Essays in Household Finance: Consumption Under Political Uncertainty and Mortgage Market Refinancing Frictions

by

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DISSERTATION ABSTRACT

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Doctor of Philosophy in Finance

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This dissertation investigates two aspects of household financial behavior. The first essay provides empirical evidence that household consumption is sensitive to political cycles, documenting a 1.19% decline in retail spending, equivalent to approximately $9.6 billion, in the month preceding U.S. presidential elections, followed by a 1.87% rebound post-election. These findings highlight the role of political uncertainty in shaping short-term consumption patterns. The second essay examines how lending process requirements affect mortgage refinancing behavior, focusing on the streamlined Interest Rate Reduction Refinance Loan program offered by the Department of Veterans Affairs. Households with access to this low-friction process are 2.2 percentage points more likely to refinance each quarter, exhibit lower trigger rates, and are more than twice as likely to refinance multiple times over a decade compared to those facing higher friction processes. Together, these essays underscore the importance of both external uncertainties and institutional design in shaping household financial decisions. By quantifying the behavioral responses to political and procedural factors, this research contributes to a deeper understanding of the mechanisms that influence household liquidity management and long-term wealth accumulation. This dissertation includes previously unpublished co-authored material.

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CHAPTER 1

INTRODUCTION

Household financial decisions are pivotal in shaping individual welfare and broader economic outcomes. From daily consumption choices to long-term commitments like mortgage refinancing, these decisions are influenced by a myriad of factors, including economic conditions, policy environments, and individual behavioral traits. This dissertation explores two aspects of household finance: the impact of political uncertainty on consumption behavior and the role of administrative lending processes in mortgage refinancing decisions.

The first essay investigates how political uncertainty, particularly surrounding elections, affects consumption patterns on ordinary household goods. Utilizing granular retail scanner data, the study reveals that consumption declines in the lead-up to elections, suggesting that uncertainty about future policies prompts households to postpone or reduce spending. Post-election periods, conversely, see a rebound in consumption, indicating a resolution of uncertainty and a return to typical spending behaviors. These findings underscore the sensitivity of household consumption to the political climate and the importance of policy predictability in economic stability. This chapter of the dissertation contains unpublished, coauthored material.

The second essay delves into the mortgage refinancing behavior of households, focusing on the role of administrative lending requirements. By comparing conventional loans with those backed by the Department of Veterans Affairs (VA), the analysis reveals that loans with streamlined administrative processes are, on average, 2.2 percentage points more likely to refinance each quarter than comparable high-friction loans. Subsample analysis across credit score bands indicates that administrative requirements, rather than borrower creditworthiness, primarily drive these differences. Furthermore, borrowers using a streamlined loan process to refinance exhibit lower trigger rates for refinancing and are more than twice as likely to refinance multiple times within the study period. These findings highlight the significant role of administrative processes in understanding household mortgage debt refinancing activity.

Together, these essays contribute to the knowledge of household financial behavior by exploring how external uncertainties and administrative process frictions influence decision-making. They offer insights into the ways in which policy environments and institutional structures can either constrain or support household financial outcomes. The findings emphasize the importance of understanding these factors, as they have direct implications for households' ability to manage short-term liquidity needs and accumulate long-term wealth.

CHAPTER 2

POLITICS IN THE PANTRY:

POLITICAL UNCERTAINTY AND HOUSEHOLD CONSUMPTION

CO-AUTHOR ACKNOWLEDGEMENT

I developed the concept and design of the study, performed the data analysis, and wrote the initial draft of the manuscript. John Chalmers and Brandon Julio provided guidance throughout the research process and contributed to the editing and refinement of the final manuscript.

ABSTRACT

We examine the impact of political uncertainty on U.S. household consumption using granular NielsenIQ Retail Scanner data. Across all product types, we find a 1.2% decrease in consumption in the month preceding a presidential election, which represents $9.6 billion decrease in revenue to the sample stores in that month, and a 1.9% rebound in consumption post-election. We also find consumption around gubernatorial election uncertainty displays similar patterns. Alcohol purchases, in contrast to other product types, increase by 5.3% in the month prior to a presidential election. Our research highlights the relation between political uncertainty and ordinary household consumption.

Researchers' own analyses calculated (or derived) based in part on data from Nielsen Consumer LLC and marketing databases provided through the NielsenIQ Datasets at the Kilts Center for Marketing Data Center at The University of Chicago Booth School of Business. The conclusions drawn from the NielsenIQ data are those of the researcher and do not reflect the views of NielsenIQ. NielsenIQ is not responsible for, had no role in, and was not involved in analyzing and preparing the results reported herein.

2.1 INTRODUCTION

An important byproduct of any political process is that future changes in government policy are uncertain. A recent literature in economics and finance has sought to investigate the impact of political uncertainty on economic outcomes. Given that government policies, such as tax and trade policies, impact many economic decisions, uncertainty about their future evolution can also affect the behavior of firms, financial markets, and households.

Most research on the effects of political uncertainty has focused on aggregate macroeconomic activity, firm-level decisions and financial market implications. For example, Baker et al. (2016) find a strong, negative relationship between macroeconomic activity and a text-based measure of economic policy uncertainty. At the firm level, Julio and Yook (2012), Gulen and Ion (2016), and Jens (2017) find that firms adopt a wait-and-see policy when faced with political uncertainty and invest less in physical capital. Jens and Page (2022) find that firms save more in terms of cash holdings when political uncertainty is high. Bonaime et al. (2018) and Chen et al. (2023) find a negative effect of political uncertainty on mergers and acquisitions, while Atanassov et al. (2024) find a positive effect on research and development expenditures. On the asset pricing side, Pástor and Veronesi (2013) and Kelly et al. (2016) find that political uncertainty is priced in equity and options markets. While relatively little work has been done investigating the effects of political uncertainty on household decisions, a notable exception, Agarwal et al. (2022) find that political uncertainty reduces household participation in stock markets.

In this paper, we examine how household consumption decisions are affected by political uncertainty. To the extent that political uncertainty translates into uncertainty about a household's future after-tax income, investment returns, and product prices, it is plausible that uncertainty affects consumption decisions. We employ granular retail consumption data and measure changes in consumption patterns in response to political uncertainty, and its resolution, across a broad range of goods. We employ the NielsenIQ Retail Scanner data, which include universal product codes (UPC) for each product scanned at checkout in sample consumer goods stores. The data include product sales, average price, location, date, and a variety of other information about the retail transactions at the store level every week. We consolidate these data into over 1.8 million county-level observations from 2006 to 2020. These data allow us to estimate the effect of political uncertainty on consumption. Given these data, we also estimate changes in the composition of consumption across products over time.

The idea that uncertainty can affect household consumption and saving has been around since at least Marshall (1920). Formal treatments of the effect of uncertainty on saving and consumption under risk aversion by Leland (1968), Sandmo (1970), and Drèze and Modigliani (1972) showed that with standard utility functions, increased uncertainty (political or otherwise) about future income leads individuals to decrease current consumption and increase saving. Sandmo (1970) shows that uncertainty can impact households through two channels. Uncertainty about future labor income leads to a precautionary savings incentive where households decrease consumption and save more to compensate for increased expected variance in future consumption. On the other hand, uncertainty over capital returns leads to an ambiguous prediction, where an increase in savings will increase both the mean and variance of future consumption, so the overall effect of uncertainty depends on how the parameters of the model are specified. Thus, whether and how political uncertainty affects household consumption is an important empirical question.

There is recent empirical work analyzing the impact of different types of uncertainty on various measures of consumption. For example, Basu and Bundick (2017) identify uncertainty shocks with fluctuations in implied stock market volatility and find a significant, negative effect on aggregate consumption. Fernández-Villaverde et al. (2015) model the relation between economic activity and fiscal volatility shocks and find a negative relation between aggregate consumption and fiscal volatility. Eberly (1994) documents that in response to the stock market crash in 1929, and the associated uncertainty over future income, consumers reduced consumption of durable goods. Coibion et al. (2024) use a randomized treatment approach with survey data to measure the causal relationship between macroeconomic uncertainty and consumption, finding that higher uncertainty leads households to decrease consumption expenditures for both durables and nondurables.

We contribute to the literature in two important ways. First, to the best of our knowledge, we are the first to examine whether political uncertainty has an effect on actual U.S. household purchases. Our paper is related to studies of partisanship, elections, and elements of consumption using survey and aggregate data (e.g. Gerber and Huber, 2009; Mian et al., 2023; and similarly Gillitzer and Prasad, 2018). Second, our data and empirical approach allow us to not only estimate the average effect of political uncertainty on household consumption, but the granular nature of our data allow us to estimate the effects separately for a wide variety of common consumption goods.

We employ two measures of political uncertainty. First, we use the timing of presidential elections in the United States as a measure of uncertainty shocks. Presidential elections are arguably the largest source of political uncertainty in the United States. Presidential elections are, by law, set to be on the second Tuesday in November every four years. Thus, the timing of presidential elections is orthogonal to other macroeconomic conditions that could affect consumption decisions. Second, we employ the timing of gubernatorial elections in US states, following the approach of Jens (2017), Jens and Page (2022), and Atanassov et al. (2024). The advantage of gubernatorial elections is that there are a large number of them in our sample, and they are staggered across time and geographic location.

We find a significant, negative effect of political uncertainty on household consumption. Our estimates imply that household consumption of retail goods declines by 1.19% in the month preceding a presidential election. The economic significance is considerable, as a 1.19% decline equates to a one-month real value consumption loss of approximately $9.6 billion (2020 dollars) per election year for the households in this sample. In the third month after the election, as uncertainty resolves, consumption shows an increase of 1.87%, which equates to a one-month consumption increase of approximately $14.2 billion (2020 dollars) per election year for the stores in this sample. When we look at the composition of consumption, we also find some interesting patterns. While most retail groups show a decline, the largest decline is found to be in dairy products. Health and beauty, dry grocery, packaged meats, non-food grocery, and general merchandise decline before a presidential election and rebound shortly thereafter. We find that purchases of alcohol significantly increase in the period before an election. Our estimates suggest that alcohol purchases increase by 5.25% relative to non-election periods. We also find that consumption of deli and fresh produce increases prior to an election.

Our results have some important implications. First, as predicted by classical economic theory, we find an average negative relation between political uncertainty and consumption.

However, the magnitude and direction of the effect of political uncertainty depends on the type of product consumed. Thus, the heterogeneity of products is an important determinant of the effect of uncertainty on consumption.

The remainder of this chapter is organized as follows. **Section 2.2** describes the data and discusses the analytical methodology. **Section 2.3** presents the empirical results. **Section 2.4** concludes.

2.2 DATA AND METHODOLOGY

We merge voting outcomes data and the retail scanner data into monthly observations, at the county level, from January 2006 through December 2020. Given the seasonal nature of household consumption, our methodology compares consumption in each county during the same months, in election and non-election years, using indicator variables to capture whether political uncertainty is resolved or unresolved. Using these data, we analyze whether household consumption within a given county differs significantly between October of a presidential election year and October of a non-election year.

Household consumption is measured with spending on retail goods scanned at NielsenIQ stores. The NielsenIQ Retail Scanner data set is obtained through the Kilts Center for Marketing at the University of Chicago. These data draw upon scans of universal product code (UPC), or barcodes, during checkout at participating NielsenIQ stores.[1] The scanner data report weekly

[1] There are 61,166 stores during the sample period that sell more than half of all U.S. sales volume for grocery and drug stores and over thirty percent of all U.S. mass merchandiser sales volume, with approximately 4.4 trillion in total consumer spending across the 15-year sample period. All consumption data is given in dollars and normalized

quantity sold and average price for each UPC at each store. We consolidate these data into monthly observations by county.

The NielsenIQ data allow us to analyze household consumption in ten product categories. The relative sales in each of these departmental product categories are in **Figure 1**. Extending previous research, which uses new car sales data or self-reported/intent-to-purchase survey responses to identify household spending behavior (Carroll et al., 1994; Aaberge et al., 2017; Gillitzer and Prasad, 2018; Bartels, 2002; Chen et al., 2022; and others), our consumption measure captures consumer spending on a variety of common retail goods. In other words, consumers buy household goods more frequently than they buy new cars, which provides us with more observations of consumption through time. The NielsenIQ scanner data are novel in that they provide a granular view of products purchased with frequent observations.

To measure political uncertainty we use the Massachusetts Institute of Technology's data on U.S. presidential election outcomes (MIT Election Data and Science Lab, 2018). For each state, these data report county-level vote counts for each candidate and each candidate's party affiliation. We also explore the impact of gubernatorial elections, using hand-collected state gubernatorial election outcomes from 2006 through 2020 for each state. For our sample period, we capture four presidential elections and 214 gubernatorial elections. Gubernatorial elections occur contemporaneously with the presidential election in some states and occur in non-presidential election years in other states (see **Table 1**). This between-state variance in gubernatorial election timing helps identify political uncertainty that presidential election timing

to December 2020 values using the monthly consumer price index (CPI) from the U.S. Federal Reserve Bank of St. Louis (FRED).

alone may not capture. Gubernatorial elections also allow us to examine a larger total number of elections during the 15-year sample period.

We examine within-year timing before and after election days, to identify changes in retail spending on consumer goods. Although we have weekly data, we use the monthly data to control for end-of-week pay period effects and to reduce measurement noise due to the fact that the end of each week of scanner data is Sunday (Aguila et al., 2017; Beatty, 2010). Since national elections occur "the Tuesday next after the first Monday in November, in every fourth year" (U.S. Code; see **Figure 2** for a detailed graphic showing example calendar year and election timing), parsing out the effect of political uncertainty in the week before and after an election might be confounded by consumer spending habits due to cash on-hand. By focusing on the months before and after each election, we reduce the impact of pay period and weekly total spending on our estimates.

Another important benefit of using national and state elections is that elections are widely covered by media, discussed publicly, debated openly, and well-known to consumers throughout America. The amount of election information and its availability is important to determining a plausible connection between the political uncertainty associated with elections and household consumption decisions.

Using these data, we estimate the following regression for household consumption in county j at month t:

$$\log(HH\ Consumption)_{jt} = \beta_0 + \beta_1 PoliticalUncertainty_{jt} + \beta_2 Population_{jt} + \alpha_t + \mu_{year} + \delta_{state} + \varepsilon_{it} \tag{1}$$

We control for population at the county-level using U.S. Census Data. We include state fixed effects (δ_{state}) to control for time-invariant state characteristics and election procedures. We include separate month and then year fixed effects (α_t, μ_{year}) to control for seasonality, unobservable patterns in monthly spending and changing macroeconomic conditions. Standard errors are clustered at the county-level to account for within-group correlation. We use the natural log of county-level aggregate store revenues to measure household spending.

Our approach is to measure household consumption before and after presidential and gubernatorial elections. Research on the timing and magnitude of pre- and post-election uncertainty in other financial settings has produced mixed results (e.g. Snowberg et al., 2007; Julio and Yook, 2012; Aaberge et al., 2017; Colak et al., 2017; Jens, 2017; Agarwal et al., 2022; Atanassov et al., 2024). It is likely that uncertainty resolution diffuses over time after the election winner is determined. The impact of cabinet choices, follow through on stated policy objectives, and public statements are all likely to contribute to the resolution of uncertainty. To account for the potential timing differences, we examine pre-election uncertainty in the months prior to the election and lagged post-election reversals in the months following the election to estimate trends in the pre- and post-election timing and magnitude.

2.3 EMPIRICAL RESULTS

Aggregating consumption at the county-level, we find statistically and economically significant reductions in consumption prior to elections, and significant increases in consumption after uncertainty is resolved by an election. **Table 2** presents our results from equation (1). In column (1), we find that in the month prior to the national election, household consumption decreases by approximately 1.19% compared to the same month in non-election years. This result is significant at the 1% level and equates to a one-month consumption loss of approximately $9.6 billion (in 2020 dollars) per election year for the counties represented in this sample. In terms of individual stores, this represents an average one-month revenue loss of approximately $157,000 for each of the 61,166 sample stores.

We find that post-election consumption rebounds by the third month, which is consistent with uncertainty resolving over the post-election months as the newly elected leader takes observable actions that reduce lingering uncertainty. By the third month, after the national election, household consumption increases by approximately 1.87% compared to the same month in non-election years. This result is significant at the 1% level and equates to a one-month consumption gain of approximately $14.2 billion (in 2020 dollars) per election year for the counties represented in the sample. This is an average one-month revenue increase of approximately $232,000 for the 61,166 individuals stores in the sample.

Columns (2) through (11) in **Table 2** present the results for the department-level analysis. These regressions explore variation in consumption among goods represented by the 10 NielsenIQ department categories. We find that the effect of election period uncertainty varies across different consumption goods. In particular, household consumption within the Health and Beauty, Dry Grocery, Dairy, Packaged Meat, Non-Food Grocery and General Merchandise departments generally follows the same negative pre-election and positive post-election consumption pattern. These product categories are a large share of total consumption and therefore are the primary drivers of the overall result (see **Figure 1**). A notable exception is that alcohol purchases increase by approximately 5.25% prior to the election and do not decrease significantly post-election. Frozen Foods show no significant effect in the pre-election period, while Deli and Fresh Produce both increase significantly prior to elections.

Table 3 adds evidence from gubernatorial elections. These results provide several additional insights. First, for political uncertainty related to gubernatorial elections, the post-election effect is stronger than the pre-election effect. In the one-month prior to a gubernatorial election, we find no significant difference in aggregate household consumption. However, in the third month following a gubernatorial election, we find that household consumption increases by approximately 1.58% compared to the same month following non-election years. The gubernatorial election effect is similar in direction but has a slightly smaller magnitude than the presidential election effect (see **Table 3**, column (1)).

Second, gubernatorial election uncertainty also displays heterogeneity across product departments. Columns (2) through (11) in **Table 3** present the results for the department-level analysis. Generally, product departments show similar patterns in household consumption due to gubernatorial elections as they do to presidential election uncertainty, however the effect displays more heterogeneity.

Figure 3 presents the relation between political uncertainty and household consumption across the four months pre-election and six months-post election. Monthly point estimates are plotted in black with gray shading depicting the 95% confidence interval. Although both gubernatorial and presidential elections generally decrease household consumption pre-election and increase household consumption post-election, the patterns differ slightly. Consumption sharply drops in the months immediately preceding a presidential election, then rebounds in the months following the presidential election. For gubernatorial elections, the negative impact of political uncertainty appears to begin gradually resolving pre-election with a strong positive rebound in the post election period. These results imply that household consumption is impacted by political uncertainty, and which offices are on the ballot matter to consumers. Somewhat unexpectedly, the gradual pre-election resolution and strength of the post-election effects for gubernatorial elections sheds some light on how and when consumers give attention to state-level elections.

2.4 CONCLUSION

We find statistically and economically significant monthly consumption changes surrounding elections. In particular, we find a decrease in household consumption in the month prior to an election, consistent with uncertainty about which candidate will be chosen. We also find a post-election rebound in consumption that peaks in the second and third months after the election, consistent with uncertainty resolving as the newly elected leader takes observable action. Second, gubernatorial elections have a similar directional effect.

These results have implications for understanding household consumption patterns, especially during periods of uncertainty. The fact that it appears non-durable consumption is sensitive to political uncertainty, and its resolution brings increased consumption, is consistent with results found in corporations which make fewer investments during times of political uncertainty (Julio and Yook, 2012; Jens, 2017; Gulen and Ion, 2016). Our research also informs theoretical work on the effect of uncertainty shocks on consumption and the economy in general (Fernández-Villaverde and Guerrón-Quintana, 2020). It would be interesting for policymakers to know where the savings in non-durable consumption is redirected, and we leave that for future work.

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CHAPTER 3

LENDING PROCESS FRICTIONS AND HOUSEHOLD MORTGAGE REFINANCING BEHAVIOR

ABSTRACT

Despite the potential for significant savings, many homeowners do not refinance when market interest rates decline below their existing mortgage rates. This study investigates the role of the administrative lending process in a borrower's decision to refinance a mortgage loan. Utilizing loan-level data from 2014 to 2023, the analysis reveals that loans with streamlined administrative processes are, on average, 2.2 percentage points more likely to refinance each quarter than comparable high-friction loans. Additionally, borrowers using a streamlined lending process require less interest rate savings to refinance and are more than twice as likely to refinance multiple times during study period. These findings highlight that the frictions caused by administrative processes have an important impact on household mortgage debt refinancing activity.

Researcher's own analyses calculated (or derived) based in part on data provided by Intercontinental Exchange, Inc. (ICE; originally provided by Black Knight Data & Analytics, LLC) and CoreLogic, Inc. The conclusions drawn from the ICE and CoreLogic data are those of the researcher and do not reflect the views of these companies. ICE and CoreLogic are not responsible for, had no role in, and were not involved in analyzing and preparing the results reported herein.

3.1 INTRODUCTION

Falling market interest rates create an environment where borrowers holding fixed rate mortgages can benefit from exercising the option to refinance their debt at a lower interest rate. Despite the potential to save hundreds of dollars per month and generate a present value of tens of thousands of dollars in interest savings over the life of a mortgage loan, studies show a large and persistent number of homeowners do not refinance (e.g. Keys et al., 2016; Agarwal et al., 2016),

In this paper, I study the role of administrative complexity and disclosures required by the lending process in driving a wedge in household refinancing behavior. Using quarterly loan-level panel data, I examine how household administrative requirements affect refinancing behavior for conventional loans, which are available to the majority of U.S. borrowers, and loans backed by the Department of Veterans Affairs (VA), which are available to active and retired members of the Armed Forces. While similar on many dimensions, the mortgage types systematically vary in the administrative requirements associated with refinancing a mortgage. The VA's Interest Rate Reduction Refinance Loan (IRRRL) program streamlines the process to refinance a mortgage when only the interest rate and term of the mortgage might be changed, so called "rate-and-term" (RT) refinancings. The VA's IRRRL process waives many standard underwriting disclosures, such as detailed current income documentation, while conventional loans backed by Fannie Mae and Freddie Mac retain these disclosures in the refinancing process (see **Table 4** for a detailed description of the administrative requirements for each lending process). This contrast provides a natural setting to identify the impact of administrative complexity in the lending processes on borrowers' refinancing behavior.

Holding the refinance type constant, I compare low-friction[2] VA loan RT refinances to high-friction conventional loan RT refinances as each individual loan's rate spread between the loan's fixed interest rate and the market interest rate varies over the 10-year period from January 2014 through December 2023. The identifying assumption is that absent administrative process frictions, these borrower types would refinance at similar rates. However, the results provide evidence that VA borrowers are, on average, 2.2 percentage points more likely to refinance each quarter than comparable conventional borrowers. This finding is robust to a variety of borrower, loan, geographic, and time controls, and the effect strengthens as the mortgage rate spread increases. Specifically, a one percentage point increase in the spread raises the refinancing likelihood for VA loans by an additional 0.43 percentage points.

One disadvantage of the across-borrower approach is that it cannot account for unobservable differences between the borrower types that are not attributable to their loan process or observable characteristics. I address this empirical challenge in several ways. First, I exploit an alternative identification strategy that examines refinancing behavior for only one borrower type: VA borrowers. Second, I provide evidence from subsample analysis by credit score bands suggesting administrative frictions, rather than borrower creditworthiness, primarily drive these differences. Third, I provide additional evidence from trigger rates, serial refinancers, and mortgage interest rate spread size heterogeneity. The evidence from these alternative specifications and additional analyses supports the conclusion from the main findings that

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[2] Throughout this paper, I refer refinancing requirements from the borrower's perspective, referring to more stringent refinancing requirements as "high-friction" and more streamlined refinancing processes as "low-friction." However, this phrasing does not imply superiority of one underwriting process, and one could easily consider the reasonable requirements to underwrite a loan from an alternative perspective, calling streamlined processes "high-benefit" or "requirement-waving."

administrative process requirements influence borrower refinancing decisions. Taken together, these results show borrowers with access to low-friction lending processes are more likely to refinance their mortgages than borrowers facing high-friction refinancing processes.

This work is closely related to a growing body of research studying mortgage market frictions and household borrowers' refinancing decisions. Agarwal et al. (2013) provide a parsimonious theoretical model for examining the theoretical "trigger point" at which a borrower might benefit financially from refinancing. They argue borrowers with lower refinancing costs have a lower interest rate threshold below which refinancing is financially beneficial to the borrower. Yet, despite potential benefits to borrowers, studies show actual refinancing behavior deviates considerably from theoretical predictions. Using a representative sample of U.S. mortgages, Keys et al. (2016) estimate that about 20% of unconstrained borrowers failed to refinance in December 2010 when interest rates declined, and over 40% of those households had still not refinanced by the end of 2012. Agarwal et al. (2016) find that 57% of borrowers made a refinancing error over their sample period from 1998 to 2011. Keys et al. (2016) and Agarwal et al. (2016) suggest that failures to refinance may be at least partially related to time pressure and inexperience with a perceived complex process.

Due to the magnitude of what appear to be suboptimal mortgage refinancing choices, research seeks to better understand why households delay refinancing. There are some established frictions within the mortgage market that impact refinancing behavior. For example, scholars have examined the slew of policy changes in the wake of the Global Financial Crisis that impacted consumers' *ability* to modify their mortgages (Lambie-Hanson and Reid, 2017; Ganong and Noel, 2020; Pence, 2022; Agarwal et al., 2023; Sandler, 2023; among others). Loan characteristics, pricing, and financial advice may also influence a borrower’s propensity to refinance (Cutts and Van Order, 2005; Chang and Yavas, 2009; Spader and Quercia, 2011; Agarwal et al., 2013; Agarwal et al., 2017).

There are also known frictions with borrower characteristics and abilities. DeFusco and Mondragon (2020) examine how borrower liquidity and unemployment limit refinancing and show these constraints are especially binding during recessions. Anderson et al. (2020) provide evidence from the Danish mortgage market that borrowers have information-gathering and psychological refinancing costs (value of time/attention gathering augmented by behavioral present bias). Agarwal et al. (2016) cite consumer busyness as a potential explanation for why consumers do not immediately refinance when their “trigger rate” is reached. Borrower skepticism, inattentiveness, and responsiveness to advertising exposure may also play a role in a borrower’s decision to refinance (Grundl and Kim, 2017; Johnson et al., 2019; Byrne et al., 2023). For most consumers, refinancing a mortgage is infrequent with few experienced and attentive borrowers.

With the complexities and disclosures required in the refinancing process, limited attentional resources can create substantial obstacles for households. Thus, reducing administrative frictions and streamlining the mortgage process may incentivize more borrowers to refinance. Although there is some suggestive evidence from the temporary Home Affordable Refinance Program (HARP) that administrative frictions may play a role in mortgage refinance activity (Agarwal et al., 2023), to the best my knowledge studies have not yet directly addressed the administrative process as a cost or benefit in refinancing decisions. This paper seeks to bridge that gap by directly investigating the role administrative requirements play in homeowners’ refinancing decisions, thus adding a novel contribution to how frictions shape households' mortgage debt use choices.

The remainder of this chapter is organized as follows. **Section 3.2** provides a brief overview of the institutional setting. **Section 3.3** describes the unique data. **Section 3.4** details the empirical strategy. **Section 3.5** presents the main results. **Section 3.6** provides evidence from alternative specifications and additional analyses, and **Section 3.7** concludes.

3.2 INSTITUTIONAL SETTING

3.2.1 Mortgage Markets and the Borrower's Refinancing Decision

The U.S. mortgage markets have three important characteristics that influence a borrower's refinancing decision. First, the majority of residential houses are purchased by households using fixed-rate mortgage (FRMs) contracts that typically amortize over a long period of time, while holding the home as collateral, which can be foreclosed upon in the event of payment default. The 30-year nominal FRM is the most common mortgage contract, with over 90% of all mortgages using this term length and amortization method (Campbell, 2013). Unlike adjustable-rate mortgages (ARMs) which dominate the mortgage market in many countries, FRMs allow consumers to pay a fixed monthly payment for the duration of the loan term based on an interest rate set at the beginning of the loan, regardless of the underlying economic conditions which may influence the market's prevailing interest rate during the loan term. A FRM bestows an interest rate option on the borrower which allows her to capitalize on favorable changes in market conditions.

Second, most mortgages can be repaid in full at the borrower's discretion during the loan term without paying prepayment penalties. This allows a consumer to enter into a new mortgage contract using the same underlying home as the collateralized asset and use the proceeds from the new contract to fully prepay the original loan. Within the context of this institution, U.S. borrowers can take advantage of favorable conditions in the mortgage market by refinancing into a new mortgage loan with favorable contract terms that replaces their existing loan with less favorable contract terms.

Third, the majority of loans in the U.S. mortgage market are backed by government-sponsored enterprises (GSEs) and agencies, including the Department of Veterans Affairs (VA) and Federal Housing Administration (FHA).[3] On behalf of lenders, the GSEs and agencies guarantee timely payment of principal and interest to investors on mortgage-backed securities (MBSs). Lenders pay fees which, in practice, are imbedded in the interest rates and fees charged to borrowers. These GSEs and agencies set lending criteria that drive many of the processes lenders use to originate new loans. The GSE and agency backing is important to my identification strategy. For loans already backed by the VA, the VA reduces the administrative complexity of an RT refinance by waiving several disclosures during the borrower's application and underwriting process (see **Table 4**). For new loans and cash-out (CO) refinances, the VA, Fannie Mae, and Freddie Mac all have similar administrative processes for applications and underwriting (see **Table 4**).[4]

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[3] In this paper, I will primarily consider conforming loans with standards set by GSEs Fannie Mae, Freddie Mac, and Ginnie Mae. In 2013, about 60% of outstanding U.S. mortgage debt was GSE/agency mortgage-backed securities (MBS) (Agarwal et al., 2023).

[4] In the aftermath of the Global Financial Crisis, the Federal Housing Finance Agency (FHFA) allowed streamlined refinancing for a subset of eligible conventional loan borrowers who were deeply underwater on their homes through the Home Affordable Refinance Program (HARP). Mortgage originations due to HARP were concentrated

3.2.2 The VA's IRRRL Program

VA-guaranteed loans are eligible for the VA Interest Rate Reduction Refinance Loan (IRRRL) program. For active VA loans, refinance borrowers are not required to submit proof of current income, current property value, or current credit score to be approved. See **Table 4** for a detailed comparison of refinance processes. The IRRRL's significant reduction in documentation results in lower time and effort required for a borrower to refinance.

Allowing a borrower to obtain a loan without verifying their current income, credit score, or the value of the property introduces uncertainty to the lender. For instance, if a borrower has recently lost her job, she may be unable to meet her repayment obligations. Additionally, if the property's value has declined substantially, a foreclosure could result in financial losses for the lender. The VA imposes two important restriction that minimize lender and GSE risk: borrowers can only refinance existing VA loans with the IRRRL, and borrowers are not allowed to borrow more with the new loan than the value of the existing loan plus any refinancing fees.[5] Thus, only "rate and term" (RT) refinances, new mortgages originated for the purpose of reducing a borrower's interest rate or otherwise changing the mortgage contract's terms favorably for the borrower, are eligible; "cash-out" refinances for the purpose of equity extraction are not eligible for the VA's administratively streamlined IRRRL.

in the first five years of the program, March 2009 through mid-2013, with few HARP refinances occurring after 2014 (Agarwal et al., 2023) and are therefore unlikely to influence the results of this study.

[5] With a few exceptions for very specific energy efficiency improvements.

Under these restrictions, one can plausibly argue as long as the new monthly payment is less than the current monthly payment, a new RT refinanced VA-backed mortgage is at *lower* risk of default than an existing VA-backed mortgage. Theoretical and empirical evidence supports this conclusion, showing reduced mortgage payments translate into fewer mortgage defaults (Di Maggio et al., 2017; Campbell et al., 2021; Gerardi et al., 2021). While allowing borrowers to refinance with IRRRL streamlined loans, then purchasing and insuring these new loans from lenders, the VA is likely reducing the risk of their portfolio, but also reducing the present value of future mortgage payments within in their mortgage portfolio.

Fannie Mae and Freddie Mac do not offer borrowers an administratively streamlined option for refinancing their existing loans (hereafter referred to as “conventional” loans). Refinance loans are treated as new loans. As a result, a prospective lender’s underwriting process has more administrative checks and requirements for borrowers than the VA’s IRRRL process. The underwriting process for loans which will be backed by Fannie Mae and Freddie Mac typically involves an updated credit score check, appraisal, inspection, land survey, proof of income and debts, and other requirements. These take time to collect from the borrower and contracted third party experts and take additional time and effort to review by the lender’s underwriting team. In contrast to the VA’s streamlined IRRRL process for RT refinances, the underwriting process for VA “cash out” refinances (hereafter referred to as CO refinances) mirrors the process for Fannie Mae and Freddie Mac CO refinances.

I exploit the regulatory difference between VA IRRRLs and otherwise similar refinance loans to examine the impact of administrative process requirements on the borrower’s decision to refinance her mortgage loan.

3.3 DATA

3.3.1 Data Sources

To produce the quarterly panel data used in this research, I merge CoreLogic's Real Estate data containing the individual-level history of transactions for individual properties with ICE-McDash's loan-level mortgage performance data. These data contain mortgage loans for Washington, Oregon, and Nevada originated in the 10-year period from 01 January 2014 through 31 December 2023.

For each unique property address, CoreLogic's data provide individual-level mortgage loan data for every across-borrower (i.e. sale from one property owner to another) and within-borrower (i.e. mortgage refinances or new home equity line of credit) transaction at the time of loan origination, but do not contain mortgage performance data after origination. These data include a variety of information recorded with each property's local assessor's office at the time of home purchase or mortgage origination, including: property address, homeowner identifying information, mortgage borrower identifying information, and a variety of mortgage origination timing and loan characteristics (see **Appendix A, Panel A** for an example of the CoreLogic data). Importantly, homes purchased "free and clear" with no mortgage are also recorded, providing the ability to disentangle loans terminated due to the sale of the underlying real estate from those terminated due to a mortgage-performance related reason, such as prepayment, default, or loan satisfaction.

For each unique mortgage loan, the ICE-McDash's data provide detailed mortgage origination and monthly mortgage performance for every loan but do not contain borrowers' identifying information. These data include a variety of information collected by the mortgage provider at the time of mortgage origination or reported each month throughout the life of the loan, including original: property zip code, property value, loan amount, interest rate, loan term length, loan-to-value, borrowers' credit score, borrowers' debt-to-income, property type, mortgage type (VA or conventional), lender identifying information, and many other variables, and monthly: payment/late payment/non-payment information, and the timing of loan payoff/termination for non-active loans or current information for active loans (see **Appendix A, Panel B** for an example of the ICE-McDash data). Importantly, these data contain both historic information for non-active loans and current information for active loans.

Using information common to both data sets at the time of mortgage origination,[6] I merge the CoreLogic and ICE-McDash data into a quarterly time series data set tracing an individual borrower's mortgage loan activity on their home across time to see exactly how and when she refinances her existing mortgage loan. These data also allow cross-sectional examination of all loans active at any given time to compare both individual and aggregate refinancing activity. The granularity of the data allows me to account for a host of loan, property, and borrower characteristics. I define credit band variables using VantageScore® ranges (DeNicola, 2024). This study uses a 210-day loan seasoning window after the start of a new

[6] Loans are matched on property type, mortgage date, loan amount, loan type, loan term duration, property location, and loan purpose. The match rate was 58.9%, and mortgage loans that did not match between the two datasets were excluded from the analysis.

mortgage to determine when a loan is eligible to refinance.[7] Using the average 30-year fixed rate mortgage interest rate in the United States from the Primary Mortgage Market Survey as the market interest rate (Freddie Mac), I define the Mortgage Rate Spread variable as an individual loan's interest rate less the market interest rate in quarter t-1 for each quarter throughout the sample.

3.3.2 Sample Selection and Description

The analysis generally follows DeFusco and Mondragon (2020) by focusing on the set of relatively standard first-lien, 30-year term, fixed-rate mortgage loans (FRMs) for single-family owner-occupied homes for which CoreLogic or McDash reports nonzero loan amounts, nonzero interest rates, and LTVs that do not exceed GSE lending limits by more than 0.05%. From this sample, I restrict my attention to VA and conventional loans. I also exclude loan-quarter observations that do not meet the VA's 210-day loan seasoning requirement. Of note, there are 202 loans in the sample that refinance without meeting loan seasoning requirements, and the results of this study are not sensitive to inclusion or exclusion of these 202 unseasoned refinances. The full details of my sample selection procedure, including the number of mortgages dropped at each step, are described in **Appendix B**. The final sample includes 29,566,916 loan-quarter observations, all representing the most common type of residential mortgage in the U.S.: 30-year fixed-rate mortgages for single-family owner-occupied homes.

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[7] This loan seasoning period is a requirement for VA loans (see https://www.ginniemae.gov/issuers/program_guidelines/Pages/mbsguideapmslibdisppage.aspx?ParamID=82) and common industry practice for conventional loans (https://www.bankrate.com/mortgages/seasoning-requirements).

Table 5 presents the descriptive statistics for this sample. At loan origination, the average borrower in the sample had a loan-to-value ratio of 76%, credit score of 750, loan amount of $327,699, and an interest rate spread between their individual loan and the market rate of 0.2%. The average U.S. mortgage interest rate (market rate) during the sample period was 3.9%. **Table 5** also disaggregates these statistics by loan type, conventional versus VA loans (**Panel B**) and cash-out (CO) versus rate and term (RT) refinances (**Panel C**).

While conventional and VA loans appear broadly similar across observable characteristics (**Table 5, Panel B**), there is a higher incidence of high-LTV loans among VA borrowers and a greater concentration of low-LTV loans among conventional borrowers. This pattern may reflect differences in private mortgage insurance (PMI) requirements, as PMI is typically mandated for conventional loans with LTV ratios above 80% but is not required for VA loans. To address this concern, I implement two strategies. First, all specifications include a control for whether the LTV is above or below the 80% threshold. Second, I examine an alternative identification strategy examining only VA borrowers who would all have similarly relaxed PMI constraints.

Similarly, CO and RT refinances are largely comparable across observables (**Table 5, Panel C**). However, the mortgage rate spread is, on average, higher for RT refinances. The mortgage rate spread distribution histograms (see **Figure 4**) provide evidence that this difference may be driven by a subset of CO borrowers who refinance at negative rate spreads, potentially to extract equity when they need a large sum of cash rather than waiting until stochastic market interest rates are below their current mortgage interest rate. This is consistent with the findings from Spader and Quercia (2011) that show borrowers extracting equity more frequently refinanced at higher interest rates than borrowers not extracting equity. Accordingly, my main identification strategy examines only RT refinances.

Although t-tests reveal that these group-level differences are statistically significant, the magnitudes of the differences are small and unlikely to be economically meaningful. For example, credit scores for VA borrowers are slightly lower than conventional borrowers;[8] however, loan underwriting and pricing are not meaningfully affected by such small differences. This suggests that, while the samples differ in a statistical sense, the practical implications of these differences for borrower behavior or loan performance are limited. Nevertheless, I add several controls for LTV, credit score band, and loan amount to account for any residual variation in observables that may confound the results.

3.4 EMPIRICAL STRATEGY

As discussed in **Sections 3.1** and **3.2**, declining market interest rates create conditions where a borrower holding a fixed rate mortgage benefits from exercising her option to refinance. This typically occurs when the interest rate spread between her FRM rate and the market rate exceeds a "trigger point" which varies with perceived refinancing costs (Agarwal et al., 2013). Borrowers facing fewer refinancing frictions are more likely to refinance for smaller interest rate spreads. In this study, I test how administrative frictions in the refinancing process influence a borrower's decision to refinance her mortgage loan by analyzing the interest rate spread that triggers refinancing behavior.

[8] Balance testing shows an approximate 26-point credit score difference between the borrower groups.

Holding the refinance type constant, I compare low-friction VA loan RT refinances to high-friction conventional loan RT refinances as each individual loan's interest rate spread varies across time with the stochastic market interest rate. This approach exploits the differential change in responsiveness to interest rate incentives for VA and conventional borrowers. The key assumption is that the difference between VA and conventional lending process requirements impact a borrower's sensitivity to interest rate incentives for exercising her option to RT refinance. To assess the differential change in RT refinancing activity, I estimate the following OLS model:

$$NewRTRefinance_{it} = \alpha + \beta_1 MortRateSpread_{it-1} + \beta_2 LowFrictionLoan_{it} + \beta_3(MortRateSpread_{it-1} * LowFrictionLoan_{it}) + X_{it} + \varepsilon_{it} \qquad (2)$$

where the dependent variable, $NewRTRefinance_{it}$, takes the value of 1 in quarter *t* during which loan *i* refinances with a RT refinance and is zero otherwise. $MortRateSpread_{it-1}$ is the difference between an individual loan's fixed interest rate and the market interest rate in the quarter prior to refinancing. $LowFrictionLoan_{it}$ takes value of 1 for loans that are eligible for the VA's IRRRL administratively streamlined refinancing process and 0 for ineligible conventional loans. The key coefficients of interest measure the differential change in the RT refinancing rate between the low-friction and high-friction groups (β_2) and how that impact changes with changes in the MortRateSpread (β_3). The full vector of controls, X_{it}, contains a set of borrower, loan, and geographic characteristics such as the borrower's credit score[9], loan-to-

[9] Credit scores are binned using the credit score ranges from Conklin, Liu, and Zhang (2024).

value ratio, mortgage loan amount, loans above or below 80% LTV, zip code fixed effects, and year-quarter fixed effects. Standard errors are clustered by lender and zip code.

3.5 RESULTS

I begin by presenting simple graphical evidence indicating that RT refinancing rates of VA borrowers experience a dramatic increase relative to conventional borrowers during periods of declining market interest rates. **Figures 5** and **6** plot the quarterly refinancing rate[10] for RT refinances for high-friction conventional loans (red line) and low-friction VA loans (blue line) from the first quarter of 2014 through the last quarter of 2023. The dashed gray line shows the national average mortgage rate for 30-year fixed rate mortgage loans ("market interest rate") from the Federal Home Loan Mortgage Corporation Primary Mortgage Market Survey (**Figure 5**) or sample's average mortgage rate spread (**Figure 6**). These figures show RT refinancing activity is sensitive to changes in the market interest rate and its influence on individual borrower's mortgage rate spreads. These changes also vary by refinance process type. Relative to high-friction loans, there is a substantial increase in RT refinancing activity for low-friction loans when the market interest rate decreases. During periods of time when the market interest rate is stable or increasing, making FRM options with below-market interest rates out-of-the-money for potential refinancers, RT refinance activity is similar for both low-friction and high-friction loans.

[10] The quarterly refinancing rate is calculated as the number of RT refinances occurring in that quarter divided by the number of mortgages eligible to refinance in that quarter, by borrower type (VA or conventional).

Table 6 presents the main results from the regression estimation. Holding the refinance type constant, **Table 6** shows the results of comparing low-friction VA loan RT refinances to high-friction conventional loan RT refinances using the OLS estimation of equation (2). Columns (1) to (4) of **Table 6** show this estimate accounting for an increasing set of borrower, loan, geographic location, and time controls. I find a strong positive relation between the mortgage rate spread and RT refinancing activity. The results also show low administrative friction VA loans are 2.2 percentage points more likely on average to refinance in each quarter than otherwise similar high administrative friction conventional loans. Additionally, I find this relationship strengthens as the mortgage rate spread increases; for every 1 p.p. increase in the mortgage rate spread, the effect of low-friction loans on the decision to RT refinance increases by 0.43 p.p. These results are statistically significant at the 1% level and robust to a variety of alternative specifications and empirical choices.

3.6 ALTERNATIVE SPECIFICATIONS AND ADDITIONAL ANALYSES

One disadvantage of the across-borrower approach is that it cannot account for unobservable differences between the borrower types that are not attributable to their loan process or observable characteristics. I address this empirical challenge in several ways. First, I exploit an alternative identification strategy that examines refinancing behavior for only one borrower type: VA borrowers. Second, I examine an alternative explanation for the main results based on the creditworthiness requirements of each lending process. Third, I provide additional evidence from trigger rates, serial refinancers, and mortgage interest rate spread size heterogeneity. Taken together, the evidence from these alternative specifications and additional analyses supports the conclusion from the main findings that administrative process requirements influence borrower refinancing decisions.

3.6.1 Within-Borrower Identification Strategy

Holding the borrower type constant, I compare low-friction VA loan RT refinances to high-friction VA loan CO refinances. The intent of this strategy is to help distinguish between effects caused by the administrative loan process, and the effects of different borrower types. Since the first identification strategy examines the effect of different administrative refinance processes on two potentially different borrower groups, this strategy provides evidence using the same pool of borrowers: VA-eligible households. See **Figure 7** for a visual comparison of the strategy methods.

To assess the differential change in VA borrower refinancing activity, I estimate the following OLS model for each type of refinance, [RT, CO]:

$$Y_{it} = \alpha + \beta_1 MortRateSpread_{it-1} + X_{it} + \varepsilon_{it} \tag{3}$$

where the dependent variable, Y_{it}, takes the value of 1 in quarter t during which loan i refinances and is zero otherwise. $MortRateSpread_{it-1}$ is the difference between an individual loan's fixed interest rate and the market interest rate in the quarter prior to refinancing. The key coefficient of interest measures the differential change in the refinancing rate between the low-friction and high-friction groups (β_1). The full vector of controls, X_{it}, contains a set of borrower, loan, and geographic characteristics such as the borrower's credit score, loan-to-value ratio, mortgage loan amount, loans above or below 80% LTV, zip code fixed effects, and year-quarter fixed effects. Standard errors are clustered by lender and zip code.

Of note, this sample does not include home equity lines of credit (HELOC), since HELOCs have a very different process for underwriting, do not require a borrower to refinance her existing mortgage, typically use adjustable interest rates, and often have much shorter repayment horizons. Thus, borrowers who choose HELOCs may differ systematically from those who pursue refinances. These differences may make them less comparable to borrowers who RT or CO refinance. As such, by excluding HELOCs, the sample remains more homogeneous, improving the comparability of borrower responses to variation in interest rate spreads.

The graphical evidence indicates that RT refinancing rates of VA borrowers experience a dramatic increase relative to CO refinancing rates of VA borrowers during periods of declining market interest rates. **Figures 8** and **9** plot the quarterly refinancing rate for VA loans for high administrative complexity CO refinances (red line) and administratively streamlined RT refinances (blue line). The dashed gray line shows market interest rate (**Figure 8**) or average mortgage rate spread (**Figure 9**). These figures show refinancing activity is somewhat sensitive to changes in the market interest rate. These changes vary considerably by refinance process type. Relative to high-friction CO refinances, there is a substantial increase in refinancing activity for low-friction RT refinances when the market interest rate decreases. The refinance activity is similar for both low-friction and high-friction loans when the market interest rate is stable or increasing.

Additionally, holding the borrower type constant, **Table 7** shows the results of comparing low-friction VA loan RT refinances to high-friction VA loan CO refinances using the OLS estimation of equation (3). Column (1) presents the results for RT refinances, and Column (2) presents the results for CO refinances. The results provide evidence of a very strong positive relation between the mortgage rate spread and refinancing activity. However, the magnitude of the effect is considerably stronger for low-friction RT refinance loans. After accounting for a full set of borrower, loan, geographic location, and time controls, I find a 1 p.p. increase in the mortgage rate spread is associated with 1.25 p.p. increase in RT refinances for low-friction loans while only a 0.36 p.p. increase for high-friction loans. These results are statistically significant at the 1% level. These results are robust to a variety of alternative specifications and empirical choices and support the findings from the main result.

3.6.2 Credit Band Subsample Analysis

It is possible that relaxed administrative requirements may allow less credit-worthy VA households to refinance who may not otherwise qualify under stringent conventional lending requirements, regardless of the administrative complexity of the process. To test this alternative explanation, I conduct subsample analysis on borrower credit scores for RT refinances using the main specification in equation (2). Borrowers with credit scores below prime (300-660) are considered riskier for debt repayment. Borrowers with credits scores in the prime (661-780) and above prime (781-850) credit bands are considered less risky. Since streamlined VA IRRRL refinances do not restrict lending based on credit qualifications while conventional lending does, I can directly test this theory. Although not a screening requirement in the mortgage underwriting process, many VA lenders still check and report credit information; credits scores still missing from refinanced loans in the data are estimated based on the mean credit score from that borrower's other loans in the sample. This research examines borrowers with different credit profiles using VantageScore® credit bands (DeNicola, 2024) to examine the differential impact of administrative requirements on refinancing for each credit band borrower type.

The credit band subsample analysis shows two results. First, all three credit band groups provide statistically significant evidence that low administrative friction loans are more likely to refinance in each quarter than high-friction loans (coefficient magnitudes vary between 1.50 p.p. for the below prime credit band subsample to 2.95 p.p. for the above prime credit band subsample; **Table 8**). Second, relative to the higher two credit score bands, the below prime credit score group is much less impacted by the type of loan process. Given that fewer disclosures in the lending process bears value for the lowest credit score sample group, one would expect the rate of refinancing for low-friction loan processes to be much higher in the lowest credit score band group if the high-friction process was merely screening out borrowers who may be eligible to refinance under a low-friction process. I do not find evidence supporting the alternative explanation. Rather, these results provide evidence that the administrative complexity of the refinancing process, and not the VA allowing less credit-worthy borrowers to qualify for loans, may be driving the main findings.

3.6.3 Trigger Rates, Serial Refinancers, and Mortgage Interest Rate Spread Heterogeneity

If reduced administrative complexity in the loan process impacts borrower decisions, one would expect borrowers to refinance sooner with low-friction loans than high-friction loans –

resulting in lower trigger rates and more frequent refinancing over time. I test this hypothesis in three ways.

First, I directly calculate the trigger rate for low-friction and high-friction refinances in the sample. As Agarwal et al. (2013) model in close-form solution, the trigger rate at which a borrower should optimally refinance is higher for high-cost loan situations. Through the trigger rates revealed by the borrowers in my study, I provide evidence that the administrative process can be one such cost. **Figure 10** plots the average mortgage rate spread by borrower type over time, showing that conventional borrowers consistently maintain higher rate spreads without refinancing. In the sample, the average trigger rate for high-friction conventional RT refinances was a 1.0% mortgage rate spread, while low-friction VA RT refinance borrowers only required a 0.6% rate spread to trigger a refinance.

Second, I calculate the percentage of serial refinancers, borrowers who refinance at least twice during the 10-year sample period divided by the total number of borrowers, by borrower type. The frequency of refinancing is an important indicator of a borrower's perceived cost of refinancing relative to the perceived gain. In the sample, low-friction borrowers were more than twice as likely to be serial RT refinancers, with 2.3% of all conventional borrowers and 5.6% of all VA borrowers rate and term refinancing multiple times in the 10-year sample period.

Third, I examine heterogeneity in the effect of mortgage rate spread size on borrowers exercising their option to refinance. To examine any potential rate spread heterogeneity, the mortgage interest rate spread variable is separated into four bins: below 0% and 0%, (0%, 1%], (1%, 2%], and above 2%. The value of each rate spread bin is equal to 1 if the loan's mortgage rate spread falls into the appropriate bin range or 0 otherwise, so exactly one rate spread bin is equal to 1 for any given loan-quarter observation. The estimated models in this test are similar to equations (2) and (3), however the $MortRateSpread_{it-1}$ is replaced by the rate spread bin variables to produce a series of coefficient estimates for each of the mortgage rate spread bins and associated interactions. The first bin is omitted, so all coefficient estimates are relative to bin 1 (i.e. relative to no positive rate spread between the individual mortgage interest rate and the market rate).

Table 9, column (2) and **Table 10**, columns (2) and (4) present the results for the rate spread heterogeneity estimation. Taken together, the results show three findings. First, the main effect of mortgage rate spreads on RT refinancing behavior monotonically increases. Second, the interaction between rate spread bins and the low-friction loan indicator variable shows a very strong positive relationship that grows rapidly stronger as the rate spread increases. Third, high-friction CO refinances do not seem to display the same magnitude of the effect relative to low-friction RT refinances as the rate spread bin increases.

The increasing coefficients across higher rate spread bins, especially for low-friction loans, indicate that as the financial incentive to RT refinance grows, VA borrowers are more responsive. This finding is consistent with the hypothesis that administrative streamlining in the VA RT refinancing process amplifies the effect of financial incentives, and is also consistent with the other findings showing lower trigger rates and more serial refinancers for VA RT refinancers. The rate bin findings might seem counterintuitive if we assume that administrative frictions become less significant when financial incentives are substantial, but these results provide evidence that administrative frictions remain persistent and influential as larger rate spreads incentivize more borrowers to consider exercising their option to refinance. The results also suggest the underlying distribution of borrowers may vary across rate spread bins with some "never taker" borrowers who may never refinance due to the perceived high cost of administrative frictions. Consequently, these seemingly counterintuitive findings may help reconcile previous research showing a large share of borrowers never refinance despite substantial financial incentives to do so (e.g. Keys et al., 2016; Agarwal et al., 2016; Lambie-Hanson and Reid, 2017).

Overall, the results from trigger rates, serial refinancers, and mortgage rate spread heterogeneity provide evidence supporting the main findings that the administrative complexity of the refinancing process may influence borrower behavior.

3.7 CONCLUSION

This study highlights the impact of administrative requirements on the mortgage refinancing behavior of household borrowers. Despite the financial benefits to the borrower of refinancing when the market interest rate falls below her current mortgage rate, many homeowners with fixed rate mortgages fail to exercise their option to refinance.

My findings reveal that refinancing behavior is sensitive to both market interest rates and the administrative complexity of the refinancing process. Low-friction VA rate and term (RT) refinances are significantly more likely to refinance and exhibit greater responsiveness to declining interest rates when compared to high-friction conventional RT refinances or VA cash-out (CO) refinances, with this effect magnified as the mortgage rate spread increases. Subsample analysis by credit score bands suggest that administrative frictions, rather than borrower creditworthiness, primarily drive these differences. Additionally, VA borrowers demonstrate lower trigger rates and higher rates of serial refinancing, reinforcing the benefit of an administratively streamlined process on a borrower's choice to refinance. The findings underscore that even when financial incentives are strong, administrative complexity in the loan process remains a persistent deterrent, helping to explain why many borrowers fail to refinance despite potential savings.

My findings provide evidence that streamlining administrative requirements in the refinancing process are likely to increase household refinancing rates. Although this study cannot provide evidence on the pareto optimality of programs that reduce refinancing process frictions, it is clear that this form of incentives increases refinancing rates. I leave the overall impact on other agents in the mortgage market (e.g. banks, loan servicers, government sponsored enterprises and agencies, and mortgage-backed security investors) and optimal equilibrium welfare effects to future research.

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CHAPTER 4

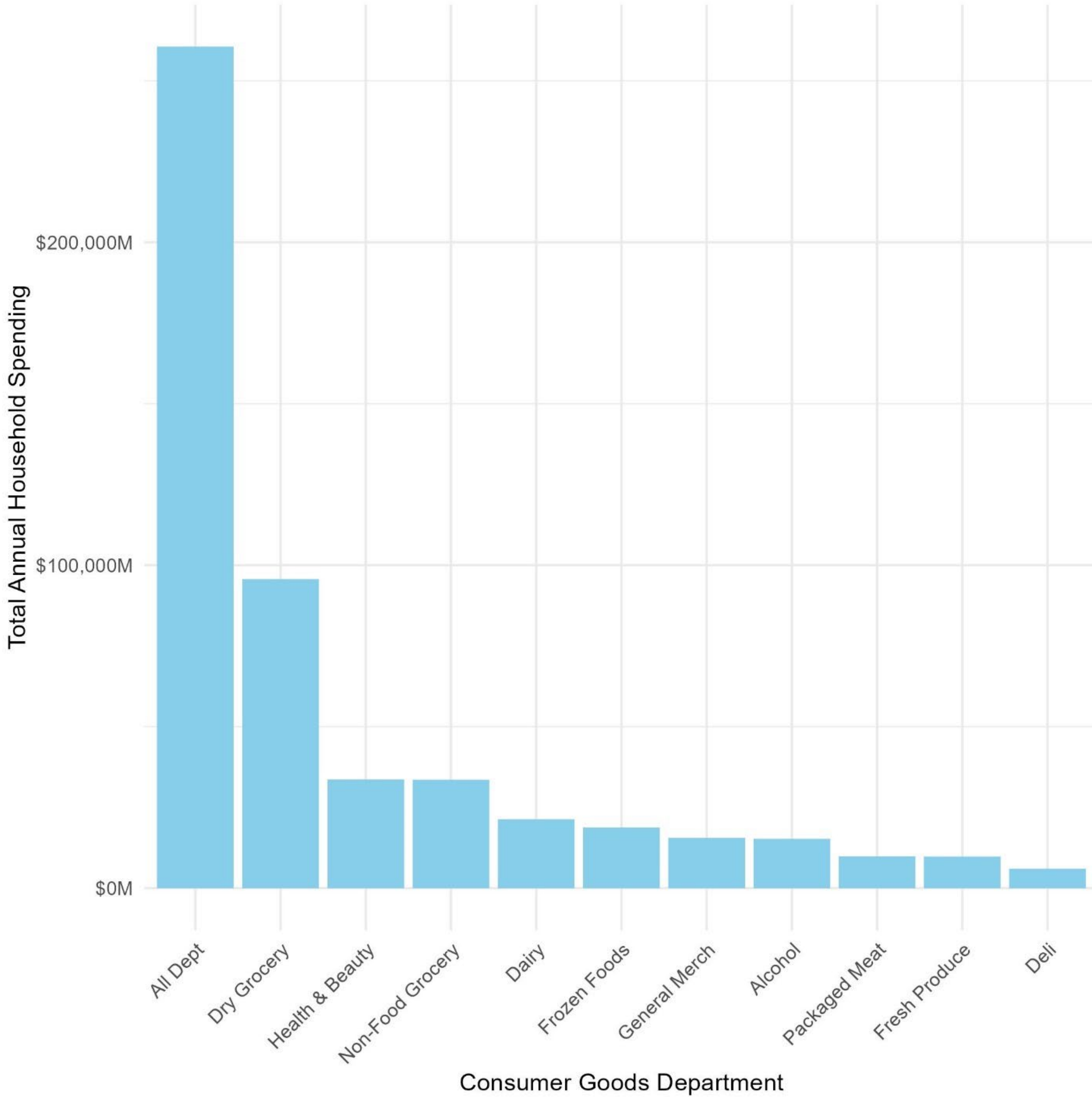
CONCLUSION

This dissertation explores two important dimensions of household financial behavior: the impact of political uncertainty on consumption and the role of administrative frictions in mortgage refinancing decisions. The first essay provides empirical evidence that political uncertainty, particularly surrounding presidential elections, leads to a measurable decline in household consumption. In the month preceding an election, retail spending decreases by 1.19%, amounting to approximately $9.6 billion in reduced consumption. This contraction is followed by a 1.87% rebound post-election, highlighting the sensitivity of household spending to political cycles.

The second essay reveals that households with access to streamlined refinancing processes, such as the Interest Rate Reduction Refinance Loan (IRRRL) offered by the Department of Veterans Affairs, are 2.2 percentage points more likely to refinance each quarter compared to those facing higher administrative friction loan processes. Moreover, these households exhibit lower trigger rates for refinancing and are more than twice as likely to refinance multiple times over a decade, indicating that reduced procedural hurdles can encourage household refinancing activity.

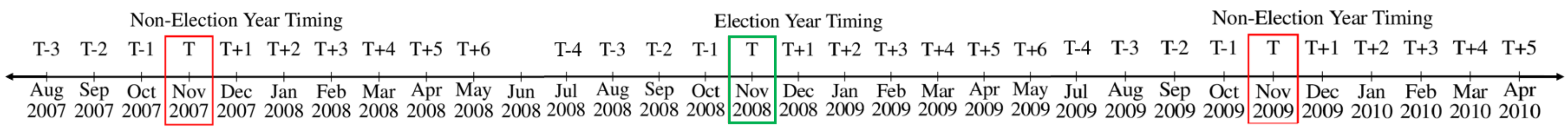
Collectively, these findings underscore the influence of both external uncertainties and institutional frictions on household financial decisions. By quantifying the effects of political uncertainty and refinancing frictions, this research contributes to a deeper understanding of the mechanisms that affect household consumption and wealth accumulation. These insights provide a basis for future research on household financial behavior amid economic and political change.

Figure 1. NielsenIQ Scanner Data: Annual Spending by Consumer Goods Department



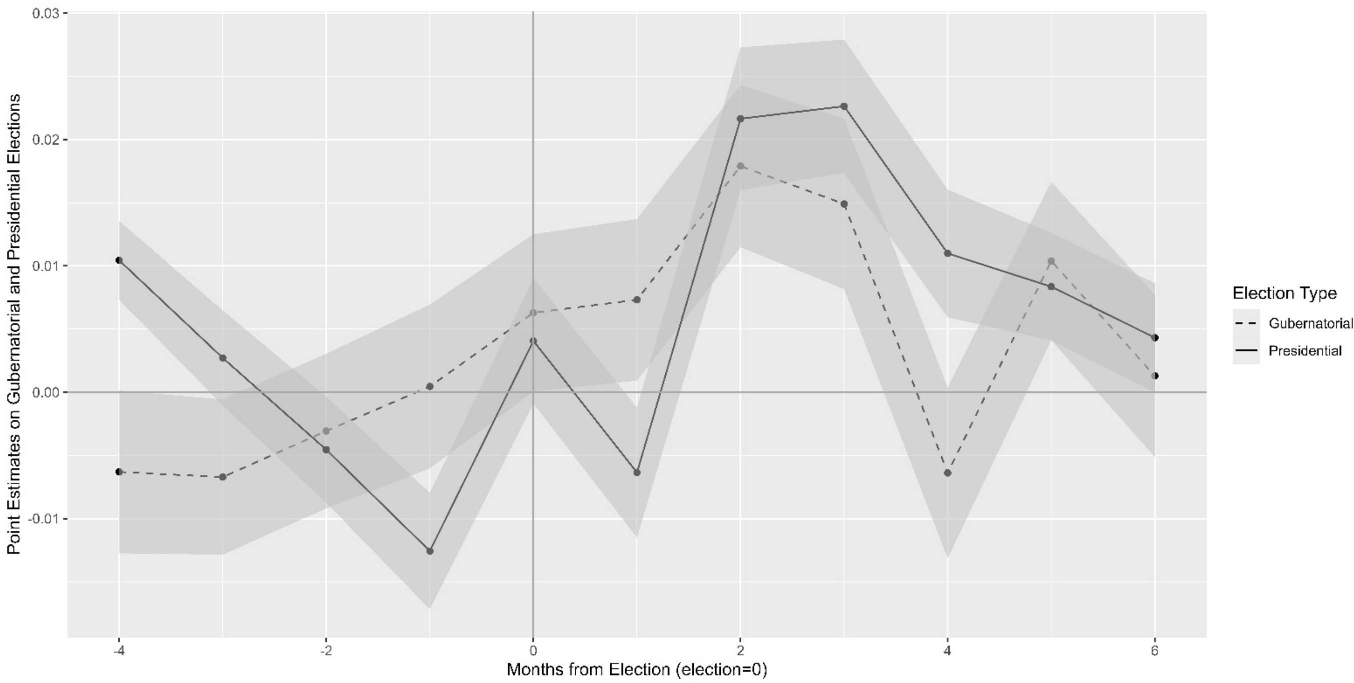
This figure presents average total annual household spending on consumer goods, the key measures of the dependent variable, across the 15-year sample period. The columns depict the total for all department categories (”All Dept”) and a breakdown for each of the 10 NielsenIQ department categories (”Dry Grocery” through ”Deli”). All dollar values are CPI-adjusted to 2020 USD.

Figure 2. Calendar Year and Election Timing



This figure shows an example crosswalk of the calendar year and election timing used in this study to compare household consumption in the same month of election and non-election years. An example election month year combination, November 2008, is shown with a green box. Two corresponding non-election month year combinations, November 2007 and November 2009, are shown with red boxes.

Figure 3. Pre- and Post-Election Timing: Coefficient Estimates



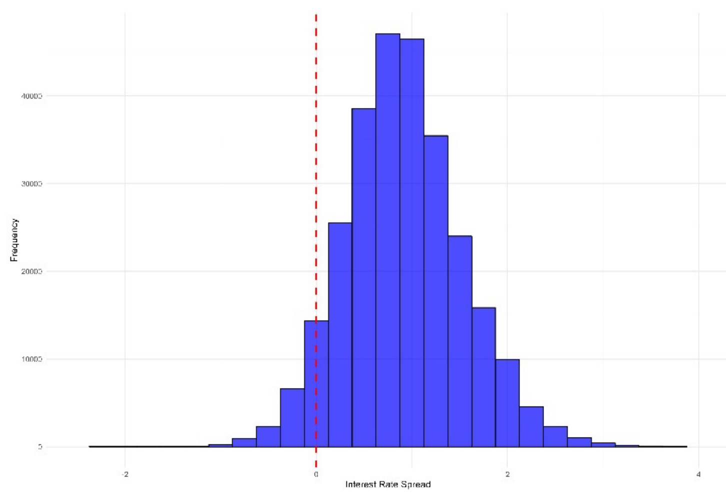
This figure shows the relation between gubernatorial and presidential election uncertainty and household consumption across months surrounding elections. The shaded area shows a 95% confidence interval. The specification is similar to Column (1) of Table IV, but we replace the time dummies with a set of monthly dummies for the four months prior to an election (t-4) through six months after an election (t+6) for both presidential and gubernatorial elections. This specification allows us to see month-by-month changes in household consumption in several months around elections.

$$\log(\text{HH Consumption})_{jt} = \beta_0 + \beta_1 \text{GubElection}_{jt-4} + \beta_2 \text{PresElection}_{jt-4} + \beta_3 \text{GubElection}_{jt-3} + \beta_4 \text{PresElection}_{jt-3} + \beta_5 \text{GubElection}_{jt-2} + \beta_6 \text{PresElection}_{jt-2} +$$
$$\beta_7 \text{GubElection}_{jt-1} + \beta_8 \text{PresElection}_{jt-1} + \beta_9 \text{GubElection}_{jt} + \beta_{10} \text{PresElection}_{jt} + \beta_{11} \text{GubElection}_{jt+1} + \beta_{12} \text{PresElection}_{jt+1} + \beta_{13} \text{GubElection}_{jt+2} + \beta_{14} \text{PresElection}_{jt+2} +$$
$$\beta_{15} \text{GubElection}_{jt+3} + \beta_{16} \text{PresElection}_{jt+3} + \beta_{17} \text{GubElection}_{jt+4} + \beta_{18} \text{PresElection}_{jt+4} + \beta_{19} \text{GubElection}_{jt+5} + \beta_{20} \text{PresElection}_{jt+5} + \beta_{21} \text{GubElection}_{jt+6} +$$
$$\beta_{22} \text{PresElection}_{jt+6} + + \beta_{23} \text{CountyPopulation}_{jt} + \alpha_t + \mu_{year} + \delta_{state}$$

Figure 4. Frequency Distribution of Mortgage Rate Spreads

These histograms illustrate the frequency distribution of the MortRateSpread variable for both RT (**Panel A**) and CO (**Panel B**) refinances in the sample. The MortRateSpread variable is defined as the difference between an individual loan's interest rate and the market interest rate in quarter t-1 for each quarter throughout the sample period. A dashed red line shows 0%. All else being equal, larger values of MortRateSpread indicate better outcomes for borrowers when they refinance. For example, suppose Borrower A has a mortgage loan with a 5% interest rate and Borrower B has a 3.5% interest rate loan. If the market rate is 3%, Borrower A's MortRateSpread is 2%, while Borrower B's MortRateSpread is 0.5%. Thus, all else equal, a refinance is more favorable for Borrower A than for Borrower B.

Panel A. Frequency Distribution of Mortgage Rate Spreads for RT Refinances



Panel B. Frequency Distribution of Mortgage Rate Spreads for CO Refinances

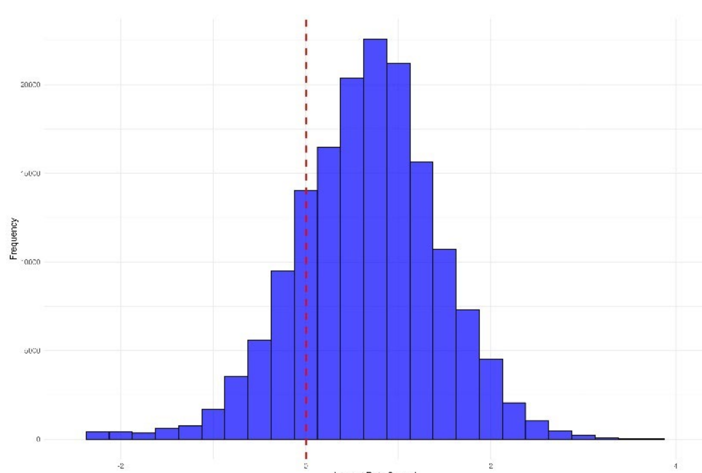


Figure 5. U.S. Market Interest Rate and Rate & Term (RT) Refinancing

This figure shows the percentage of loans conducting an RT refinance in a given quarter from 2014 through 2024. The red line shows conventional (high-friction) loans. The blue line shows VA (low-friction) loans. The dashed gray line shows the national average mortgage rate for 30-year fixed rate mortgage loans ("market interest rate") from the Federal Home Loan Mortgage Corporation Primary Mortgage Market Survey.

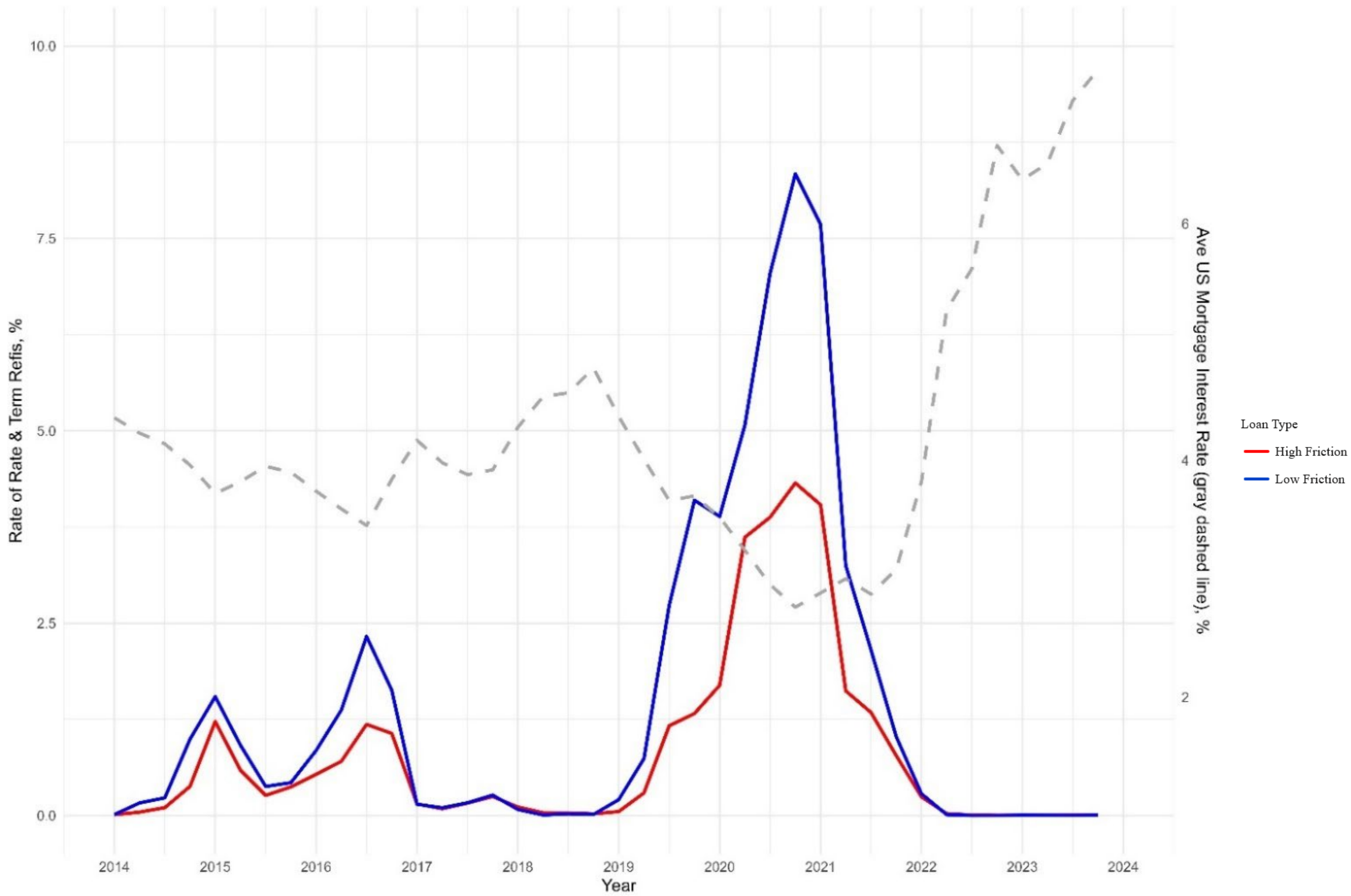


Figure 6. Mortgage Rate Spread and Rate & Term (RT) Refinancing

This figure shows the percentage of loans conducting an RT refinance in a given quarter from 2014 through 2024. The red line shows conventional (high-friction) loans. The blue line shows VA (low-friction) loans. The dashed gray line shows the average mortgage rate spread for the loans in this study's sample, calculated as difference between an individual loan's mortgage interest rate and the national average mortgage rate for 30-year fixed rate mortgage loans ("market interest rate") from the Federal Home Loan Mortgage Corporation Primary Mortgage Market. Survey in the quarter prior to refinance (or not) for each quarter throughout the sample period.

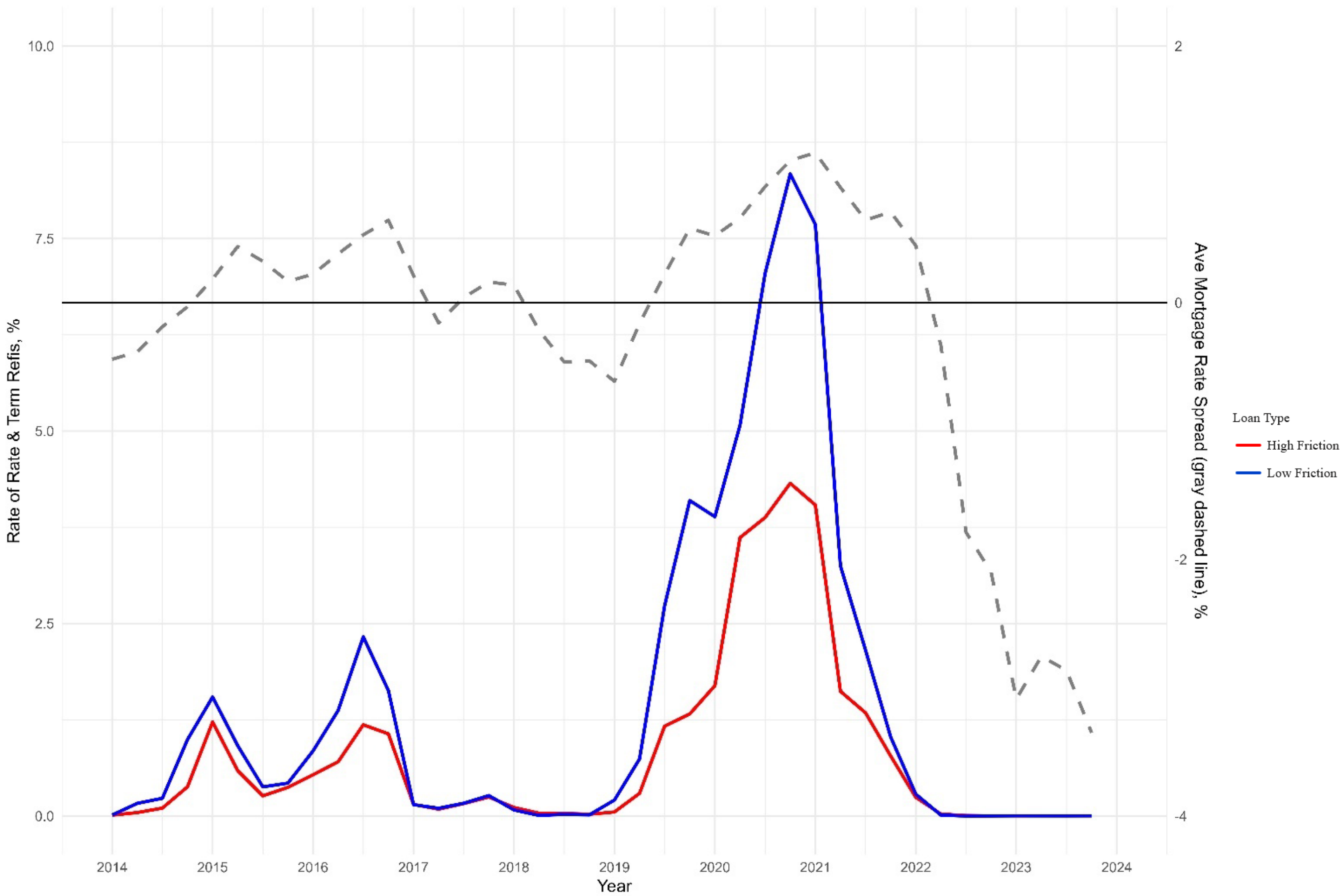
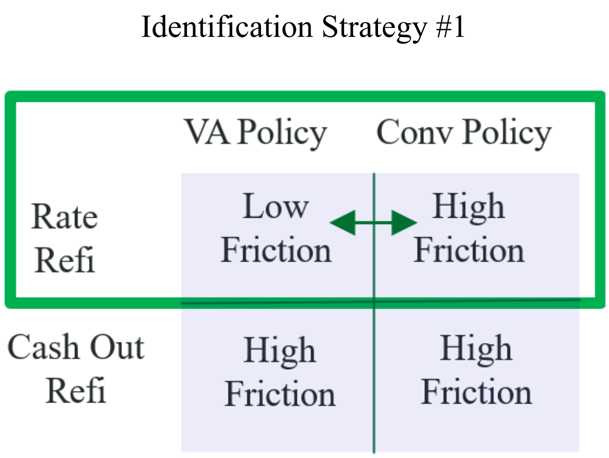


Figure 7. Visual Identification Strategy Comparison

Identification Strategy #1: holding the refinance type constant, I compare low-friction VA loan RT refinances to high-friction conventional loan RT refinances. Identification Strategy #2: holding the borrower type constant, I compare low-friction VA loan RT refinances to high-friction VA loan CO refinances.



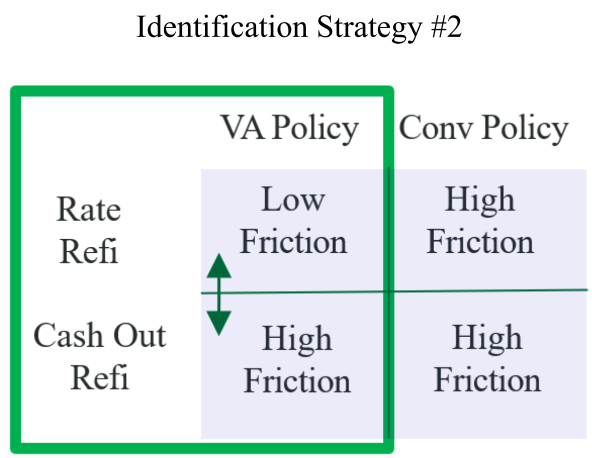


Figure 8. U.S. Market Interest Rate and VA Refinancing (CO and RT)

This figure shows the percentage of VA loans refinancing in a given quarter from 2014 through 2024. The red line shows cash out (high-friction) refinance loans. The blue line shows rate and term (low-friction) refinance loans. The dashed gray line shows the national average mortgage rate for 30-year fixed rate mortgage loans ("market interest rate") from the Federal Home Loan Mortgage Corporation Primary Mortgage Market. Survey.

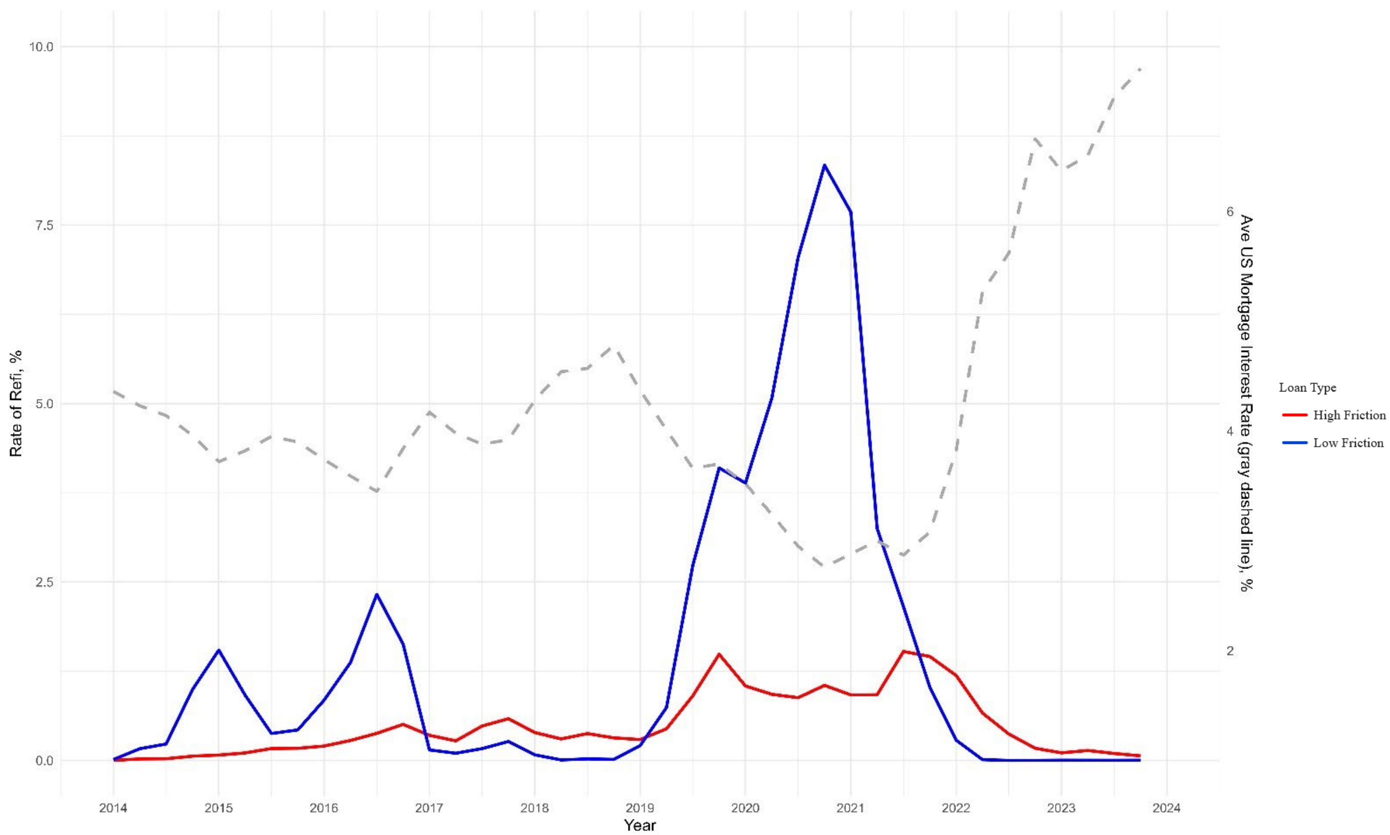


Figure 9. Mortgage Rate Spread and VA Refinancing (CO and RT)

This figure shows the percentage of VA loans refinancing in a given quarter from 2014 through 2024. The red line shows cash out (high-friction) refinance loans. The blue line shows rate and term (low-friction) refinance loans. The dashed gray line shows the average mortgage rate spread for the loans in this study's sample, calculated as difference between an individual loan's mortgage interest rate and the national average mortgage rate for 30-year fixed rate mortgage loans ("market interest rate") from the Federal Home Loan Mortgage Corporation Primary Mortgage Market. Survey in the quarter prior to refinance (or not) for each quarter throughout the sample period.

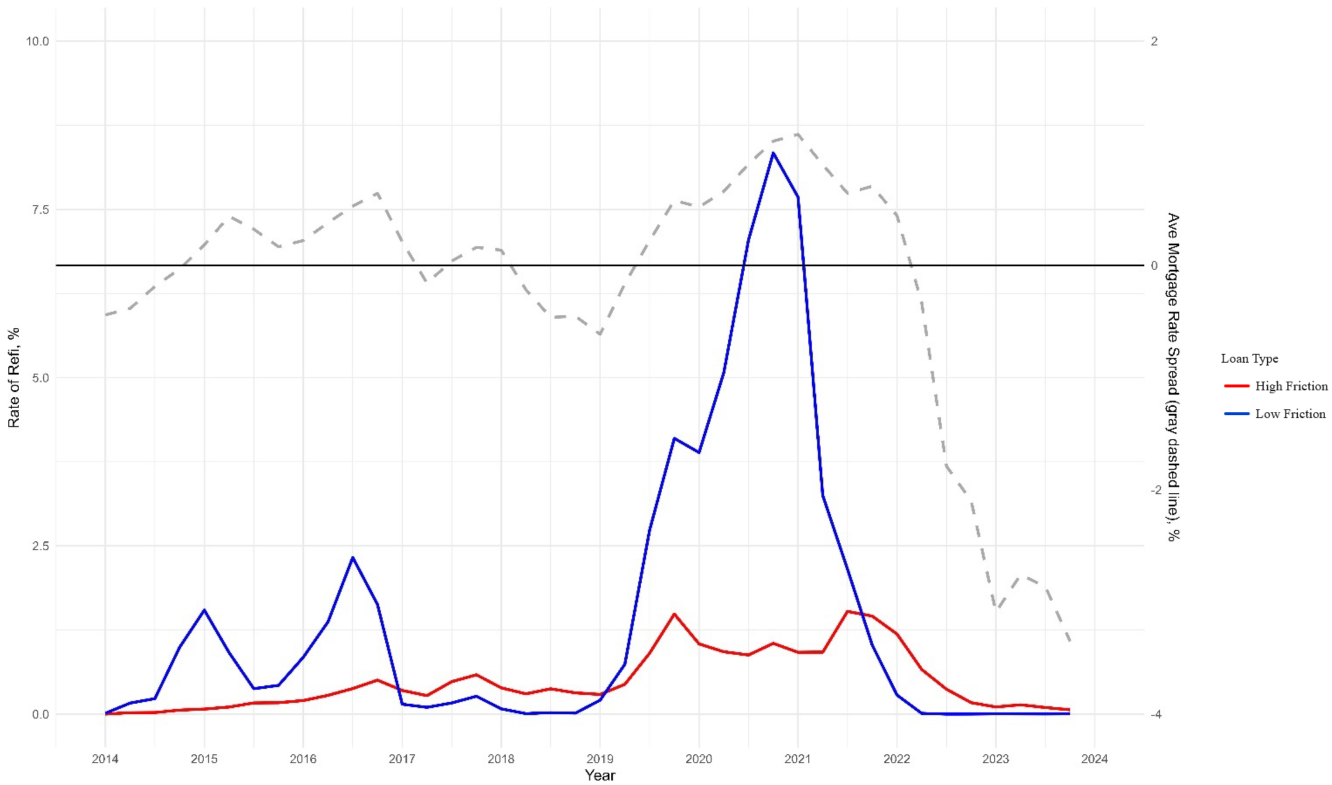


Figure 10. Mortgage Rate Spread

This figure shows the average mortgage rate spread from 2014 through 2024. The red line shows conventional loans. The blue line shows VA loans. An individual loan's mortgage rate spread is calculated as difference between an individual loan's mortgage interest rate and the national average mortgage rate for 30-year fixed rate mortgage loans ("market interest rate") from the Federal Home Loan Mortgage Corporation Primary Mortgage Market. Survey in the quarter prior to refinance (or not) for each quarter throughout the sample period.

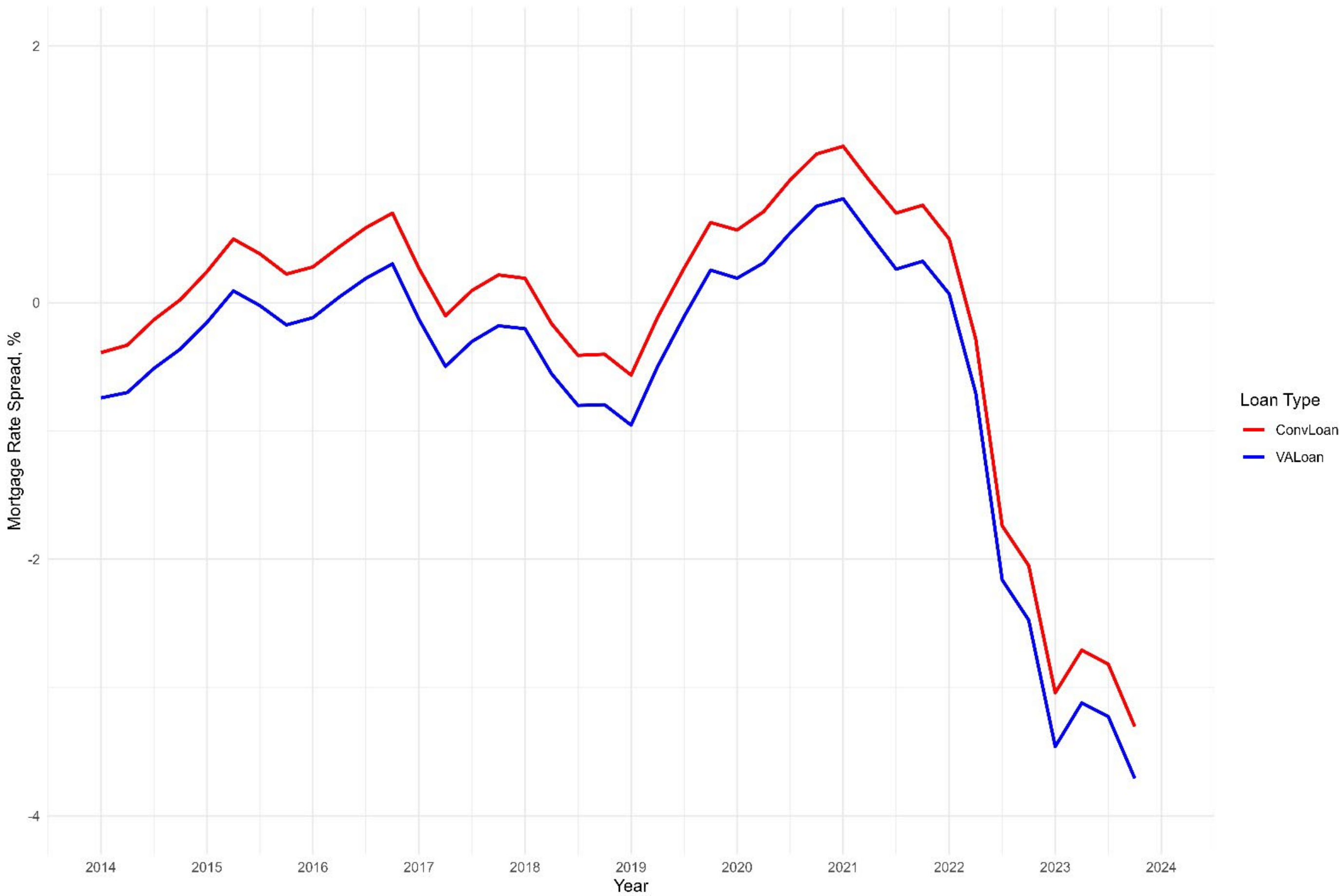


Table 1.

Election Timing Variance: Presidential and Gubernatorial Election Years by State

This table presents which states held elections for governor, president, or both in each year from 2006 to 2020. An asterisk (*) denotes special elections that deviate from that state's normal election timing.

States with Elections	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020
Total	37	3	11	2	38	4	12	2	37	3	12	2	37	3	11
ALABAMA	Governor				Governor				Governor				Governor		
ALASKA	Governor				Governor				Governor				Governor		
ARIZONA	Governor				Governor				Governor				Governor		
ARKANSAS	Governor				Governor				Governor				Governor		
CALIFORNIA	Governor				Governor				Governor				Governor		
COLORADO	Governor				Governor				Governor				Governor		
CONNECTICUT	Governor				Governor				Governor				Governor		
DELAWARE			Pres. & Gov.				Pres. & Gov.				Pres. & Gov.				Pres. & Gov.
FLORIDA	Governor				Governor				Governor				Governor		
GEORGIA	Governor				Governor				Governor				Governor		
HAWAII	Governor				Governor				Governor				Governor		
IDAHO	Governor				Governor				Governor				Governor		
ILLINOIS	Governor				Governor				Governor				Governor		
INDIANA			Pres. & Gov.				Pres. & Gov.				Pres. & Gov.				Pres. & Gov.
IOWA	Governor				Governor				Governor				Governor		
KANSAS	Governor				Governor				Governor				Governor		
KENTUCKY		Governor				Governor				Governor				Governor	
LOUISIANA		Governor				Governor				Governor				Governor	
MAINE	Governor				Governor				Governor				Governor		
MARYLAND	Governor				Governor				Governor				Governor		
MASSACHUSETTS	Governor				Governor				Governor				Governor		
MICHIGAN	Governor				Governor				Governor				Governor		
MINNESOTA	Governor				Governor				Governor				Governor		
MISSISSIPPI		Governor				Governor				Governor				Governor	
MISSOURI			Pres. & Gov.				Pres. & Gov.				Pres. & Gov.				Pres. & Gov.
MONTANA			Pres. & Gov.				Pres. & Gov.				Pres. & Gov.				Pres. & Gov.
NEBRASKA	Governor				Governor				Governor				Governor		
NEVADA	Governor				Governor				Governor				Governor		
NEW HAMPSHIRE	Governor		Pres. & Gov.		Governor		Pres. & Gov.		Governor		Pres. & Gov.		Governor		Pres. & Gov.
NEW JERSEY				Governor				Governor				Governor			
NEW MEXICO	Governor				Governor				Governor				Governor		
NEW YORK	Governor				Governor				Governor				Governor		
NORTH CAROLINA			Pres. & Gov.				Pres. & Gov.				Pres. & Gov.				Pres. & Gov.
NORTH DAKOTA			Pres. & Gov.				Pres. & Gov.				Pres. & Gov.				Pres. & Gov.
OHIO	Governor				Governor				Governor				Governor		
OKLAHOMA	Governor				Governor				Governor				Governor		
OREGON	Governor				Governor				Governor		Pres. & Gov.*		Governor		
PENNSYLVANIA	Governor				Governor				Governor				Governor		
RHODE ISLAND	Governor				Governor				Governor				Governor		
SOUTH CAROLINA	Governor				Governor				Governor				Governor		
SOUTH DAKOTA	Governor				Governor				Governor				Governor		
TENNESSEE	Governor				Governor				Governor				Governor		
TEXAS	Governor				Governor				Governor				Governor		
UTAH			Pres. & Gov.		Governor*		Pres. & Gov.				Pres. & Gov.				Pres. & Gov.
VERMONT	Governor		Pres. & Gov.		Governor		Pres. & Gov.		Governor		Pres. & Gov.		Governor		Pres. & Gov.
VIRGINIA				Governor				Governor				Governor			
WASHINGTON			Pres. & Gov.				Pres. & Gov.				Pres. & Gov.				Pres. & Gov.
WEST VIRGINIA			Pres. & Gov.			Governor*	Pres. & Gov.				Pres. & Gov.				Pres. & Gov.
WISCONSIN	Governor				Governor		Pres. & Gov.*		Governor				Governor		
WYOMING	Governor				Governor				Governor				Governor		

Table 2. Household Consumption and Presidential Elections

Regression results relating U.S. presidential elections to the natural logarithm of total household (HH) spending on consumer goods for each j county and t month. Model 1 is the main result for all departments, for reference. Models 2-11 use identical specifications but only include household consumption from products within a specific department of a consumer goods store (see Table I for a more detailed description of the department categories). $PresElection_{t-1}$ is a pre-election indicator variable equal to 1 in the month prior to a presidential election and 0 otherwise. $PresElection_{t+3}$ is a post-election indicator variable equal to 1 in the third month following a presidential election and 0 otherwise. County population per 100,000 is a continuous variable and is used as a control to account for varying county population sizes within this sample. State fixed effects are included to account for time-invariant state characteristics and election procedures in the county-level analysis. Both month and year fixed effects are included to account for seasonality, unobservable patterns in monthly spending and changing macroeconomic conditions. Standard errors are clustered at the county level and presented in parentheses.

$$\log(\text{HH Consumption})_{jt} = \beta_0 + \beta_1 \text{PresElection}_{jt-1} + \beta_2 \text{PresElection}_{jt+3} + \beta_3 \text{CountyPopulation}_{jt} + \alpha_t + \mu_{year} + \delta_{state}$$

Dependent Variables:	All Depts	HealthBeauty	DryGrocery	FrozenFoods	Dairy	Deli	PackagedMeat	FreshProduce	NonFoodGrocery	Alcohol	GeneralMerch
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
$PresElection_{t-1}$	-0.0119***	-0.0119***	-0.0125***	0.0035	-0.0354***	0.0090**	-0.0094**	0.0442***	-0.0087***	0.0525***	-0.0110***
	(0.0015)	(0.0017)	(0.0017)	(0.0032)	(0.0033)	(0.0035)	(0.0043)	(0.0114)	(0.0013)	(0.0087)	(0.0017)
$PresElection_{t+3}$	0.0187***	0.0266***	0.0143***	0.0181***	0.0394***	0.0286***	-0.0189***	-0.0584***	0.0133***	0.0016	0.0027
	(0.0019)	(0.0019)	(0.0020)	(0.0040)	(0.0038)	(0.0042)	(0.0052)	(0.0101)	(0.0019)	(0.0128)	(0.0020)
County Population	0.2418***	0.2524***	0.2435***	0.2733***	0.2738***	0.2874***	0.2887***	0.2512***	0.2320***	0.2459***	0.2534***
	(0.0648)	(0.0679)	(0.0652)	(0.0751)	(0.0749)	(0.0789)	(0.0796)	(0.0706)	(0.0610)	(0.0674)	(0.0682)
Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,860,911	1,860,897	1,860,912	1,834,968	1,849,146	1,841,818	1,816,650	1,366,116	1,860,899	1,555,974	1,860,853
R^2	0.395	0.383	0.382	0.342	0.344	0.354	0.324	0.328	0.407	0.358	0.393

*Signif. Codes: *** 0.01, ** 0.05, * 0.1*

Table 3. Household Consumption, Gubernatorial and Presidential Elections

Regression results relating U.S. presidential and gubernatorial elections to the natural logarithm of total household (HH) spending on consumer goods for each county j in month t. Model 1 is the main result for all departments, for reference. Models 2-11 use identical specifications but only include household consumption from products within a specific product department. Election_{t-1} is a pre-election indicator variable equal to 1 in the month prior to a state's gubernatorial (or U.S. presidential) election and 0 otherwise. Election_{t+3} is a post-election indicator variable equal to 1 in the third month following a state's gubernatorial (or U.S. presidential) election and 0 otherwise. County population per 100,000 is a continuous variable and is used as a control to account for varying county population sizes within this sample. State fixed effects are included to account for time-invariant state characteristics and election procedures in the county-level analysis. Both month and year fixed effects are included to account for seasonality, unobservable patterns in monthly spending and changing macroeconomic conditions. Standard errors are clustered at the county level and presented in parentheses.

$$\log(\text{HH Consumption})_{jt} = \beta_0 + \beta_1 \text{GubElection}_{jt-1} + \beta_2 \text{PresElection}_{jt-1} + \beta_3 \text{GubElection}_{jt+3} + \beta_4 \text{PresElection}_{jt+3} + +\beta_5 \text{CountyPopulation}_{jt} + \alpha_t + \mu_{year} + \delta_{state}$$

Dependent Variables:	All Depts	HealthBeauty	DryGrocery	FrozenFoods	Dairy	Deli	PackagedMeat	FreshProduce	NonFoodGrocery	Alcohol	GeneralMerch
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
GubElection_{t-1}	-0.0008	-0.0074**	-0.0019	-0.0083	-0.0023	-0.0079	-0.0128*	-0.0539***	0.0024	0.0112	0.0062**
	(0.0029)	(0.0030)	(0.0032)	(0.0056)	(0.0056)	(0.0058)	(0.0069)	(0.0143)	(0.0026)	(0.0100)	(0.0031)
$\text{PresElection}_{t-1}$	-0.0124***	-0.0127***	-0.0132***	0.0022	-0.0365***	0.0074**	-0.0112**	0.0398***	-0.0089***	0.0520***	-0.0106***
	(0.0015)	(0.0017)	(0.0017)	(0.0032)	(0.0033)	(0.0036)	(0.0044)	(0.0112)	(0.0014)	(0.0087)	(0.0018)
GubElection_{t+3}	0.0158***	-0.0010	0.0193***	0.0171***	0.0379***	0.0299***	0.0186**	-0.0662***	0.0215***	0.0660***	0.0142***
	(0.0031)	(0.0035)	(0.0034)	(0.0065)	(0.0059)	(0.0060)	(0.0076)	(0.0147)	(0.0029)	(0.0124)	(0.0037)
$\text{PresElection}_{t+3}$	0.0203***	0.0267***	0.0161***	0.0199***	0.0430***	0.0316***	-0.0168***	-0.0618***	0.0153***	0.0066	0.0038*
	(0.0019)	(0.0019)	(0.0021)	(0.0041)	(0.0039)	(0.0042)	(0.0052)	(0.0102)	(0.0019)	(0.0128)	(0.0020)
CountyPopulation	0.2418***	0.2524***	0.2435***	0.2733***	0.2738***	0.2874***	0.2887***	0.2512***	0.2320***	0.2459***	0.2534***
	(0.0648)	(0.0679)	(0.0652)	(0.0751)	(0.0749)	(0.0789)	(0.0796)	(0.0706)	(0.0610)	(0.0674)	(0.0682)
Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,860,911	1,860,897	1,860,912	1,834,968	1,849,146	1,841,818	1,816,650	1,366,116	1,860,899	1,555,974	1,860,853
R^2	0.395	0.383	0.382	0.342	0.344	0.354	0.324	0.328	0.407	0.358	0.393

*Signif. Codes: *** 0.01, ** 0.05, * 0.1*

Table 4. Mortgage Refinancing Process Comparison

This table shows a detailed comparison of the mortgage refinancing process for all four types of refinances studied in this paper: Conventional Cash Out Refinances (high-friction), Conventional Rate and Term Refinances (high-friction), VA Cash Out Refinances (high-friction), and VA Rate and Term Refinances (low-friction).

Aspect	**<u>High-Friction Refi Loans:</u>** Conventional Mortgage Loan Refinance (RT and CO) and VA CO Loan Process	**<u>Low-Friction Refi Loans:</u>** VA's Interest Rate Reduction Refinance Loan (IRRRL) Process for RT Refi Loans[11]
Eligibility Requirements	Available for all existing mortgage loans (seasoning requirements vary by lender by 6 consecutive months of on-time payments are typically required)	Available for VA-backed mortgage loans (must season for 210 days and 6 consecutive months of on-time payments)
Credit Score Review	Generally, 620+ (for credit fee pricing and prime lending)[12]; application impacts credit score	Not required; no credit impact
Loan-to-Value (LTV) Ratio Limits[13]	Generally, up to 97% LTV allowed for conventional RT refi loans (although Private Mortgage Insurance is required if LTV > 80%), 90% for VA CO refi loans, and 80% for conventional CO refi loans	Not required
Funding Fee / Costs[14]	Credit report, inspection, land survey, and appraisal fees plus standard closing costs (varies by lender and can be financed)	Funding fee of 0.5% of loan amount (can be financed) but may be waived for eligible recipients, plus standard closing costs
Appraisal Requirements	Typically required	Not required
Inspection Requirements	May be required (varies by lender)	Not required
Land Survey Requirements	May be required (varies by lender)	Not required

[11] Federal Deposit Insurance Corporation.
[12] <640 and <620 are the current standards set by Freddie Mac in the Single-Family Seller/Servicer Guide, Bulletin 2024-01, Exhibit 19 for various credit fees (Freddie Mac, 2024), but this number and scoring methodology has fluctuated over time with 620 being the generally accepted lowest credit score bucket threshold for prime loans by most lenders.
[13] Fannie Mae, Freddie Mac, and Ginnie Mae.
[14] Federal Reserve Board.

Table 4 (continued).

Occupancy Requirements	Primary residence, second home, or investment	Prior occupancy as primary residence, but can be a current primary residence, second home, or investment
Closing Time Frame	30-45 days on average	20-30 days on average, but may be as fast as 7-14 days
Income Requirements	Proof of income required	Not required
Interest Rate Restrictions	Rate depends on lender and borrower qualifications	Must result in lower interest rate (except for certain exceptions)
Equity Extraction (“cash-out”) Restrictions	Only limited by LTV and DTI ratios	Generally not allowed except for making specific energy efficiency improvements
Debt-to-Income (DTI) Ratio Limits[15]	Typically 45-50% DTI limit (varies by lender)	Not required

[15] Fannie Mae.

Table 5. Descriptive Statistics

This table presents loan level descriptive statistics. Panel A shows descriptive statistics for the full sample. Panel B shows descriptive statistics for the sample split into Conventional and VA loans for above and below 80% loan-to-value ratios (LTV). Panel C shows descriptive statistics for the sample split into Rate & Term (RT) and Cash Out (CO) refinance loans for above and below 80% loan-to-value ratios (LTV). Observations with exactly 80% LTVs are included with below 80%.

Panel A. Full Sample

Variable	Mean	SD
LTV	76%	17%
Credit Score	750	47
Loan Amount	$327,699	$169,439
Rate Spread	0.2%	0.8%
U.S. Market Interest Rate	3.9%	1.0%
Number of Observations	29,566,916	

Panel B. Conventional and VA Loans

Below 80% LTV

	Conv Loans		VA Loans	
Variable	Mean	SD	Mean	SD
LTV	66%	14%	66%	12%
Credit Score	756	45	742	56
Rate Spread	0.3%	0.8%	0.2%	1.0%
Loan Amount	$327,914	$187,423	$292,559	$126,533
Number of Obs	18,068,363		587,047	

Above 80% LTV

	Conv Loans		VA Loans	
Variable	Mean	SD	Mean	SD
LTV	91%	4%	97%	6%
CreditScore	748	42	720	56
RateSpread	0.2%	0.7%	0.0%	0.8%
LoanAmount	$331,177	$139,837	$326,258	$127,891
Number of Obs	7,811,800		3,099,706	

Table 5 (continued).

Panel C. CO and RT Refinance Loans

Below 80% LTV

Variable	CO Refi Loans		RT Refi Loans	
	Mean	SD	Mean	SD
LTV	64%	14%	63%	14%
Credit Score	743	47	759	46
Rate Spread	0.6%	0.9%	0.8%	0.8%
Loan Amount	$299,732	$136,570	$308,250	$160,391
Number of Obs	3,812,198		6,186,575	

Above 80% LTV

Variable	CO Refi Loans		RT Refi Loans	
	Mean	SD	Mean	SD
LTV	87%	3%	91%	6%
Credit Score	711	53	737	51
Rate Spread	0.0%	1.1%	0.5%	0.8%
Loan Amount	$339,569	$121,480	$303,051	$113,188
Number of Obs	167,874		2,123,902	

Table 6. RT Refinancing Rate

The dependent variable, New RT Refinance, takes the value of 1 in quarter *t* during which loan *i* refinances with a RT refinance and is zero otherwise. Mort Rate Spread is the difference between an individual mortgage loan's fixed interest rate and the market interest rate in each quarter. Low Friction Loan takes value of 1 for loans that are eligible for the VA's IRRRL administratively streamlined refinancing process and 0 for ineligible conventional loans. The full vector of controls, X_{it}, contains a set of borrower, loan, and geographic characteristics such as the borrower's credit score, loan-to-value ratio, mortgage loan amount, loans above or below 80% LTV, zip code fixed effects, and year-quarter fixed effects. These controls are iteratively added, as specified, in models (1) through (4). Standard errors are clustered by lender and zip code in all models.

$$NewRTRefinance_{it} = \alpha + \beta_1 MortRateSpread_{it-1} + \beta_2 LowFrictionLoan_{it} + \beta_3(MortRateSpread_{it-1} * LowFrictionLoan_{it}) + X_{it} + \varepsilon_{it}$$

Dependent Variable:	New RT Refi			
Model:	(1)	(2)	(3)	(4)
Constant	0.0108***	0.0356***		
	(0.0009)	(0.0025)		
Mort Rate Spread	0.0050***	0.0063***	0.0074***	0.0076***
	(0.0003)	(0.0004)	(0.0005)	(0.0005)
Low Friction Loan	0.0125***	0.0212***	0.0221***	0.0221***
	(0.0030)	(0.0033)	(0.0033)	(0.0033)
Mort Rate Spread × Low Friction Loan	0.0044***	0.0043***	0.0043***	0.0043***
	(0.0010)	(0.0010)	(0.0010)	(0.0010)
Borrower Controls		Yes	Yes	Yes
Year-Quarter FE			Yes	Yes
Zipcode FE				Yes
Observations	29,566,916	29,566,916	29,566,916	29,566,916
R^2	0.0094	0.0164	0.0298	0.0303
Dependent Variable Mean	0.0183	0.0183	0.0183	0.0183

*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 7. VA Refinancing Rate

For each type of refinance [RT,CO], the dependent variable, Yit, takes the value of 1 in quarter t during which loan i refinances and is zero otherwise. Mort Rate Spread is the difference between an individual loan's fixed interest rate and the market interest rate in each quarter. The full vector of controls, X_{it}, contains a set of borrower, loan, and geographic characteristics such as the borrower's credit score, loan-to-value ratio, mortgage loan amount, loans above or below 80% LTV, zip code fixed effects, and year-quarter fixed effects. Standard errors are clustered by lender and zip code.

$$Y_{it} = \alpha + \beta_1 MortRateSpread_{it-1} + X_{it} + \varepsilon_{it}$$

Dependent Variables:	New RT Refi	New CO Refi
Model:	(1)	(2)
Mort Rate Spread	0.0125***	0.0036***
	(0.0013)	(0.0005)
Borrower Controls	Yes	Yes
Zipcode FE	Yes	Yes
Year-Quarter FE	Yes	Yes
Observations	3,686,753	3,686,753
R^2	0.0479	0.0145
Dependent Variable Mean	0.0243	0.0096

*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 8. RT Refinancing Rate for Credit Score Bands

This table estimates the regression from Table 6, Column (4) without the credit score control variable. Instead, three data subsamples are examined based on credit ranges determined using VantageScore(R) credit bands. Column (Below Prime) shows the subsample of data for only borrowers with Subprime and Near Prime credit (300-660). Column (Prime) shows the subsample of data for only borrowers with Prime credit (661-780). Column (Above Prime) shows the subsample of data for only borrowers with Super Prime credit (781-850). Column (All) shows the triple interactions relative to the omitted group, borrowers with below Prime credit (300-660).

Dependent Variable:	New RT Refi			
Model:	(Below Prime)	(Prime)	(Above Prime)	(All)
Mort Rate Spread	-0.0004	0.0064***	0.0135***	0.0044***
	(0.0003)	(0.0004)	(0.0009)	(0.0003)
Low Friction Loan	0.0150***	0.0228***	0.0295***	0.0208***
	(0.0024)	(0.0034)	(0.0045)	(0.0025)
Mort Rate Spread × Low Friction Loan	0.0042***	0.0055***	0.0059***	0.0041***
	(0.0009)	(0.0011)	(0.0014)	(0.0009)
Credit Prime				0.0068***
				(0.0005)
Credit Above Prime				0.0093***
				(0.0008)
Mort Rate Spread × Credit Prime				0.0031***
				(0.0002)
Mort Rate Spread × Credit Above Prime				0.0056***
				(0.0004)
Low Friction Loan × Credit Prime				0.0031***
				(0.0011)
Low Friction Loan × Credit Above Prime				0.0062***
				(0.0020)
Mort Rate Spread × Low Friction Loan × Credit Prime				0.0014***
				(0.0004)
Mort Rate Spread × Low Friction Loan × Credit Above Prime				0.0019***
				(0.0006)

Table 8 (continued).

Borrower Controls	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes
Zipcode FE	Yes	Yes	Yes	Yes
Observations	1,284,857	15,761,264	8,358,341	25,404,462
R^2	0.0191	0.0286	0.0452	0.0331
Dependent Variable Mean	0.0165	0.0189	0.0219	0.0183

*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 9. RT Refinancing Rate with Mortgage Rate Spread Bins

Column (1) in this table presents the regression from Table 6, Column (4), and Column (2) replaces the $MortRateSpread_{it-1}$ variable from that estimation by a set of four rate spread bin variables, with mortgage rate spreads below 0% and 0%, (0%, 1%], (1%, 2%], and above 2%. The value of each $RateSpreadBin_{it-1}$ is equal 1 if the mortgage rate spread falls into the appropriate bin range or 0 otherwise, so exactly one rate spread bin is equal to 1 for any given loan-quarter observation. The first bin is omitted, so all coefficient estimates are relative to bin 1 (i.e. relative to no positive rate spread between the individual mortgage interest rate and the market rate).

Dependent Variable:	New RT Refi	
Model:	(1)	(2)
Mort Rate Spread	0.0076***	
	(0.0005)	
Low Friction Loan	0.0221***	0.0099***
	(0.0033)	(0.0008)
Mort Rate Spread × Low Friction Loan	0.0043***	
	(0.0010)	
Rate Spread Bin 2		0.0055***
		(0.0005)
Rate Spread Bin 3		0.0169***
		(0.0014)
Rate Spread Bin 4		0.0227***
		(0.0016)
Rate Spread Bin 2 × Low Friction Loan		0.0188***
		(0.0044)
Rate Spread Bin 3 × Low Friction Loan		0.0285***
		(0.0070)
Rate Spread Bin 4 × Low Friction Loan		0.0371***
		(0.0094)
Borrower Controls	Yes	Yes
Zipcode FE	Yes	Yes
Year-Quarter FE	Yes	Yes
Observations	29,566,916	29,566,916
R^2	0.0303	0.0307
Dependent Variable Mean	0.0183	0.0183

*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 10. VA Refinancing Rate with Mortgage Rate Spread Bins

Columns (1) and (3) in this table presents the regressions from Table 7, and Columns (2) and (4) replace the $MortRateSpread_{it-1}$ variable from that estimation by a set of four rate spread bin variables, with mortgage rate spreads below 0% and 0%, (0%, 1%], (1%, 2%], and above 2%. The value of each $RateSpreadBin_{it-1}$ is equal 1 if the mortgage rate spread falls into the appropriate bin range or 0 otherwise, so exactly one rate spread bin is equal to 1 for any given loan-quarter observation. The first bin is omitted, so all coefficient estimates are relative to bin 1 (i.e. relative to no positive rate spread between the individual mortgage interest rate and the market rate).

Dependent Variables:	New RT Refi		New CO Refi	
Model:	(1)	(2)	(3)	(4)
Mort Rate Spread	0.0125***		0.0036***	
	(0.0013)		(0.0005)	
Rate Spread Bin 2		0.0176***		0.0034***
		(0.0024)		(0.0007)
Rate Spread Bin 3		0.0354***		0.0082***
		(0.0045)		(0.0014)
Rate Spread Bin 4		0.0489***		0.0111***
		(0.0068)		(0.0020)
Borrower Controls	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes
Zipcode FE	Yes	Yes	Yes	Yes
Observations	3,686,753	3,686,753	3,686,753	3,686,753
R^2	0.0479	0.0483	0.0145	0.0142
Dependent Variable Mean	0.0243	0.0243	0.0096	0.0096

*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Appendix A. Chapter 3 Example Data

This appendix shows example CoreLogic data, ICE-McDash data, and merged CoreLogic-ICE-McDash data used in Chapter 3. Of note, only a few of the available variables are shown, and variable names have been changed for easier readability. Borrower names and full street addresses are removed from these example data for homeowner privacy but exist in the actual data.

Panel A. CoreLogic Example Data

PropertyID	BorrowerFullName	City	State	zipcode	YearBuilt	LenderType	MORTGAGE TYPE CODE	MORTGAGE AMOUNT	MORTGAGE DATE	MORTGAGE DUE DATE	MORTGAGE INTEREST RATE
1000008718	Name 1 (removed for privacy)	HENDERSON	NV	890113165	NA	VA	P	599732	20170615	20470701	NA
1000008718	Name 1 (removed for privacy)	HENDERSON	NV	890113165	2017	VA	R	605060	20180120	20480201	NA
1000008718	Name 1 (removed for privacy)	HENDERSON	NV	890113165	2017	VA	R	583748	20200304	20500401	NA
1000008718	Name 1 (removed for privacy)	HENDERSON	NV	890113165	2017	VA	R	582200	20201214	20511101	NA
1000025961	Name 2 (removed for privacy)	RENO	NV	89521	2019	CNV	P	474273	20190927	20491001	2.25
1000025961	Name 2 (removed for privacy)	RENO	NV	895214528	2019	CNV	R	470000	20210319	20510401	NA
1000027066	Name 3 (removed for privacy)	SPARKS	NV	89436	NA	CNV	P	397814	20190514	20490601	NA
1000027066	Name 3 (removed for privacy)	SPARKS	NV	894369358	2019	CNV	R	400600	20200326	20500401	NA
1000027066	Name 3 (removed for privacy)	SPARKS	NV	894369358	2019	CNV	R	396893	20210213	20510301	NA
1000027066	Name 4 (removed for privacy)	SPARKS	NV	894369358	2019	FHA	P	360479	20230315	20530401	NA
1000071619	Name 5 (removed for privacy)	LAS VEGAS	NV	89141	NA	CNV	P	361446	20180618	20480701	NA
1000071619	Name 5 (removed for privacy)	LAS VEGAS	NV	89141	2018	CNV	R	360000	20190621	20490701	NA
1000071619	Name 5 (removed for privacy)	LAS VEGAS	NV	891418786	2018	CNV	R	398800	20200606	20500701	NA
1000071619	Name 6 (removed for privacy)	LAS VEGAS	NV	891418786	2018	CNV	P	413250	20210217	20510301	NA

Panel B. ICE-McDash (Loan, Loan Current, Loan Delinquency) Example Data

loanid	zip	producttypeid	closingmonth	originalinterestrate	originalterm	originalloanamount	originalpropertyvalue	originalcreditscore	originalltv
1344958385	89120	4	509	0.0699	360	217000	290000	762	0.75
82968255	89120	2	472	0.05625	360	270000	303000	749	0.8911
82981999	89120	1	478	0.0325	360	296000	355000	722	0.8329
84142470	89120	1	470	0.045	359	285000	293000	783	0.9718
84421416	89120	6	522	0.06875	360	528000	587000	738	0.9
85232399	89120	2	505	0.0225	360	196000	204000	NA	0.9598
86086851	89120	2	506	0.0325	360	149000	189000	727	0.7885
89072906	89120	3	516	0.12375	240	66000	525000	729	0.1257
89274858	89120	1	459	0.0475	360	175000	178000	761	0.9819
90948407	89120	1	476	0.04125	360	239000	282000	624	0.8479

Appendix A (continued).

Panel C. Merged Example Data

Quarter	PropertyID	borrowerfullname	zipcode	loantype	loanpurpose	mortgage date	RefiEligibleAgain	NewRTRefi
2017 Q1	1014001743	Name 1 (removed for privacy)	89131	VALoan	Purchase	20160114	1	0
2017 Q2	1014001743	Name 1 (removed for privacy)	89131	VALoan	Purchase	20160114	1	0
2017 Q3	1014001743	Name 1 (removed for privacy)	89131	VALoan	Purchase	20160114	1	0
2017 Q4	1014001743	Name 1 (removed for privacy)	89131	VALoan	Purchase	20160114	1	0
2018 Q1	1014001743	Name 1 (removed for privacy)	89131	VALoan	Purchase	20160114	1	0
2018 Q2	1014001743	Name 1 (removed for privacy)	89131	VALoan	Purchase	20160114	1	0
2018 Q3	1014001743	Name 1 (removed for privacy)	89131	VALoan	Purchase	20160114	1	0
2018 Q4	1014001743	Name 1 (removed for privacy)	89131	VALoan	Purchase	20160114	1	0
2019 Q1	1014001743	Name 1 (removed for privacy)	89131	VALoan	Purchase	20160114	1	0
2019 Q2	1014001743	Name 1 (removed for privacy)	89131	VALoan	RTrefi	20190422	0	1
2019 Q3	1014001743	Name 1 (removed for privacy)	89131	VALoan	RTrefi	20190422	0	0
2019 Q4	1014001743	Name 1 (removed for privacy)	89131	VALoan	RTrefi	20190422	0	0
2020 Q1	1014001743	Name 1 (removed for privacy)	89131	VALoan	RTrefi	20190422	1	0
2017 Q1	1028448001	Name 2 (removed for privacy)	89123	ConvLoan	Purchase	20140815	1	0
2017 Q2	1028448001	Name 2 (removed for privacy)	89123	ConvLoan	Purchase	20140815	1	0
2017 Q3	1028448001	Name 2 (removed for privacy)	89123	ConvLoan	Purchase	20140815	1	0
2017 Q4	1028448001	Name 2 (removed for privacy)	89123	ConvLoan	Purchase	20140815	1	0
2017 Q4	1028448001	Name 2 (removed for privacy)	89123	ConvLoan	RTrefi	20171107	0	1
2018 Q1	1028448001	Name 2 (removed for privacy)	89123	ConvLoan	RTrefi	20171107	0	0
2018 Q2	1028448001	Name 2 (removed for privacy)	89123	ConvLoan	RTrefi	20171107	0	0
2018 Q3	1028448001	Name 2 (removed for privacy)	89123	ConvLoan	RTrefi	20171107	1	0
2018 Q4	1028448001	Name 2 (removed for privacy)	89123	ConvLoan	RTrefi	20171107	1	0
2019 Q1	1028448001	Name 2 (removed for privacy)	89123	ConvLoan	RTrefi	20171107	1	0
2019 Q2	1028448001	Name 2 (removed for privacy)	89123	ConvLoan	RTrefi	20171107	1	0
2019 Q3	1028448001	Name 2 (removed for privacy)	89123	ConvLoan	RTrefi	20171107	1	0
2019 Q3	1028448001	Name 3 (removed for privacy)	89123	ConvLoan	Purchase	20190930	0	0
2019 Q4	1028448001	Name 3 (removed for privacy)	89123	ConvLoan	Purchase	20190930	0	0
2020 Q1	1028448001	Name 3 (removed for privacy)	89123	ConvLoan	Purchase	20190930	0	0

Appendix B. Chapter 3 Sample Selection

The initial ICE-McDash data contain 3,863,279 unique mortgage loans originated in Washington, Oregon, and Nevada in the 10-year period from 01 January 2014 through 31 December 2023. The initial data include mortgages for various borrower types, lender types, and real estate asset types. From this initial ICE-McDash data, I retain observations for residential real estate mortgages for single family/condos/townhouses, removing 787,581 multifamily/business/investment/rehab construction loans. Next, I remove 257,315 loans for non-owner-occupied properties. Then, I remove 142,665 jumbo loans and 23,611 second lien/HELOCs. I retain only Conventional and VA mortgage loans, removing 365,582 other loan types (e.g. FHA loans).

Next, I retain all fixed rate fully amortized loans, the predominant mortgage loan type in the United States (Campbell, 2013), removing 44,746 adjustable rate, interest only, teaser rate, ballooning, or graduated payment mortgages. Unlike adjustable-rate mortgages (ARMs), borrowers with FRMs can exercise their option to refinance when market interest rates fall below their current mortgage rate. Then, I further restrict the sample to only 30-year mortgage terms, removing 448,273 loans with other payment term lengths. Lastly, I remove 223,895 observations with missing or 0% interest rates, missing or $0 loan amounts, and loans that exceed the published conventional and VA LTV lending limits by a margin of error greater than 0.5% (Fannie Mae, Freddie Mac, Ginnie Mae).

Appendix B (continued).

The ICE-McDash data uniquely match to the CoreLogic data producing a data sample with 924,486 individual mortgage loans.[16] After merging, I remove loan-quarter observations where the loan is not eligible to refinance due to loan seasoning requirements. Of note, there are 202 loans that refinance without meeting loan seasoning requirements, and the results of this study are not sensitive to inclusion or exclusion of these 202 unseasoned refinances.

This study uses a final sample consisting of 29,566,916 loan-quarter observations. These observations consist of VA and conventional mortgage loans that are eligible for refinancing for the most common type of residential mortgage in the United States: 30-year fixed-rate mortgages (FRMs) for single-family owner-occupied homes.

[16] Loans are matched on property type, mortgage date, loan amount, loan type, loan term duration, property location, and loan purpose. The match rate was 58.9%, and mortgage loans that did not have a unique match between the two datasets were excluded from the analysis.

Appendix B (continued).

Figure 11. Sample Selection Data Waterfall

This figure shows how the data filters impact the final sample used in this study. The initial data include more than 3.8 million mortgages in Washington, Oregon or Nevada from 01 January 2014 through 31 December 2023 for all borrower types, lender types, and real estate types. The final sample includes nearly 1 million fixed-rate, 30-year term, fully amortized, conventional and VA mortgages for single-family owner-occupied homes that uniquely match between ICE-McDash and CoreLogic data.