households with $X_{3,j,t} &gt; Q_{0.6}^X$ and $X_{3,j,t} \leq Q_{0.7}^X$</td>
<td>0.009</td>
<td>0.009</td>
<td>0.001</td>
</tr>
<tr>
<td>Mean of $\rho_t$ for households with $X_{3,j,t} &gt; Q_{0.7}^X$ and $X_{3,j,t} \leq Q_{0.8}^X$</td>
<td>0.011</td>
<td>0.011</td>
<td>0.001</td>
</tr>
<tr>
<td>Mean of $\rho_t$ for households with $X_{4,j,t} = 1$</td>
<td>0.005</td>
<td>0.006</td>
<td>0.000</td>
</tr>
<tr>
<td>Mean of $\rho_t$ for households with $X_{4,j,t} = 2$</td>
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<td>0.009</td>
<td>0.000</td>
</tr>
<tr>
<td>Mean of $\rho_t$ for households with $X_{5,j,t} = 1$</td>
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<td>0.01</td>
<td>0.001</td>
</tr>
<tr>
<td>Mean of $\rho_t$ for households with $X_{5,j,t} = 2$</td>
<td>0.005</td>
<td>0.005</td>
<td>0.000</td>
</tr>
<tr>
<td>Slope of $\rho_t$ against $\hat{R}_t - R^M$</td>
<td>0.002</td>
<td>0.003</td>
<td>0.002</td>
</tr>
<tr>
<td>Slope of $\rho_t$ against $\Delta HPI_t \times (\hat{R}_t - R^M)$</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
</tr>
<tr>
<td>Slope of $\rho_t$ against $U_t \times (\hat{R}_t - R^M)$</td>
<td>0.001</td>
<td>0.001</td>
<td>0.000</td>
</tr>
<tr>
<td>Slope of $\rho_t$ against $\hat{R}<em>t - R^M$, for households with $X</em>{1,j,t} &gt; Q_{0.4}^X$ and $X_{1,j,t} \leq Q_{0.5}^X$</td>
<td>0.001</td>
<td>0.001</td>
<td>0.001</td>
</tr>
<tr>
<td>Slope of $\rho_t$ against $\hat{R}<em>t - R^M$, for households with $X</em>{1,j,t} &gt; Q_{0.3}^X$ and $X_{1,j,t} \leq Q_{0.5}^X$</td>
<td>0.002</td>
<td>0.002</td>
<td>0.001</td>
</tr>
<tr>
<td>Slope of $\rho_t$ against $\hat{R}<em>t - R^M$, for households with $X</em>{1,j,t} &gt; Q_{0.4}^X$ and $X_{1,j,t} \leq Q_{0.6}^X$</td>
<td>0.003</td>
<td>0.002</td>
<td>0.001</td>
</tr>
<tr>
<td>Slope of $\rho_t$ against $\hat{R}<em>t - R^M$, for households with $X</em>{2,j,t} &gt; Q_{0.4}^X$ and $X_{2,j,t} \leq Q_{0.5}^X$</td>
<td>0.002</td>
<td>0.002</td>
<td>0.002</td>
</tr>
<tr>
<td>Slope of $\rho_t$ against $\hat{R}<em>t - R^M$, for households with $X</em>{2,j,t} &gt; Q_{0.5}^X$ and $X_{2,j,t} \leq Q_{0.6}^X$</td>
<td>0.002</td>
<td>0.003</td>
<td>0.002</td>
</tr>
<tr>
<td>Slope of $\rho_t$ against $\hat{R}<em>t - R^M$, for households with $X</em>{3,j,t} &gt; Q_{0.4}^X$ and $X_{3,j,t} \leq Q_{0.5}^X$</td>
<td>0.003</td>
<td>0.004</td>
<td>0.002</td>
</tr>
<tr>
<td>Slope of $\rho_t$ against $\hat{R}<em>t - R^M$, for households with $X</em>{3,j,t} &gt; Q_{0.5}^X$ and $X_{3,j,t} \leq Q_{0.6}^X$</td>
<td>0.004</td>
<td>0.004</td>
<td>0.002</td>
</tr>
<tr>
<td>Slope of $\rho_t$ against $\hat{R}<em>t - R^M$, for households with $X</em>{3,j,t} &gt; Q_{0.6}^X$ and $X_{3,j,t} \leq Q_{0.7}^X$</td>
<td>0.004</td>
<td>0.004</td>
<td>0.001</td>
</tr>
<tr>
<td>Slope of $\rho_t$ against $\hat{R}<em>t - R^M$, for households with $X</em>{3,j,t} &gt; Q_{0.7}^X$ and $X_{3,j,t} \leq Q_{0.8}^X$</td>
<td>0.005</td>
<td>0.003</td>
<td>0.002</td>
</tr>
<tr>
<td>Slope of $\rho_t$ against $\hat{R}<em>t - R^M$, for households with $X</em>{3,j,t} = 1$</td>
<td>-0.002</td>
<td>-0.003</td>
<td>0.001</td>
</tr>
<tr>
<td>Slope of $\rho_t$ against $\hat{R}<em>t - R^M$, for households with $X</em>{3,j,t} = 2$</td>
<td>0.003</td>
<td>0.003</td>
<td>0.001</td>
</tr>
<tr>
<td>Slope of $\rho_t$ against $\hat{R}<em>t - R^M$, for households with $X</em>{3,j,t} = 1$</td>
<td>0.003</td>
<td>0.004</td>
<td>0.002</td>
</tr>
<tr>
<td>Slope of $\rho_t$ against $\hat{R}<em>t - R^M$, for households with $X</em>{3,j,t} = 2$</td>
<td>0.000</td>
<td>0.000</td>
<td>0.001</td>
</tr>
</tbody>
</table>

*Table 3: Moments for Parameter Estimation. Notes: The Table reports the targeted moments used in the GMM estimation of the household refinancing parameters, in the data versus the model along with the standard error corresponding to each moment.*
aggregate refinancing and variables that are common for all households. The cross-sectional parameters characterize the household-specific cost to refinancing and marginal value of the refinancing incentive for each household.

To identify the aggregate parameters, I take moments about the time series of aggregate refinancing. Specifically, the mean level of the aggregate refinancing rate is used, as well as the slope of the refinancing rate when regressed against the other aggregate variables, so the aggregate refinancing incentive, the interaction of home price growth and the incentive and the interaction of unemployment and the incentive.

For the cross-sectional parameters, the refinancing rates conditional on the value of household characteristics are considered. I take moments along the conditional refinancing rates presented in Section 4, such as mean and slope of each rate against the aggregate refinancing incentive. For the categorical variables, race or ethnicity and gender, the mean and slope for a set of conditional rates shown in Figure 3 are used. For the continuous variables, Figures 2 and 3 present the conditional refinancing rates for 10 deciles along each characteristic. As moments, the rates corresponding to the deciles about the mean value of the characteristic are used. This allows the convexity of the conditional rate against the incentive to be captured. For example, in order to identify the cross-sectional parameters relating to loan amount $\alpha_{2,1}$ and $\beta_{2,1}$, the rates for the 4th, 5th and 6th loan amount deciles are used, as the average loan amount falls in the 5th decile. Refer to Table 3 for the full list of moments used in the estimation, as well as the values calculated using the data and the final model prediction.

6.4 Refinancing Decision Results

Figure 6 shows the model prediction for aggregate refinancing and Table 4 presents the estimates of the parameters in the model. For results in the cross-section, Figure 7 shows the mean refinancing rate for different households along the distribution of loan amount, income, home value, race or ethnicity and gender, from the data alongside the model prediction. The model closely fits the aggregate refinancing rate and fits closely the refinancing cross-section for the great majority of household groups. The performance is weaker for the highest end of the income distribution and the lowest end of the loan amount and home value distributions. As this model is a logit form that captures aggregate refinancing by integrating over refinancing households, the logit parameters can be interpreted by considering how the refinancing probability of a household changes for a
1% change in the respective variables. In order to further highlight how refinancing varies along the distribution of households, the refinancing rates for households with different loan amounts, incomes, home values and the refinancing rate by race or ethnicity and gender are shown in Figures 8 and 9. The refinancing application rates against the corresponding origination rates are also plotted to highlight which households are more impacted by credit constraints. Note that there is not enough data to draw large enough samples during the entire analysis period for the highest deciles of loan amount, income and home value, so no model predictions are presented.

Table 4 includes the estimated household refinancing parameters, specific to Equation (6). The first column includes estimated values for all mean parameters, so \( \alpha_1, \beta_1, \gamma_1 \) and \( \gamma_2 \). The parameter capturing the refinancing cost for the average household \( \alpha_1 \) is -3.795 and statistically significant. This means that when the aggregate refinancing incentive is at 0, the probability the average household refinances their mortgage in one period is

\[
\exp(-3.795) = 2.20%.
\]

For the marginal value of the aggregate refinancing incentive assigned by the average household, \( \beta_1 \), the estimate is 1.381 and statistically significant. Therefore, the monthly probability an average household refinances their mortgage is 0.62% for a 1% increase in the aggregate refinancing incentive at the average level of house price growth and unemployment when the incentive was around 1% over the period (5.40% and 6.89% respectively). As expected, households are more likely to refinance their mortgage when the aggregate refinancing incentive increases. Then, the parameter characterizing the effect that a relative change in house price growth will have on any household, \( \gamma_1 \), gives the difference in the sensitivity of a household to the refinancing incentive at different levels of house price growth and is small in magnitude. Likewise, the parameter characterizing the effect that a relative change in unemployment will have on any household, \( \gamma_2 \), gives the difference in the sensitivity of a household to the refinancing incentive at different levels of unemployment. The value for \( \gamma_2 = -0.362 \), is statistically significant and negative as expected.

The rest of the columns of this Table present the estimates of parameters characterizing the interactions with the characteristics of each household. Starting with the cost parameters \( \alpha_{2,k} \), where \( k \in \text{[Loan Amount, Income, |Income|, Home Value, |Home Value|, White, Asian or Other Race household dummy, Female household dummy]} \). For loan amount, the estimate of 2.428 is statistically significant and means that a household with loan amount higher than average will be more likely to refinance at a 0% level of the aggregate refinancing incentive. For income, both the linear and the absolute value term are negative, at -2.864 and -0.437. With respect to home value, the
linear term is negative and statistically significant at -1.319 and the absolute value term is statistically significant at 0.186. Finally, the model estimates show that White, Asian or Other Race and Female households assign a higher cost to refinancing compared to their counterparts, with values -0.260 and -0.396. For the marginal value of the aggregate refinancing incentive, households with loan amounts higher than average assign a lower value to the aggregate refinancing incentive, with a parameter value -0.909. With respect to income, both the linear and absolute value terms are positive, and the home value terms are positive and negative for the linear and nonlinear term respectively. Finally, White, Asian or Other households assign a greater value to the refinancing incentive, with a statistically significant term of 0.759 and Female households are less sensitive to the incentive, with their marginal value at -0.167.

Figure 6: Model Results for Aggregate Refinancing. Notes: The Figure plots the model fit to the data for the aggregate refinancing rate. The plot shows the model-predicted and actual aggregate refinancing rate against the aggregate refinancing incentive, after sorting the incentive values into 8 bp wide bins.
### Table 4: Parameter Estimates

**Notes:** The Table quotes estimates of all model parameters, under the baseline specification. I run the model for the full population of refinanced mortgages, over the 2004-2019 period. In line with related literature ([Berger et al., 2020](#)), the aggregate refinancing rate incentive is measured in month $t + 1$ to account for the 1-2 month lag from application to origination. The household characteristics are standardized, in order for the linear parameters to represent average marginal utilities ([Imbens and Wooldridge, 2007](#)). Asterisks denote significance levels (***=1%, **=5%, *=10%)*.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Loan Amount</th>
<th>Income</th>
<th>Income</th>
<th>Home Value</th>
<th>Home Value</th>
<th>White, Asian or</th>
<th>Female</th>
</tr>
</thead>
<tbody>
<tr>
<td>Refinancing Cost</td>
<td>$-3.795^{***}$</td>
<td>$2.428^{***}$</td>
<td>$-2.864^{***}$</td>
<td>$-0.437^{***}$</td>
<td>$-1.319^{***}$</td>
<td>$0.186^{***}$</td>
<td>$-0.260^{***}$</td>
</tr>
<tr>
<td></td>
<td>(0.056)</td>
<td>(0.035)</td>
<td>(0.031)</td>
<td>(0.029)</td>
<td>(0.041)</td>
<td>(0.045)</td>
<td>(0.020)</td>
</tr>
<tr>
<td>Marginal Value of Refinancing Incentive</td>
<td>$1.381^{***}$</td>
<td>$-0.909^{***}$</td>
<td>$1.732^{***}$</td>
<td>$0.119^{***}$</td>
<td>$0.559^{***}$</td>
<td>$-0.238^{***}$</td>
<td>$0.759^{***}$</td>
</tr>
<tr>
<td></td>
<td>(0.133)</td>
<td>(0.044)</td>
<td>(0.031)</td>
<td>(0.029)</td>
<td>(0.041)</td>
<td>(0.044)</td>
<td>(0.060)</td>
</tr>
<tr>
<td>Relative House Price Growth</td>
<td>$-0.031^{**}$</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.014)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Relative Unemployment</td>
<td>$-0.362^{***}$</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
Figure 7: Model Results for Refinancing in the Cross-Section. Notes: The Figure plots the model fit for different household groups, with respect to loan amount, income, home value, race or ethnicity and gender. For each point in the distribution of the characteristics the mean refinancing rate in the data is shown next to the corresponding mean rate predicted by the model.

As shown in Equations (3) and (4), these estimates can be used to determine the willingness of heterogeneous households to refinance. To provide further intuition, in Figures 8 and 9, the mean refinancing application probability for the distribution of households along each characteristic consid-
ered is plotted. The application probability captures only the behavioral factors that play a role in refinancing, independent of any credit constraints. Note that households with higher loan amounts are more likely to refinance, which agrees with the findings presented by Green and LaCour-Little (1999). Refinancing behavior along the income distribution follows an inverted U-shape, which could agree with conclusions drawn by Andersen et al. (2020). Namely, that richer households are less likely to refinance efficiently due to state-dependent inaction and lower-income households are also less likely to refinance, but due to time-dependent inaction. Figure 9 shows a similar pattern along the home value distribution. In terms of race or ethnicity, Gerardi et al. (2020) present equivalent results: that Black or Hispanic borrowers are less sensitive to the refinancing incentive compared to other households and refinance less. Last, with regards to gender, Female households refinance less than Male households.
Figure 8: Model Results for Refinancing in Cross-Section - Loan Amount and Income. Notes: The Figure shows the model results for refinancing application and origination propensities, conditional on the loan amount or income of the household. On the left, Panel a depicts the median refinancing origination rate for different values of loan amount, as well as range of possible refinancing rates between the 75th and 25th percentile. Equivalently, Panel c plots the same values along the income distribution. On the right, the graphs present the median application and origination rates by loan amount in Panel b and income in Panel d.
Figure 9: Model Results for Refinancing in Cross-Section - Home Value, Race or Ethnicity and Gender. Notes: The Figure shows the model results for refinancing application and origination propensities, conditional on home value, race or ethnicity and gender. Panel a depicts the median refinancing origination rate for different home values, as well as range of possible refinancing rates between the 75th and 25th percentile. Also with respect to home value, Panel b presents the median application and origination rates. Panel c and d are box-whisker plots for the application and origination rate by race or ethnicity and gender respectively.

By considering separately the probability of applying to refinance and the probability of an application being approved, we can get a thorough understanding of the impact behavioral factors and households’ access to credit have on the refinancing originations that materialize. In Figures 8 and 9 on the right, the mean refinancing application probability and the mean origination probability for households along the distribution of loan amount and income are plotted, when the refinancing incentive is 1% and the change in home prices and unemployment take average values, like before. The difference between the two gives the impact credit constraints have on refinancing in the cross-section. Observe that the households most impacted by access to credit constraints are the ones...
at the higher end of the loan amount distribution and the lower end of the income distribution. On the left of the same Figures, the refinancing origination probability is plotted again against the characteristics. The dispersion of the refinancing rate at each level of loan amount and income is also shown using the 25th to 75th percentile range of refinancing rates. These patterns match the empirical findings presented in Section 4 as expected. Finally, in the previously mentioned Figure 9 the refinancing application and origination probabilities are plotted by home value, race or ethnicity and gender, in box-whisker plot form. The patterns presented here match the empirical findings. Black or Hispanic households are most affected with respect to race or ethnicity, as the median origination probability is approximately equal to the lower quartile of their application probability and similarly for female households with respect to gender.

7 Credit Constraint Tightening and Distributional Effects

Using the framework developed, where parameters for the probability of refinancing approval have been estimated separately to the parameters corresponding to the probability of applying to refinance, the effect that credit constraints have on the distribution of refinancing households can be examined in detail. Figure 4 informs us about net aggregate changes in credit constraints applied from banks to mortgage financing. The observed tightening in constraints in different periods during the years of this analysis can be used to quantify the supply side changes in refinancing originations and in turn the distributional effects can be revealed.

<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></td>
<td>-0.225*** 0.047***</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.001) (0.005)</td>
</tr>
<tr>
<td>LTI × Income Dummy</td>
<td></td>
<td>-0.223*** -0.091***</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.003) (0.020)</td>
</tr>
<tr>
<td>LTV</td>
<td></td>
<td>-0.079*** -0.050***</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.001) (0.005)</td>
</tr>
<tr>
<td>White, Asian or Other</td>
<td></td>
<td>0.676*** -0.187***</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.002) (0.013)</td>
</tr>
<tr>
<td>Female</td>
<td></td>
<td>-0.238*** 0.129***</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.001) (0.010)</td>
</tr>
</tbody>
</table>

Table 5: Estimates for Refinancing Approval Parameters for Period of Tight Credit Constraints. Notes: Estimates for the coefficients of the refinancing application approval probability in the first half of 2014, a period of tight credit constraints implemented by financial institutions when granting mortgage credit. As was done in the main analysis, the table shows the estimates of an unistrumented Logit model first, and then an IV Probit model. For each model the 'Δ Tight Constraint Period' column shows the change in parameters corresponding to the first half of 2014 and the 'Baseline' shows the parameters for the rest of the 2004-2019 period. Asterisks denote significance levels (***=1%, **=5%, *=10%).
I consider the first half of 2014 for examining the effects of credit constraint tightening. To do this I run the same specification as in Section 2 and add an interaction term for every variable with a dummy for this ‘tight constraint period’. The results show the change in the weighing of the criteria for mortgage refinancing during the period compared to the rest of the 2004-2019 years. Table 5 presents the estimates, where the ‘Δ Tight Constraint Period’ column shows the change in parameter values corresponding to the first half of 2014, or else the change in parameters when the tight period dummy is 1 and the ‘Baseline’ shows the parameters for the rest of the 2004-2019 period.

Focusing on the IV Probit model, the estimates for the ‘Baseline’ are very close to the estimates for the main analysis, presented in Table 2, as expected. With respect to the ‘Δ Tight Constraint Period’ results, notice that credit standards tighten significantly against LTI for lower income households and relax for higher income borrowers. The two opposite effects have approximately equal magnitudes, with the LTI coefficient changing by -3.989 for incomes below the median and 3.538 for incomes above the median. Any advantageous treatment of White, Asian or Other households over Black and Hispanic households is shrunk, as the relevant coefficient of 0.447 decreases by -3.62. On the contrary, the coefficient on LTV is increased by 0.914 and the coefficient for Female households rises by 0.431.

To determine the distributional effects of the tighter credit constraints however, it is necessary to understand these results by incorporating the covariance of characteristics of different households. Therefore, the model results for the first half of 2014 is simulated using the parameters referring to the ‘Baseline’ and then those referring to the ‘Tight Constraint Period.’ Figure 10 shows the result by loan amount, income and home value decile, as well as by race or ethnicity and gender. Note that there is not enough household refinancing data to simulate the final decile in terms of loan amount, income and home value. Comparing the mean refinancing rate during the first half of 2014 for different groups of households under ‘Baseline’ credit constraints vs. under ‘Tight Credit Constraints’ can show which households were mostly affected by the change in lending standards. Because the refinancing application probability remains constant under both scenarios, it is possible to identify the result of the tighter constraints, without effects from any demand side changes.

With respect to loan amount first, it appears that under the tighter credit constraints, financial institutions approved applications at a uniformly lower level than under the baseline conditions.
Because refinancing rates are higher for higher loan amounts, the policy change affected mostly households applying to refinance at higher loan amounts. A similar pattern is observed with respect to the lower to middle of the income distribution, but for income levels at the 8th decile or above, financial institutions appear to approve as many applications under tight constraints as they do in the baseline case. For the home value distribution, again banks approved applications at a uniformly lower level than under the baseline conditions. Since the application rates where the highest for the sixth, seventh, eighth and ninth deciles, the tighter credit standards had the greatest effects for applicants with higher home values. In terms of race or ethnicity, White households were clearly the ones less affected by the constraint tightening, and Female households were more affected than Male households, with their refinancing rate dropping to half what it would be under the baseline scenario.
Figure 10: Distributional Effects of Credit Constraint Tightening. Notes: The Figure shows the refinancing rate for different households grouped based on their loan amount, income, home value, race or ethnicity and gender, under the 'Baseline' and 'Tight' level of credit constraints, as defined in Table 5. In either case, household refinancing behavior is the same, so the difference between the results of the two scenarios give the distributional effects of credit constraint tightening during the first half of 2014.
8 Monetary Policy Transmission and Distributional Effects

8.1 Monetary Policy Transmission in the Aggregate

The model is applied to further study monetary policy transmission through the refinancing channel. The effect of a downward monetary policy shock to the aggregate refinancing rate under different economic conditions is examined, in line with the model experiments performed by Beraja et al. (2018) and Berger et al. (2020). To do this, three different 5-year periods are considered, starting in January 2008, 2013 and 2015 respectively. These three periods are chosen so that the model predictions for a downward shock in mortgage market rates can be interpreted after a recent increase in the aggregate refinancing incentive, as is the case for 2013, a decrease in the incentive, as for 2015 and after the incentive has remained steady, like in 2008. Refer to Figure 11 Panel c, where the shock is applied at month 0. The same Figure plots the other macroeconomic variables relevant to the model for the three periods considered, namely the annual change in home price index and the level of unemployment. The highlighted differences in response to a shock can be attributed to the macroeconomic variables rather than the household characteristics, since the sample of households corresponding to each period are largely similar, as shown in Figure A.

For each period, a -100bps shock to the mortgage market rate is applied, the mortgage rate is held at that level and refinancing for different household groups is tracked for the next 60 months. During this period, the corresponding cross-section of households for that period is used. Panels a and b of Figure 11 show the effect of the shock to aggregate refinancing. Note that we can comment on the immediate refinancing response, or up to a year after the shock, as well as the medium term response, between years 2 and 5 from the shock. The short-term effect is smallest under the 2008 economic conditions, as expected. Because in this case the shock follows a period of a stable refinancing incentive, as well as the refinancing boom of the early 2000’s, most of the households who were willing and able to refinance have already done so. This period is also characterized by tighter credit constraints, as discussed in Section 4. The largest short-term effect is noted for the 2013 economic conditions, because the refinancing incentive after the shock rises to a very high level, since the gap between the aggregate mortgage rate and the market mortgage rate is high enough for even households with lower refinancing application propensities to apply now choose to refinance as well.
**Figure 11:** Monetary Policy Transmission - Economic Variables. *Notes:* The Figure shows the model-predicted monthly aggregate refinancing rate (Panel a), the cumulative aggregate refinancing rate (Panel b) and aggregate refinancing incentive (Panel c), following a shock of -100bps to the market mortgage rate for these three points in time. The Figure also depicts other economic variables in these three periods, the year-on-year change in House Price Index (Panel d) and the Unemployment Rate (Panel e).
8.2 Monetary Policy Transmission in the Cross-Section

To study how monetary policy is transmitted through the distribution of households, I consider the economic conditions under which the largest aggregate response is observed, i.e. from the start of 2013 onwards. The model is then used to predict how refinancing originations would vary at different levels of loan amount, income, home value and for households of different race or ethnicity and gender. The results are shown in Figures 12 and 13.

Staring from the refinancing rate for households with different levels of loan amount, note that predicted refinancing originations are higher as loan amounts increase, as shown for the second, fifth and eighth loan amount decile. The difference between the groups is amplified when considering the cumulative refinancing measure, as households with lower loan amounts consistently miss out on opportunities to take advantage of lower mortgage rates by refinancing. With respect to income, again higher income households refinance more and the difference between groups becomes starker as months pass after the shock. However, this increasing trend does not hold for the very top of the distribution, where refinancing rates no longer increase for the ninth decile. It is interesting to point out that the refinancing originations of households at the right-most end of the income distribution (decile 8 in the graph), converge to the originations of households at the median of the distribution in the long term. In addition, it can be observed that at the bottom of the income distribution, there is little reaction in refinancing originations after the monetary policy shock. For home value similar patterns to income hold. In terms of race or ethnicity, there is a stark difference between Black and Hispanic households vs the rest. Black and Hispanic households not only refinance a lot less, but also react less to the monetary policy shock. The difference in refinancing further increases the gap between the households with respect to missed opportunities to refinance, as shown in the cumulative refinancing graph. Finally, Male households refinance more than Female households, as expected from earlier results.
Figure 12: Monetary Policy Transmission in the Cross-Section I. Notes: The Figure presents the model-predicted refinancing rate, conditional on different household characteristics. A 100bps shock is applied to the market mortgage rate in January 2013 and the model is used to predict what would be the refinancing rate for different groups of households, by loan amount, income and home value. The plots on the left show the monthly refinancing rate, out to 60 months after the shock is applied. The plots on the right depict the cumulative refinancing rate for the same groups and over the same period.
Figure 13: Monetary Policy Transmission in the Cross-Section II. Notes: The Figure presented the model-predicted refinancing rate, conditional on different household characteristics. A -100bps shock is applied to the market mortgage rate in January 2013 and the model is used to predict what would be the refinancing rate for different groups of households, by race or ethnicity and gender. The plots on the left show the monthly refinancing rate, out to 60 months after the shock is applied. The plots on the right depict the cumulative refinancing rate for the same groups and over the same period.

8.3 Effects of Credit Constraints on Monetary Policy Transmission

Finally, in order to understand the distributional effects that credit constraints have on policy transmission, the limit case is considered, which is a scenario where there are no credit constraints and all households applying to refinance are able to do so. By modelling the cross-sectional refinancing rates absent of credit constraints and comparing them with the baseline prediction, the dampening effect of credit constraints on monetary policy can be identified. So I simulate refinancing rates following again a -100bps shock to the mortgage market rate on January 2014, I keep the rates at that level for 60 months and track the model prediction for the refinancing of different groups of households. In Figure 14 the solid lines indicate the cumulative refinancing rate under the baseline scenario, which is predicted with the refinancing approval parameters quoted in Table 2 and the
dashed lines are the model predictions for when the approval probability is constant and equal to 1 for all applicants.

As expected, the common finding for all household groups is that the refinancing rate under the limit case of no credit constraints is higher than the baseline refinancing rate prediction. More specifically, we see that for the household groups at the lower end of the distribution, their refinancing rate reaches the level of their counterparts in the absence of credit constraints. Example of this is the second income decile, which under the limit case approximately equals the baseline level for the fifth decile and similarly along the income and home value dimension. This pattern also holds with respect to race or ethnicity, where under no constraints, Black and Hispanic households would be able to refinance as much as White and Asian or Pacific Islander households in the baseline scenario. Although the limit case simulated is only a theoretical scenario, this experiment is useful for us to understand how streamlined refinancing programs can make monetary policy transmission more efficient, with more households taking advantage of lower rates for their mortgage payments, as well as shrink the difference between households that consistently appear to miss out on chances to refinance and households that show much higher refinancing originations.
Figure 14: Monetary Policy Transmission in the Cross-Section with No Credit Constraints. Notes: The Figure presents the model-predicted refinancing rate, conditional on different household characteristics with the solid lines, and for a counterfactual scenario where there are no credit constraints with the dashed lines.
9  Robustness

9.1  Household-Specific Refinancing Incentive

Equation (5) that determines when a household refines in the model is defined with respect to the aggregate refinancing incentive. Define the spread $S_{i,t}$ of the rate currently paid by the borrower, over the average rate of all outstanding mortgages in period $t$, i.e. $S_{i,t} = r_{i,t} - \hat{r}_t$. Ignoring the controls for now, rewrite $y_{i,t}$:

$$y_{i,t} = \alpha_i + \beta_i R_t + \delta_i S_{i,t} + \epsilon_{i,t}$$  \hspace{1cm} (12)

The borrower-specific spread is not observed in the data and hence not included in the model. This assumption introduces bias in the estimate of $\beta_i$. Using Equation (12), an expression can be derived for the bias:

$$\beta_i^\text{true} = \beta_i + \delta_i \left( R'_t R_t \right)^{-1} (R'_t S_{i,t}) \delta_i$$  \hspace{1cm} (13)

where $\delta_i$ is defined in (12) and $(R'_t R_t)^{-1} (R'_t S_{i,t})$ is the slope of $S_{i,t}$ on $R_t$. Using this, (14) can be written as:

$$\beta_i^\text{true} = \beta_i + \delta_i \frac{\text{Cov}(R_t, S_{i,t})}{\text{Var}(R_t)}$$  \hspace{1cm} (14)

From this expression, the direction of bias in the estimate can be determined. Specifically, $\delta_i > 0$ always, since as $S_{i,t}$ increases, so does the borrower’s rate incentive to refinance. For the covariance term, the relationship between the borrower spread over the average outstanding rate and the aggregate refinancing incentive needs to be specified. Because borrowers are observed only when they choose to refinance, it is expected that their mortgage rates will be on the right end of the rate distribution of outstanding mortgages. Note now that $R_t = \hat{r}_t - r^M_t$ also summarizes the recent history of mortgage rates. If $\hat{r}_t - r^M_t$ widens, then that means that borrowers with higher current mortgage rates will refinance first and it can be inferred that $S_{i,t} \geq 0$ for most observed borrowers. Thus it can be expected the covariance term to be positive. With $\delta_i > 0$ and $\frac{\text{Cov}(R_t, S_{i,t})}{\text{Var}(R_t)} > 0$, the estimate of $\beta_i$ will be biased downwards.

9.2  Cash-out Refinancing and Moving

A note on the significance of using a choice-based sample is in order. Section 3 refers to the fact that the micro data on household characteristics from HMDA is a repeated cross-section of borrowers,
who applied to refinance their mortgage. This makes the micro data sample a pure choice-based sample, i.e. refers to the case where the researcher draws decision-makers from the subgroup of the population who made the choice of interest. Even more, in this case the borrowers considered are the entirety of the population who choose to refinance. Train (2009) discusses the implication of using such data in logit models. According to Manski and Lerman (1977), if the formulation includes an alternative-specific constant in the model for individual choice of the action modelled, then estimating the model as if the sample was exogenous gives consistent results for all parameters except for the alternative-specific constant.

In this application, the alternative-specific constant is the cost of refinancing $\alpha_i$, which, due to the above, includes also the cost associated with cash-out refinancing and moving. Train (2009) shows that it is possible to retrieve the fixed cost of rate refinancing, excluding cash-out refinancing and moving if the share of mortgages that are cash-out refinances and the share of refinancings made because the household needs to move were known. For each of these two alternatives, it would be possible to estimate:

$$E[\hat{\alpha}_{ij}] = \alpha_{ij}^* - \ln(A_j/S_j)$$  \hspace{1cm} (15)

where $j \in \{1, 2, 3\}$ for rate refinancing, cash-out refinancing and moving choices respectively, $A_j$ the share in the population of borrowers who choose option $j$ and $S_j$ the share in the choice-based sample of borrowers choosing option $j$. Calculating $E[\hat{\alpha}_{i,2}]$ and $E[\hat{\alpha}_{i,3}]$ and subtracting the sum from the estimate of the mean fixed cost of refinancing would give the true value of the parameter for the rate refinancing case.

10 Conclusion

The refinancing channel of monetary policy transmission has been of central interest in the literature after the Global Financial Crisis. This paper studies the transmission of monetary policy in the U.S. economy through the refinancing channel in the presence of credit constraints, by incorporating heterogeneity in refinancing behavior and approval. Using aggregate as well as micro data, I first present empirical refinancing patterns that show the combined effect of demand side and supply side effects to refinancing. In order to separately identify credit constraints to refinancing from household refinancing behavior, I follow a modelling approach where the refinancing application probability for different households is considered separately to their probability of refinancing ap-
proval by using an instrument for the LTI of households. This approach allows me to produce new results on the heterogeneity of households’ credit constraints to refinancing.

The model manages to fit the aggregate refinancing rate in the U.S. for the period between 2004 and 2019 closely. The parameter estimates reveal heterogeneity in household access to credit, where households with a high loan amount, low income, as well as Black and Hispanic and Female households are the ones most affected by credit constraints. I also show that the approval rate decreases as the LTI ratio of the applicant increases for households with lower incomes, whereas the opposite is true for higher incomes. In addition, the parameter estimates confirm a number of findings in the literature on refinancing in the U.S. mortgage market. Specifically, with respect to household willingness to refinance, households with higher loan amounts are more likely to refinance and household refinancing probabilities along the income and home value distributions follow an inverted U-shape. In terms of race or ethnicity, Black or Hispanic borrowers are less likely to apply to refinance, as are Female households.

The first application of the model aims to reveal the effect of credit constraints on monetary policy transmission through the refinancing channel, particularly in an event of tightening credit constraints. I show that in the first half of 2014, during which financial institutions reportedly tightened their credit constraints on aggregate, banks reduced the approval likelihood to a common level for all households along the loan amount distribution. As households with higher loan amounts have higher refinancing rates in a normal period, the tightening event hurt mostly these borrowers. With respect to income, low and middle income households saw the greatest reduction in their refinancing approval probability, whereas the approval probability for high incomes remained largely unchanged. In terms of race or ethnicity, Asian or Pacific Islander and Hispanic households were most affected by tightening credit constraints, as were Female borrowers in terms of gender.

To study the short and medium term effects to refinancing after a monetary policy shock, two types of policy experiments are performed. First, a shock is applied to the mortgage market rate at the start of 2008, 2013 and 2015 respectively. The largest short-term effect is noted for the 2013 economic conditions, because the refinancing incentive after the shock rises to a very high level, so that households who refinance at large gaps between the aggregate mortgage rate and the market mortgage rate now choose to refinance. Second, the mortgage rate is shocked at the start of 2013 and the monthly and cumulative refinancing rates following the shock were tracked for dif-
ferent groups of households, in order to study the distributional effects of the refinancing channel. As expected, predicted refinancing originations increase as loan amounts increase. The difference between the groups is amplified when considering the cumulative refinancing measure, as households with lower loan amounts consistently miss out on opportunities to take advantage of lower mortgage rates by refinancing. With respect to income, higher income households have a higher initial reaction to the shock, but at the top of the distribution, the refinancing rate does not rise further for higher levels of income. A similar pattern is observed for the home value distribution. In terms of race or ethnicity, there is a stark difference between Black and Hispanic households vs the rest, which is further emphasized in time as shown in the cumulative refinancing graph. Lastly, Male households refinance more than Female households, which is in agreement with earlier results.

Finally, the model is used to predict the limit case, where after the mortgage rate shock, households refinance without any credit constraints. The monthly and cumulative refinancing rates following the shock are once again tracked for different groups of households, and the response between the baseline predicted refinancing rates and the predicted refinancing rate in the absence of credit constraints are compared. The difference between the two predictions reveals the distributional effect of credit constraints on households. Through consideration of the limit case, it is evident that households who are predicted to have the lowest refinancing rate in the distribution are not missing out on opportunities to refinance mostly due to their smaller probability of applying, but rather due to the credit constraints they face. Specifically, when constraints are removed, borrowers at the lower end of the loan amount, income and home value distributions reach the refinancing levels of households in the median and Black and Hispanic households reach the refinancing rate of White and Asian and Pacific Islander households. These findings can help us understand how streamlined refinancing programs can make monetary policy transmission more efficient and shrink the difference between households that consistently appear to miss out on chances to refinance and households that have much higher refinancing originations.
References


Arlene Wong. Refinancing and the transmission of monetary policy to consumption. 2019.
Appendix

A Data Description

A.1 Survey of Consumer Finances

I use the SCF waves between 2004 and 2019 to calculate the share of the total mortgage outstanding balance owed by the different groups of households used in the analysis, with respect to mortgage debt, income and home value. Specifically, from the Summary Extract Public Data of the SCF, for each household, the amount under HELOC for the total value of home equity lines of credit secured by the primary residence is deducted from NH_MORT, which is the total value of mortgages and home equity loans secured by the primary residence for the amount of regular mortgage debt corresponding to each household. Only households with positive outstanding regular debt are retained and using fields HOUSECL and HPRIM_MORT, I choose households that own a house and have a first lien mortgage on their primary residence. To calculate shares of households by mortgage balance, the outstanding mortgage debt is summed by debt decile. Similarly for income and home value, fields INCOME and HOUSES are used to sum the outstanding mortgage debt by household income and home value decile. All dollar amounts are 2019 dollars. The amounts in field CPI_DEFL are also retained across waves to convert all dollar amounts in the HMDA data to 2019 dollars. The survey data are weighed using the field WGT for the sample weight.

A.2 American Housing Survey

I use the AHS waves between 2003 and 2019 to calculate the share of the total mortgage outstanding balance owed by the different groups of households used in the analysis, with respect to race or ethnicity and gender. In order to filter the data as before so as to keep only households with regular mortgage debt, the Table Specifications documentation is followed, available publicly for each wave of the survey on the Census website. The fields change significantly by wave over the period considered, so the methodology is adjusted accordingly. With respect to the sample weights, the recommended weights by the AHS are used, so field WEIGHT for National survey years 1997, 1999, and 2015 and later and field WGT90GEO for survey years 2001 to 2013.

For waves 2015 to 2019, fields INTSTATUS, TENURE and MORTLINE are used to choose households that completed the survey interview, own their residence and have a primary mortgage. Also, BLD is used to exclude manufactured homes. For outstanding mortgage debt, field TOT-
BALAMT is used and only households that have positive debt are kept. For race and ethnicity, fields HHRACE and HHSPAN are used to match the race or ethnicity of a household to the categories available in the HMDA data. For gender, field HHSEX is used. The survey data is weighted using field WEIGHT, which is the final survey weight.

For waves 2011 and 2013, fields STATUS, TENURE and MCNT are used to choose households that completed the survey interview, own their residence and have a primary mortgage. Field NUNIT2 is then used to exclude mortgages for manufactured homes. For the outstanding mortgage balance of each household, fields UNPBAL, UNPBAL2, UNPBAL3 and UNPBAL4 are summed and only mortgages for which this sum is positive are retained. For race, ethnicity and gender fields HHRACE, HHSPAN and HHSEX are used respectively. For weights field WGT90GEO is used, which is the final weight using geography as of 1990.

For waves 2003 to 2009, fields STATUS, TENURE, MCNT and NUNIT2 are used to choose households that completed the survey interview, own their residence, have a primary mortgage and to exclude mortgages for manufactured homes. All AHS waves before 2011 do not ask for the outstanding mortgage debt, but the AHS follows a methodology for approximating the value using other survey answers. The resulting values are included in the survey’s National Summary Reports and the methodology is detailed in the Table Specification files, as mentioned earlier. The same methodology is followed for calculating the outstanding balance in all relevant waves. Like before, for race, ethnicity and gender fields HHRACE, HHSPAN and HHSEX are used respectively. For weights field WGT90GEO is used, which is the final weight using geography as of 1990.

A.3 HMDA

As mentioned in Section 3, the HMDA applications are filtered following Greenspan and Kennedy (2005) and Greenspan and Kennedy (2008). Two main conditions are applied, regarding Manufactured Homes and Home Equity Loans.

Manufactured homes are primarily financed by personal property loans instead of mortgages, therefore the originations that would not flow through the mortgage outstanding debt series are excluded. Before 2004, HMDA did not identify originations backed by mobile homes, but HUD provided a list of lenders that mainly originated loans backed by manufactured homes. All mortgages originated by those lenders are excluded. After 2004, manufactured home loans are tagged in the data, so only a random sample of 30% of these originations is retained.
Home equity loans are excluded in this analysis and therefore removed from the mortgage application data used. Lenders report two types of home equity loans: originations made for home improvement and piggyback loans. The latter are home purchase or refinance loans that are second lien. Home improvement loans are tagged in the data, and thus excluded. Second lien loans are only identified after 2004 and just for sold loans. These are taken out. To include purchased second lien loans originated after 2004, all purchased loans under $25,000 are excluded.

In addition, although HMDA reporters provide the date at which they receive a mortgage origination application, this information is not publicly disclosed and the loans’ date is only identified by year. The CFPB provides public tables on the number and total value of loan applications by month for all years after 2004. The loans are randomly allocated to the different months in any given year, based on these proportions. By doing this, the household characteristics of mortgage applications are assumed to remain stable within each year considered.

A.4 Call Report Data

To calculate the liquidity of each financial institution, the Federal Reserve’s Report of Condition and Income, otherwise known as ‘Call Reports’ are used. These reports include bank-level data, submitted by insured banks to the Federal Reserve at a quarterly frequency. For the mortgage data in each year, I use the corresponding call reports from the last quarter of the previous year. The specific fields I use are field RCFD1754, the total Held-to-Maturity securities, field RCFD1773, the Available-for-Sale debt securities and the field RCFD2170, for the total assets on the bank’s balance sheet. The on-balance sheet liquidity definition follows Kashyap and Stein (2000), and equals the ratio of liquid assets, i.e. the sum of fields RCFD1773 and RCFD1754 over total assets RCFD2170.

A.5 Branch Data

The data on the location of branches of different banks over the 2004-2019 period comes from the Summary of Deposits, an annual survey of branch office deposits for all FDIC-insured institutions. The data includes the latitude and longitude of each branch and the financial institution it belongs to. Therefore, we use the coordinates of the centroid of the census tract corresponding to each application to find the two closest branches in that year.
B Estimation Methodology

B.1 Weighting Matrix for GMM Estimation

The literature recommends different ways to choose the optimal weighting matrix, such as the two-step procedure of estimating the $\theta_1$ using the identity matrix first and then updating the weighting matrix using those initial estimates. Another approach is using Monte Carlo.

I use another alternative, by which the form for $Q_T(\theta_1)$, defined in (11) is minimized. I define the optimal weighting matrix, the Jacobian of the moment conditions and its true value:

$$\hat{\Lambda} \equiv \frac{1}{T} \sum_{t=1}^{T} [g(R_t, \Delta HPI_t, U_t, X_t, \theta_1)]' [g(R_t, \Delta HPI_t, U_t, X_t, \theta_1)]'$$  \hspace{1cm} (16)

$$G' = \left. \frac{\partial g(R_t, \Delta HPI_t, U_t, X_t, \theta_1)}{\partial \theta_1'} \right|_{\theta_1 = \hat{\theta}_1, T}$$  \hspace{1cm} (17)

$$G_0' = E[G']$$  \hspace{1cm} (18)

By the Delta method, the asymptotic distribution of $\sqrt{T}(\hat{\theta}_1 - \theta_{1,0})$ is $N(0, V)$, where $V \equiv [G_0 \Lambda^{-1} G_0']^{-1}$. Taking the derivative of (11) and the mean-value expansion of $\sum_{t=1}^{T} g(R_t, \Delta HPI_t, U_t, X_t, \theta_1)$, Newey and McFadden (1994) show that:

$$\sqrt{T}(\hat{\theta}_1 - \theta_{1,0}) = -(G_0 E_0 G_0')^{-1} G_0 E_0 \left[ T^{-1} \sum_{t=1}^{T} g(R_t, \Delta HPI_t, U_t, X_t, \theta_1) \right]$$  \hspace{1cm} (19)

Newey and McFadden (1994) define a function $\phi(R_t, \Delta HPI_t, U_t, X_t, \theta_1)$ that has the same asymptotic variance as the GMM estimator, i.e.:

$$\sqrt{T}(\hat{\theta}_1 - \theta_{1,0}) = \frac{1}{\sqrt{T}} \sum_{t=1}^{T} \phi(R_t, \Delta HPI_t, U_t, X_t, \theta_1) + o_P(1)$$  \hspace{1cm} (20)

$$E[\phi(R_t, \Delta HPI_t, U_t, X_t, \theta_1)] = 0$$  \hspace{1cm} (21)

$$E[\phi(R_t, \Delta HPI_t, U_t, X_t, \theta_1) \phi(R_t, \Delta HPI_t, U_t, X_t, \theta_1)']$$ exists

$$\phi(R_t^M, X_t, \hat{R}_t, \theta_1)$$ is the influence function of $\hat{\theta}_1$.  

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Comparing (20) to (19), the influence function for the GMM estimator is:

\[- (G_0 \Xi_0 G_0')^{-1} G_0 \Xi_0 g(R_t, \Delta \text{HPI}_t, U_t, X_t, \theta_1) \]  

(23)

The optimal weighting matrix is:

\[ \frac{1}{T^2} \Phi' \Phi \quad \text{where} \quad \Phi \equiv \left( \hat{\phi}_1(R_t, \Delta \text{HPI}_t, U_t, X_t, \theta_1) \ldots \hat{\phi}_L(R_t, \Delta \text{HPI}_t, U_t, X_t, \theta_1) \right) \]  

(24)

with \( L \) the number of moments (Erickson and Whited 2002).

### B.2 Variance of Estimated Parameters

By Newey and McFadden (1994), we know that using (19), we arrive to the following:

\[ \mathbb{E}[(\theta_1 - \theta_{1,0})(\theta_1 - \theta_{1,0})'] \equiv - (G_0 \Xi_0 G_0')^{-1} G_0 \Xi_0 \Xi_0' (G_0 \Xi_0 G_0')^{-1} \]  

(25)

To determine the variance of the parameter estimates, \( \Lambda \) is defined such that it takes into account all the possible sources of variance of our estimators. By Berry et al. (1995), Berry et al. (2004a) and Berry et al. (2004b), this should capture the sampling error involved in the estimation. The sampling error can be quantified by calculating the covariance matrix of the empirical moments, which has been done for calculating the weighting matrix in (24).

In addition to the above, the variance that is introduced by using the estimate of the refinancing application approval parameters \( \theta_2 \) needs to be included. By Erickson and Whited (2002), the variance \( V \) is adjusted to be:

\[ V \equiv \frac{1}{T} \sum_{t=1}^{T} \left[ g(R_t, \Delta \text{HPI}_t, U_t, X_t, \theta_1) - \mathbb{E} \left[ \frac{\partial g(R_t, \Delta \text{HPI}_t, U_t, X_t, \theta_1)}{\partial \theta'^2_2} \right] \phi^{\theta_2}(R_t, X, \theta_2) \right] \left[ g(R_t, \Delta \text{HPI}_t, U_t, X_t, \theta_1) - \mathbb{E} \left[ \frac{\partial g(R_t, \Delta \text{HPI}_t, U_t, X_t, \theta_1)}{\partial \theta'^2_2} \right] \phi^{\theta_2}(R_t, X, \theta_2) \right]' \]  

(26)

where \( \phi^{\theta_2}(R_t, X, \theta_2) \) the influence function of \( \theta_2 \).
B.3 Computation

For computing the aggregate refinancing rate, the integral of Equation (10) is approximated using Monte-Carlo integration:

\[
\tilde{\rho}_t = \frac{X_{1,t}}{1 + \exp \left( \alpha_r + \beta_r R_t + \gamma_1 \Delta \text{HPI}_t R_t + \gamma_2 U_t R_t \right)} \times \frac{\exp \left( \omega_1 + \omega_2 D_{r,t} \right)}{1 + \exp \left( \omega_1 + \omega_2 D_{r,t} \right)}
\]

Note that for the probability distribution of household characteristics \( X_{k,i,t} \), draws are weighed by the corresponding household’s loan amount, so that the aggregate refinancing rate is defined with respect to the aggregate mortgage balance being refinanced.
Figure A: Monetary Policy Transmission - Household Characteristics. Notes: The Figure shows the distribution of characteristics for the sample of households used in the three periods, starting 2008, 2013 and 2015. Each of the three samples were drawn from households refinancing in the 5 years after the shock is applied.