Essays on Mortgages and Government Debt

A dissertation presented
by
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to
The Department of Economics
in partial fulfillment of the requirements
for the degree of
Doctor of Philosophy
in the subject of
Economics
Harvard University
Cambridge, Massachusetts
November 2016
Abstract

This dissertation focuses on mortgages and government debt. The first chapter explores the microelasticity of mortgage demand to interest rates. Using a novel regression discontinuity approach and using novel administrative data alongside individual loan- and credit-level data, I find a large intensive and extensive margin response. A 25 basis point decrease in mortgage rates for high-FICO individuals is associated with a 50% increase in the likelihood of a potential borrower to demand a loan and an increase in loan size of approximately $15k, or approximately 10% of the average origination volume. I also document that for both the intensive and extensive margin, borrowers with high FICOs tend to be more sensitive to interest rate changes, elasticities are relatively constant over time, and the marginal responsiveness to interest rates is decreasing.

The second chapter, joint with Paul Willen and Andreas Fuster, studies the time-varying price of financial intermediation in the mortgage market. We find that the price of intermediation, measured as a fraction of the loan amount at origination, is large – 142 basis points on average over the period 2008-2014. At daily frequencies, intermediaries pass on price changes in the secondary market to borrowers in the primary market almost completely. At lower frequencies, the price of intermediation fluctuates significantly. It is highly sensitive to application volume. Over 2008-2014, the price of intermediation increased about 30 basis points per year, potentially reflecting increased mortgage servicing costs and increased legal and regulatory burdens. Finally, increases in volume associated with “quantitative easing” (QE) led to substantial increases in the price of intermediation, which attenuated the benefits of QE to borrowers.
The third chapter studies how the U.S. government primary surplus (separating out expenditures and revenues) has responded to debt historically. I focus on three main themes. First, I find that recent government policy (1950-2012) has been less responsive to debt than the historical period (1792-1950). Second, I provide evidence of non-linearity in the debt function, with governments responding more strongly to higher levels of debt. Finally, I explore the reaction of the U.S. government not only to its own debt, but also to U.S. sector-level debt.
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Acknowledgments

I thank my advisers, Kenneth Rogoff, Gabriel Chodorow-Reich, and N. Gregory Mankiw for their constant support of these projects.

I am grateful for the support and resources provided by the Federal Reserve Bank of Boston. In particular, Paul Willen has served as an invaluable informal adviser and mentor.

I am grateful for the support of informal mentors and advisers throughout the last four and a half years: Benjamin Friedman, Andreas Fuster, Marc Melitz, Jeff Miron, and Christina Wang. I am thankful for my colleagues, especially Joshua Abel, Vishal Chanani, Yin Chen, and Nathan Hipsman.

These projects also benefited from helpful discussions from the participants of Harvard’s macro lunch, the lunch seminar at the St Louis Fed, and the NBER Summer Institute session of Capital Markets and the Economy.

I acknowledge the financial support of the Harvard international economics summer grant, the AEA CSWEP summer grant, Harvard GSAS Scholarship, Harvard GSAS Dissertation Completion Fellowship, and the John Meyer Fellowship at the Joint Center of Housing Studies.

I am also thankful for the support of the graduate administrator, Brenda Piquet, who went above and beyond the call of duty to support my projects.

And finally, I am grateful for my family: my parents and my brothers. And, my future husband, Ben Roth, for his constant love and support.
Introduction

This dissertation consists of three essays applying economic analysis toward understanding the mortgage market and the government response to debt more broadly. The first essay documents the microelasticity of mortgage demand to interest rates. The second essay documents the time-varying price of financial intermediation in the mortgage market. The third essay gives detail on the historical response of the U.S. government to national and sectoral debt.

The first essay documents measures the microelasticity of mortgage demand to interest rates. Despite the importance of this parameter for models of monetary policy efficacy, little is known about the intensive and extensive margins of mortgage demand to interest rates. I propose an identification strategy using novel microdata on mortgage rates. I exploit the fact that, due to regulatory factors, spreads in mortgage rates across borrowers exhibit a cutoff at certain FICO scores, and show using default and securitization data that a regression discontinuity design across mortgage pricing breakpoints isolates demand, not supply, margins. I show that the intensive and extensive margins of demand for mortgages are sensitive to interest rates and are economically large: a 25 basis point decrease in mortgage rates for high-FICO individuals is associated with a 50% increase in the likelihood of a potential borrower to demand a loan and an increase in loan size of approximately $15k, or approximately 10% of the average origination volume. I additionally find that for both the intensive and extensive margin, borrowers with high FICOs tend to be more sensitive to interest rate changes, elasticities are relatively constant over time, and the marginal responsiveness to interest rates is decreasing.
The second essay, which is joint work with Andreas Fuster and Paul Willen, documents the time-varying price of financial intermediation in the mortgage market. The U.S. mortgage market links homeowners in the U.S. with savers all over the world; in this paper, we focus on the intermediaries who facilitate those transactions and ask how much of the flow of money from savers to borrowers actually goes to these intermediaries. We develop a new methodology and use a new administrative dataset to answer the question. We find that the price of intermediation, measured as a fraction of the loan amount at origination, is large — 142 basis points on average over the period 2008-2014. At daily frequencies, intermediaries pass on price changes in the secondary market to borrowers in the primary market almost completely. At lower frequencies, the price of intermediation fluctuates significantly. It is highly sensitive to volume: a one standard deviation increase in applications for new mortgages leads to a 30-35 basis point increase in the price of intermediation. Additionally, over 2008-2014, the price of intermediation increased about 30 basis points per year, potentially reflecting increased costs of mortgage servicing and an increased legal and regulatory burden. Finally, increases in volume associated with “quantitative easing” (QE) led to substantial increases in the price of intermediation, which attenuated the benefits of QE to borrowers.

The third essay asks how the U.S. government has historically reacted to debt. Has it been largely passive, letting times of high growth decrease the overall debt/GDP ratio, or has it tended to react by decreasing expenditures in times of high debt? This paper estimates a historical fiscal reaction function to investigate whether the U.S. government has tended to be fiscally prudent. My work highlights a few new findings. First, by separating out the effects of the two components of the primary surplus – revenues and expenditures – I find that the government typically reacts to debt by changing expenditures, rather than simply allowing revenues to constitute the entire change in the primary surplus. Second, I investigate whether the government reaction function has been nonlinear, finding evidence that the government reacted strongly to relatively high levels of debt by raising its primary surplus in earlier decades, but the nonlinearity is not evident over the past six decades or
so. Third, I investigate the reaction function of the government not only to its own debt, but also to the debt of households, corporations, and financial institutions, finding evidence that changes in sector-level debt correspond to increases in the primary surplus. I conclude with directions for further work.
Chapter 1

What is the Microelasticity of Mortgage Demand to Interest Rates?

1.1 Introduction

An important parameter for understanding the impact of macroeconomic policy is the elasticity of new mortgage borrowing to interest rates. Housing is a major component of the business cycle, and one channel of monetary policy transmission centers on the premise that decreases in interest rates will ultimately pass through to residential investment by decreasing the cost of mortgages and increasing the demand for housing. Yet, in the aftermath of the financial crisis, even as unconventional monetary policy put downward pressure on interest rates of varying maturities, the number of purchase mortgages hardly budged.

The measurement of the elasticity of mortgage demand to interest rates is not as straightforward as it may seem. Using macroeconomic data obscures the measurement of the mortgage elasticity since low interest rates tend to be driven by negative macroeconomic shocks, which in turn have large negative impacts on mortgage demand. Figure 1.1 shows the time series of the headline mortgage rate and the total purchase mortgage volume from 2000 to 2014. From 2008 onward, in the aftermath of the crisis, mortgage rates fell from 6% to
4%, yet mortgage originations also fell over this period. This is not surprising given that the financial crisis was accompanied by a macroeconomic slowdown and may have discouraged borrowers. Yet it highlights the econometric challenge of identifying the true responsiveness of mortgage demand to interest rates, since estimation using broad macroeconomic data must make a number of structural assumptions for the impact of other macroeconomic factors, and in doing so may introduce a lot of uncertainty about the elasticity parameter estimate itself.

In this paper, I measure the mortgage microelasticity of demand to interest rates using a novel identification method that uses interest rate discontinuities across certain borrower credit scores. This empirical method measures the “local” or “micro” elasticity of mortgage demand – the responsiveness of borrowers to interest rates, holding all else constant, such as borrower wealth and house prices.\(^1\) I show that, for my sample, these discontinuities in pricing are completely determined by regulation, namely Loan Level Pricing Adjustments.

\(^1\)The term “microelasticity” has been used to think about labor elasticity, where the micro elasticity is the partial equilibrium response and the macro elasticity is the general equilibrium response.
(LLPAs), which cause breakpoints in mortgage pricing depending on credit scores and leverage, typically referred to in the mortgage context as the loan-to-value ratio (LTV). I use a novel proprietary dataset to derive the exact wholesale mortgage rates offered on a daily basis, and tie the mortgage rate breakpoints across FICO scores to subsequent mortgage origination demand using detailed loan-level mortgage origination data. I provide evidence that, for borrowers with the credit scores that I consider, the change in mortgage behavior across breakpoints is driven by mortgage demand rather than lender-driven supply.

I find large and statistically significant effects of interest rate changes on the demand for purchase mortgages. On the extensive margin, I find that a decrease in interest rates by 25 basis points results in an increase in the propensity to obtain a mortgage of about 50%. On the intensive margin, I find that the average borrower increases the amount of mortgage borrowing by approximately 10% for a 25 basis point decrease in interest rates. While the average estimate indicates the loan to value ratio increases as interest rates fall, for most of the estimates, a zero effect cannot be ruled out.

I find evidence of heterogeneity in the responsiveness to mortgage rates. Across credit scores, higher FICO borrowers seem to be more responsive, both by increasing selection into obtaining a mortgage and also by obtaining larger mortgages. Across mortgage rate changes, there appears to be concavity in borrower responsiveness, with a decreasing elasticity as the interest rate changes become larger.

The potential policy implications of my study are large. Purchase mortgages have fallen after the crisis despite decreases in mortgage rates. The total number of first-lien purchase mortgages was 2.74 million in 2012, a 44.4 percent decline since 2011 and a 54.5 percent decrease from the peak volume of 2005. This decrease in purchase mortgages has not translated one-for-one to lower sales activity; all-cash purchases have increased to partially offset the mortgage decline, and overall house sales have only decreased 20 percent from 2001 to 2012. Evidence points to a differential change in mortgage demand across FICO scores: Figure 1.2 shows the impact for high versus low credit scores. The percent

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2Numbers from Goodman et al. (2014).
Figure 1.2: Originations (top) and refinances (bottom) for low and high-credit consumers. Count on left panel and amount or right panel, both as percent of total across all FICOs. The other categories not shown (FICO 660-719) have approximately constant percentage shares over this period. Source: McDash LLC, author’s calculations.

of originations and refinances, both by count and by loan volume, rose for the strongest borrowers after the financial crisis. The fraction of loans going toward the best (720+ FICO) borrowers increased from 55% in early 2010 to 65% in 2015, while the share of loans from low-FICO borrowers (FICO 620-659) fell from over 18% in 2010 to less than 10% in 2015.

While some of the decrease in borrowing for the lowest-FICO (particularly subprime) individuals was driven by supply constraints, my results indicate that for higher FICO borrowers, the margin of adjustment was likely on the demand side. Since my analysis focuses on relatively high credit score borrowers after the financial crisis, my estimates have direct implications for the efficacy of monetary policy after the crisis. The LLPAs essentially function as a credit surface, with borrowers facing different interest rates depending on their credit score and LTV. My estimates indicate that, holding fixed borrower characteristics, the responsiveness of mortgage borrowing to interest rates was relatively constant over the

3 For low credit score borrowers, lenders may have been more sensitive to putback risk and therefore more cautious to make the mortgages at all.
period, pointing to the role in regulatory-induced credit spreads in facilitating a decrease in overall purchase mortgage originations, particularly amongst low credit score borrowers.

My work contributes to many strands of literature. Empirical estimates of the elasticity of mortgage demand to interest rates are sparse. Glaeser and Shapiro (2003) investigate the elasticity of housing demand to interest rates by using state-level variation in the home mortgage interest deduction, but do not find a significant response in homeownership levels across states to the policy. Focusing on house prices rather than housing demand, Glaeser et al. (2012) find that house prices are less responsive to interest rates than the standard pricing model used in housing market analysis would predict. Fuster and Zafar (2014) attempts to measure the sensitivity of housing demand using a survey that asks the respondents’ willingness to pay under various financing conditions, including different mortgage rates. An increase in mortgage rates by two percentage points is found to change the willingness to pay for a home by only about five percent on average. The extensive margin choice of whether to purchase a home is not explored. Best et al. (2015) exploits quasi-experimental variation in interest rates due to notched mortgage contracts in the UK; that is, mortgage interest rates follow a step function of the loan-to-value ratio (LTV) at the time of loan originations. Examining bunching estimates at LTV breakpoints at time of refinancing (i.e. holding constant the purchased house), Best et al. find that the mortgage demand elasticity is about 0.3 on average and is strongly heterogeneous, in particular increasing in leverage. Best et al.’s study has important implications for the elasticity of intertemporal substitution – remortgagors are deciding how much consumption to give up now to lower interest payments in the future.

My paper is the first to study the impact of interest rates on purchase mortgage originations for a recent time period. The closest paper is DeFusco and Paciorek (2014), which uses bunching at an interest rate discontinuity at the jumbo-conforming spread to measure the elasticity of demand for pre-2007 loans. In terms of broader trends in the elasticity

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4My paper differs from DeFusco and Paciorek in several ways. First, I have direct pricing from lender rate sheets, whereas DeFusco and Paciorek must estimate the jumbo-conforming spread using rates for different borrowers and trying to condition on observables – a method which could be biased if unobservables drove
of demand for loans to interest rates, Karlan and Zinman (2013) run an experiment in Mexico in which the researchers are able to exogenously impose lower interest rates. By showing that there does not appear to be credit rationing for high-quality borrowers, my paper touches on themes in Li and Goodman (2014), and is consistent with the estimate in Anenberg et al. (2015) that credit supply was unchanged for high-FICO borrowers from about 2008 to 2015.

The structure of the paper is as follows. Section 1.2 discusses data and measurement, briefly introducing mortgage market mechanics as necessary. Section 1.3 outlines a simple model that describes how mortgage rates might be expected to respond to mortgage rates. Section 1.5 gives an overview of the specific regression discontinuity approach, discussing the baseline specification and multiple pieces of evidence suggesting that the approach is valid. Section 1.4 discusses the estimation results. Section 1.5 discusses empirical robustness. Section 1.6 concludes.

1.2 Mortgage Background and Data

In this section, I give a brief overview of my regression discontinuity strategy. I provide a brief background of the mortgage market to give a sense for why this regression discontinuity design can be used, and give details on the underlying data and measurement.

Figure 1.3 shows an example of the regression discontinuity design at the heart of my paper. The plot shows the “mortgage propensity” – defined as the number of mortgages

the sorting and rates offered near the jumbo-conforming breakpoint. Second, I claim that borrowers just below and above the FICO thresholds are identical and hence interest rate variation from their perspective is exogenous, whereas variation in the jumbo-conforming spread could be endogenous. Third, one might believe the conforming loan limit is subject to supply thresholds, in the sense that lenders may be more likely to offer loans just below the threshold since these are considered less risky. Finally, my method has the benefit of estimating potentially heterogeneous elasticities across borrower types, time, and interest rate gaps.

5The researchers find that the price elasticity of demand for credit is quite elastic: outstanding loan balances and the number of loans each increase by more than 10% from the 10 percentage point reduction in the interest rate (on a base of roughly 100% APR). While their setting is obviously quite different – due in part to being situated in a developing country with less formal credit markets and higher baseline interest rates – the finding lends support that the extensive and intensive margins of borrowing increases can be quite “elastic”, in the sense that the amount of credit demanded changes by a greater percentage than the percentage by which the price of credit changes when a shift in price occurs.
Figure 1.3: Example of RD strategy. Primary y-axis shows the measure of mortgage propensity (number of mortgages obtained in the week relative to the estimate of potential borrowers). The secondary y-axis shows the estimated mortgage rate for a borrower with the given FICO score; note the discontinuous jump at FICO 720. For 2009 week 5 purchase mortgages only. Graph shows simple linear regression on each side of the breakpoint. Panels B and C show different “pseudo” RD breakpoints. Source: NY Fed CCP / Equifax, McDash LLC, Optimal Blue, author’s calculations.
originated per individual in the population – per FICO score for 2009 week 5 (approximately Jan 29 - Feb 5) against the rate spread. The mortgage rate discretely jumps from almost 5.9 percent for FICO 719 to 5.4 percent for FICO 720. Linear fits for the mortgage propensity over the relevant ranges (700-719 and 720-739) are shown. The mortgage propensity increases as FICO increases, and the graph shows a discrete jump upward at FICO 720, just where the mortgage rate falls. In my empirical exercise, I would calculate the extensive elasticity by taking the jump size (approximately 20 mortgages per 10,000 individuals) divided by the rate spread (approximately 50bp). As with all regression discontinuity designs, this estimate is sensitive to the type of function estimated on each side of the breakpoint.

The time period studied is October 2008 - December 2014. I study conforming purchase mortgages and restrict the baseline analysis to first-lien mortgages. For my baseline regression discontinuity analysis, I construct a table with the count of the potential borrower population over time (from Equifax tables reflecting the population per credit score), the count of conventional mortgages originated, mortgage rates, origination amounts, and appraisal amounts, by week for each FICO score. For robustness, I create a similar table for FHA mortgages, as well as separate tables for default and securitization trends.

I discuss the details underlying each of these data in the following subsections.

1.2.1 Mortgage rates

One of the most distinctive data sources used in this project is lender ratesheet data, from a vendor called LoanSifter (now part of Optimal Blue), available from October 2008 onward. This is a rare dataset, accessed through the Federal Reserve, that reflects mortgage rates being offered on the primary mortgage market conditional on borrower characteristics. That is, this database allows the user to pose as a loan officer, inputting desired loan size amount, loan-to-value (LTV), debt-to-income (DTI), MSA, and credit score. The database then searches through a collection of lender-uploaded rate sheets (typically updated at least once per day).
once daily) and finds a menu of rate/point combinations to offer to the borrower. The data is collected from an actual software platform that loan officers use to search for mortgage rates.

Rate sheets offer several combinations of points ("Yield spread premiums", or YSPs; also known as the Service Release Premium or negative discount points) and rates and reflect the willingness-to-pay of an investor for a given mortgage. The yield spread premium reflects the amount, as a percentage-point of the loan amount ("point"), transacted upon closing the loan, where 100 reflects no additional payment or rebate. YSPs above 100 reflect payments from the investor, and are often split equally toward the loan officer’s commission and the borrower’s closing costs on the loan. Lower YSPs correspond to lower mortgage rates and reflect that the borrower must compensate the investor for the lower cash flow.

In the estimates throughout this paper, I hold borrower characteristics (except for FICO) constant and YSP constant at 0.

The ability to access rate/point combinations is important for a few reasons. First, perhaps contrary to popular belief, there is no single mortgage rate, even conditional on all borrower characteristics. Rather, the borrower has the option to pay points upfront, quoted as a percentage of the loan amount, to lower the ongoing rate; conversely, borrowers may actually choose to pay "negative" points to help cover the downpayment and closing costs in exchange for a higher mortgage rate. Second, most datasets used in the academic literature only have the mortgage rate, but do not contain any information on points, and hence may misrepresent the actual trend in mortgage costs. Third, many papers try to control for pricing on characteristics by backing out the relationship of mortgage rates and borrower parameters such as the LTV and credit score, which is imperfect with a small sample size. In contrast, I can input these parameters directly.

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7 Fuster et al. (2015) discusses other important implications of using point-normalized mortgage rates, such as correctly evaluating the passthrough from mortgage backed securities prices to the effective prices of mortgages that borrowers see.

8 See, for instance, the jumbo-conforming spread estimates in Sherlund (2008).
Table 1.1: LLPAs for all Fannie Mae loans from 2007 to 2015. For each change in LLPAs, the change was first announced via a press release and later became effective. Each LLPA change corresponded to a new matrix of LLPAs across credit scores and LTV ranges. Source: Fannie Mae.

<table>
<thead>
<tr>
<th>Date announced</th>
<th>Date effective</th>
<th>Overview of changes</th>
</tr>
</thead>
<tbody>
<tr>
<td>November 6, 2007</td>
<td>March 1, 2008</td>
<td>First LLPA announcement</td>
</tr>
<tr>
<td>March 31, 2008</td>
<td>June 1, 2008</td>
<td>LLPAs increase for low-FICO borrowers</td>
</tr>
<tr>
<td>August 11, 2008</td>
<td>November 1, 2008</td>
<td>LLPAs decrease for high-LTV loans</td>
</tr>
<tr>
<td>December 29, 2008</td>
<td>April 2, 2009</td>
<td>LLPAs generally increased</td>
</tr>
<tr>
<td>September 22, 2009</td>
<td>January 1, 2010</td>
<td>Increased mortgage insurance.</td>
</tr>
<tr>
<td>December 23, 2010</td>
<td>April 1, 2011</td>
<td></td>
</tr>
<tr>
<td>April 17, 2015</td>
<td>September 1, 2015</td>
<td></td>
</tr>
</tbody>
</table>

LLPAs

Over my sample, mortgage rates have only varied across borrowers due to regulatory Loan Level Price Adjustments (LLPAs). Even though default risk is insured against in securitized loans, pricing of mortgages across FICO scores has historically varied as lenders offered lower rates to higher credit score borrowers.\(^9\) There was no systematic premium for having a low credit score until November 6, 2007, when the FHFA announced the implementation of loan-level price adjustments (LLPAs), applicable to all Fannie/Freddie loans, which over this period accounted for approximately 80% of all mortgages.\(^10\) LLPAs were issued as additional fees, paid upfront by the lender to Fannie/Freddie, to compensate the perceived additional risk imposed in mortgages. LLPAs increase in leverage (LTV) and FICO, with discrete breakpoints that incentivize remaining just below certain LTV cutoffs.

Table 1.1 describes the relevant changes to LLPAs over the sample period. Over the period analyzed in my paper (October 2008 to December 2014), there were only four LLPA changes that affected the loans of interest, although the full history of relevant changes is

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\(^9\)One potential explanation for this is that lenders prefer to keep safer loans on portfolio (rather than securitize them) and were willing to pay more – or offer a lower rate – to attract the higher credit score mortgages. Also, servicing could be more profitable on higher credit score investors, who are less likely to default and therefore require less costly action on the part of the servicer.

\(^10\)See announcement at https://www.fanniemae.com/content/announcement/0716.pdf
included in Table 1.1 for completeness. Untabulated results indicate that lenders typically price LLPAs into mortgage rates at announcement.

I find that LLPAs, once instituted, completely determine mortgage spreads. By matching my proprietary rate sheet data with the time series of LLPAs, I test whether the wholesale mortgage rates include additional “overlays” – premiums charged to individuals with different credit scores. Even though some lenders may price differentially, on average, the gap between (say) a FICO 680 and FICO 740 loan, all else equal, is exactly equal to the LLPA charged by the GSEs.

Figure 1.4 illustrates the LLPA charges for the LLPA matrix effective April 1, 2011, which was in effect for a large part of my sample period. While most conventional loans are LTV 80 and below, it is possible that borrowers pay private mortgage insurance (PMI) and increase their LTV. In practice, this is relatively rare, but I include the LLPAs for higher LTVs for completeness. The LLPAs are about the same across LTVs for any given FICO score, with the exception of lower LLPAs for LTV 70 and below.

A key implication of the fact that LLPAs explain the exact spread between borrowers with different FICO scores is that the actual mortgage rate obtained by the mortgage investor is constant across the cutoff, even though the mortgage rates that the borrowers face vary, with the LLPA “wedge” between the lender and borrower rates paid directly to the GSEs. Hence, lenders are acting optimally, in the sense that they charge the same mortgage rate to virtually identical borrowers with virtually identical default and putback risk.

How big are the rate differences across FICO scores induced by LLPAs? The answer depends on how the upfront payment (required by the LLPA to Fannie Mae) is translated into the mortgage rate (which depends on what mortgage rate would equilibrate the present value of payments to the upfront payment, which in turn depends primarily on projected prepayment speeds). The rate spreads estimated are shown in Figure 1.5. Rate spreads

11 As a back of the envelope, consider that the LLPA for a FICO 700 borrower with LTV 80 on April 30, 2011 was 1 percentage point of the loan amount. The median loan amount for my sample is approximately $200k, which would correspond to an LLPA of $2k. While this is an upfront payment paid by the lender, my ratesheet data indicates that lenders price the entire LLPA into mortgage rates by increasing mortgage rates to offset this fee. Exactly how much mortgage rates need to rise depends on projected prepayment rates, which can
Figure 1.4: LLPAs for LLPA matrix effective April 1, 2011. This time period dominates the sample (effective until August 31, 2015). LLPAs are virtually constant across LTVs but vary much more across FICO scores. For the analysis, I assume the LLPAs are always those for a maximum LTV of 80, since borrowers tend to bunch at 80 LTV. Source: Fannie Mae

Figure 1.5: Rate spreads used for estimation. Rates are normalized to a yield spread premium of 100 (no points) and averaged across weeks, as described in Section 1.2.1. Spreads are shown in percentage points, with the spread defined as mortgage rate corresponding to the lower FICO bin minus the mortgage corresponding to the higher FICO bin. Source: Author’s calculations and Optimal Blue.
Table 1.2: Summary statistics, mortgage rates. Rates are for conforming 30-year FRM. The numbers shown reflect the mean across the entire baseline sample for the exact FICO score shown, on the weekly level, from October 2008 to December 2014. Higher FICO scores tend to benefit from lower mortgage rates due to lower upfront payments induced by LLPAs. Source: Optimal Blue and Fannie Mae; author’s calculations.

<table>
<thead>
<tr>
<th>FICO Score</th>
<th>Mean</th>
<th>SD</th>
<th>Min</th>
<th>Max</th>
<th>P10</th>
<th>P25</th>
<th>P50</th>
<th>P75</th>
<th>P90</th>
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<td>13.71</td>
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<tr>
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<td>3.32</td>
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<td>3.77</td>
<td>4.15</td>
<td>4.73</td>
<td>4.91</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Mortgage Rate Differences</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean</td>
</tr>
<tr>
<td>---------------</td>
</tr>
<tr>
<td>660</td>
</tr>
<tr>
<td>680</td>
</tr>
<tr>
<td>700</td>
</tr>
<tr>
<td>720</td>
</tr>
<tr>
<td>740</td>
</tr>
</tbody>
</table>

were the largest in the early part of the sample (October 2008 - October 2009), with spreads between FICO 680-700 and FICO 700-720 hovering above 40 basis points at times.

Table 1.2 shows summary statistics on mortgage rates in the sample. The table shows that over the entire sample, the mortgage rate difference hovered around 11bp on average for FICO 719 to 720. (The mortgage rate for FICO 700-719 is flat and is denoted on the table as the rate for FICO 700). There is significant variation in the mortgage rate differences, with the 719-720 jump having a minimum difference of 4 bp and a maximum difference of 47 bp. For the empirical exercises performed in this paper, I omit any weeks when the rate difference is less than 5bp as the results may be driven by noise.
FICO scores

FICO scores are meant as a ranking of borrower credit quality, made by a company formerly called the Fair Isaac Corporation (and now simply called FICO). The possible range runs from 350 to 850, with a low score signaling a low credit quality borrower. Typically lenders call subprime borrowers those who fall below FICO 620.

There are two other standard credit bureaus, TransUnion and Experian, which use similar inputs but different models to determine credit scores. Mortgage lenders typically pull all three credit scores and use the median as the score at which to price a mortgage. The exact FICO score recorded at origination is available in the McDash LLC data, and I use this value in the regression discontinuity to determine which mortgage rates borrowers were quoted.

I have three major credit scores via the NY Fed Consumer Credit Panel (CCP). Table 1.3 shows the variation of credit scores for borrowers in the sample. The mean and median credit score across the different metrics is similar. The summary statistics, which combine both cross-sectional and panel variation, also indicate how FICO scores vary quite a lot, with a standard deviation of about 50 credit score points. Much of this variation does exist for the same borrower across time; as shown in Figure 1.12, even in the space of 6 months, FICO scores can vary substantially. While the credit score formula changes over time and remains a closely guarded secret, discrete events such as defaults or the opening of new tradelines may be drivers of large changes in credit scores even month to month.

12In the case of joint loans, meaning two borrowers jointly applying for a mortgage, it is typically the lower of the two median credit scores, known as the “minimum FICO rule”. Joint applications for mortgages may help alleviate borrowing limits by documenting extra income, but may come at the cost of increasing the overall mortgage rate if the FICO scores fall in different bins.

13For the purpose of comparing the Equifax credit bureau data to loan origination data, I can use the merged CRISM data to create a mapping from the Equifax credit score to the FICO score. For the relevant range of credit scores, the mapping is actually one-for-one with a small positive adjustment.
Table 1.3: Summary statistics about credit scores, sample. Subsample taken for all borrowers in dataset, up to 6 months before mortgage origination, as available in the New York Fed CCP / Equifax data. Source: New York Fed CCP / Equifax.

<table>
<thead>
<tr>
<th></th>
<th>FICO Beacon 5.0</th>
<th>Vantage Score Solutions</th>
<th>Equifax Risk Score</th>
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<td>min</td>
<td>300</td>
<td>501</td>
<td>280</td>
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<tr>
<td>max</td>
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</tr>
<tr>
<td>mean</td>
<td>758</td>
<td>746</td>
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<td>sd</td>
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<td>62</td>
<td>52</td>
</tr>
<tr>
<td>p1</td>
<td>608</td>
<td>568</td>
<td>606</td>
</tr>
<tr>
<td>p5</td>
<td>659</td>
<td>621</td>
<td>661</td>
</tr>
<tr>
<td>p10</td>
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<td>824</td>
</tr>
<tr>
<td>p99</td>
<td>816</td>
<td>830</td>
<td>829</td>
</tr>
</tbody>
</table>

Source: New York Fed CCP / Equifax

1.2.2 Mortgage activity

My mortgage data comes from McDash LLC. The data cover approximately 70% of all mortgage originations in the United States. The data include characteristics of the mortgage (fixed or adjustable rate; the term; jumbo; conventional vs. FHA, etc.); relevant dates (origination, first payment, first appearance in data); and further loan-level data such as the loan-to-value ratio, origination amount; and outcome data such as foreclosure dates. The data also include unique individual IDs, which allows the mortgages to be linked to individuals in the New York Fed Consumer Credit Panel (discussed below), and unique loan IDs, which allows loans to be tracked over time.

I focus on purchase mortgages. I restrict to 30-year fixed-rate mortgages, which are by far the most common share of mortgages. I use data for only the first-lien mortgage and

14 15-year mortgages and adjustable-rate mortgages take some share of the market. The rates on across different loan terms (durations) tend to move together. Previous literature has examined borrower choice of ARM versus FRM, most of which, to my knowledge, is not focused on a price mechanism.
consider only data that has recorded FICO at origination. I also aggregate the data to a weekly level.\textsuperscript{15}

While the detailed loan data is available by origination date, the relevant decision date for borrowers is the application date, which happens well before the loan is approved and originated. Unfortunately, due to data limitations, the exact lag between application and origination date of any given loan is unknown. I therefore use the average lag across approved loans, which is approximately 35 days (5 weeks) in my sample. The lag across time varies slightly but is dwarfed by the heterogeneity within a day even for borrowers with similar characteristics. While this assumption adds noise to my exercise, it should not introduce any bias.

The mortgage data are linked on an individual level to each individual’s credit report data, which provides some demographic data (age, geography, household size) and facilitates the tracking of all credit trends of individuals who have a mortgage, on a monthly level, starting six months before origination and ending six months after the loan is removed from the data set due to termination. The data on default and securitization trends comes from the mortgage servicing data. The data track the status of the mortgage for each month after origination. I consider a loan securitized if it is securitized within 36 months of origination. I consider a loan to have defaulted if it is ever 60 days or more delinquent within 36 months of origination. Given that the data runs through 2014, the restriction to examining the first 36 months helps to limit the potential bias resulting from the fact the last years of the data haven’t yet existed for 36 months and are therefore censored.

1.2.3 Potential borrowers and credit trends

Credit trends and other individual-level data come from one of the major credit reporting agencies, the credit bureau Equifax, via the New York Fed Consumer Credit Panel. The data

\textsuperscript{15}Loan officers tend to record rounded dates (typically the first and last of each month). I drop these observations, which causes some noise but should not result in any bias. Monthly robustness checks, which include all data points, confirm the estimated magnitudes are approximately the same. I use a weekly baseline since this gives me more granular mortgage rate spread measurement.
contain a random 5% of the U.S. population with a Social Security Number. The Equifax data contain useful individual-level credit trends such as credit score, debt balances, debt payments, number of accounts, and a few demographic data such as zipcode and age of borrower. The Equifax data is available quarterly.

FICO distributions are “smooth”, meaning that there is no discontinuity between the number of mortgage borrowers from one FICO score to the next, so comparing the number of loans across thresholds gives a good sense for whether a true breakpoint exists at that cutoff. Still, to facilitate comparison across thresholds, I normalize the number of loans received by the number of “potential borrowers” for the relevant credit score. Since the NY Fed CCP is a 5% sample of the population, I scale this up appropriately. I then aggregate the number by credit score. The Equifax data only contains “riskscore”, which is not equivalent to FICO score, but historical regressions indicate that a linear offset can approximately correct for this, which I do.\footnote{The McDash LLC mortgage data has the true FICO score recorded at time of mortgage origination. This exact measure is crucial to study the response of borrowers to the breakpoint in mortgage pricing. The approximation of the credit score is only relevant for the denominator of the mortgage propensity measure and mortgage shopping sections. This is discussed further in the Appendix.}

Figure 1.6 shows the distribution of total individuals in the sample in 2008 and 2013. The distribution of individuals over credit score changes over time in the sample. While the distribution of borrowers has remained roughly constant over time, in 2013, fewer borrowers were at the very low end of the distribution, and instead more mass was concentrated at good credit scores (around 700).

I refer throughout the paper to “mortgage propensity”, which refers to the fraction of the population that actually originates a purchase mortgage in any given week. (While one could theoretically use the number of mortgage applicants as the denominator, this suffers from selection biases).\footnote{The reason that mortgage applicants are not considered as the “eligible borrower” pool is that there seems to be selection into formally applying for a mortgage. Loan officers may discourage a borrower from submitting a formal application if they think she will be rejected. This is consistent with the fact that rejection rates were actually highest in the housing boom, and fell in the aftermath. Moreover, individuals with a lot of cash on hand may choose not to apply for a mortgage, but may be willing to switch to mortgage financing if mortgage rates are sufficiently low.}

Over the breakpoints from 620-760, the average mortgage propensity in
Figure 1.6: Total borrowers by credit score, as measured using the NY Fed CCP. All primary (5% sample) borrowers are pulled from the data, then observations missing risk score are removed (approx. 11% of data). The quarterly data is collapsed to a yearly frequency using a mean of the count over all quarters for a given year. To facilitate comparison with the loan data, which contains FICO score at origination, the Equifax risk-score is roughly converted to FICO using historical relationship using borrower-level data. Source: NY Fed CCP/Equifax, author’s calculations

Table 1.4: Summary statistics, RD. The numbers shown reflect the mean across the entire baseline sample for the exact FICO score shown, on the weekly level (i.e. there are 21 purchase mortgages per week originated for FICO 680). The total borrowers is the count of all individuals with a credit history in the data, scaled to account for the fact that the data is a random 5% of the U.S. population. Source: McDash LLC and NY Fed CCP/Equifax.

<table>
<thead>
<tr>
<th>FICO</th>
<th>N mortgages</th>
<th>Total population</th>
<th>Mortgage propensity</th>
<th>Origination amount</th>
<th>Appraisal amount</th>
<th>LTV</th>
<th>DTI</th>
</tr>
</thead>
<tbody>
<tr>
<td>620</td>
<td>5</td>
<td>167377</td>
<td>1.4</td>
<td>246,468</td>
<td>0.69</td>
<td>32.2</td>
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<tr>
<td>640</td>
<td>7</td>
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<td>1.8</td>
<td>171,328</td>
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</tr>
<tr>
<td>660</td>
<td>11</td>
<td>490,996</td>
<td>2.8</td>
<td>174,968</td>
<td>0.71</td>
<td>32.9</td>
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<tr>
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<td>5.2</td>
<td>194,279</td>
<td>0.72</td>
<td>31.9</td>
<td></td>
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<tr>
<td>700</td>
<td>34</td>
<td>534,861</td>
<td>8.3</td>
<td>202,698</td>
<td>0.72</td>
<td>31.3</td>
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<td>30.6</td>
<td></td>
</tr>
</tbody>
</table>
my sample is 8 in 100,000. The higher FICO scores have much higher propensities, with the best borrowers in my baseline estimate group (700) having a mortgage propensity of approximately 8.3 (per 100,000), which is nearly an order of magnitude larger than the worst borrowers I consider (1 in 100,000).  

1.3 Theory

1.3.1 A basic model

For this analysis I focus on the consumer demand for mortgages. For ease of analysis and to isolate the effects that are important for my purposes, I assume that all consumers have already chosen to purchase a house worth $p$. Hence my analysis focuses on the decision of how much to borrow (origination amount), which then determines the loan to value ratio. The extensive margin can be interpreted as borrowers deciding to pay cash rather than borrow mortgage funds.

The model follows that of Brueckner (1994) closely, except that I consider the payment (“debt-to-income”) constraint binding rather than the loan-to-value constraint. The difference between the two constraints is essentially one of upfront collateral constraints (if the downpayment is prohibitive) or a longer-term affordability constraint. The rationale behind the choice of the payment, rather than upfront collateral constraint, is because we are studying breakpoints in conforming loans, which already have quite large downpayments (20%); individuals who are particularly collateral constrained are likely to pursue FHA loans, which require a lower down payment constraint.

Consider a two-period model, which is easily extended to multiple periods. Utility is a function of housing consumption $h$ and the numeraire nonhousing good $x$. Decisions made in the current period affect future wealth $z$, and the discounted value of future utility is

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18To give a sense that this mortgage propensity is reasonable, note that approximately 1.3 MM conforming purchase mortgages are given out per year. Considering the main mass of borrowers are between FICO 660-780, this means that there are about 10,000 mortgages per FICO score. Dividing by the 400k potential borrowers per FICO score, this is a 0.025 mortgage propensity per year, or 0.0005 per week. This aligns with Table 1.4.
given by $\delta V(z)$, where $V$ is a strictly concave function and $\delta < 1$ is the discount factor.

The consumer enters the current period with wealth $w$, which is the sum of current income and assets and is taken as exogenous. $w$ can be allocated toward housing consumption, non-housing consumption, or saving. Current wealth cannot be supplemented by borrowing against future income, but consumers may use a mortgage to make a house purchase. Let $m$ denote the size of the mortgage, $s$ denote the amount of saving, and $p$ denote the purchase price per unit of housing. Denote $\alpha < 1$ be the maximum mortgage loan-to-value ratio, and suppose the maximum payment-to-income fraction is given by $\beta$.

The problem faced by the borrower is as follows:

$$\max U(x, h) + \delta V(z)$$

subject to the current-period budget constraint:

$$x = w - s - (ph - m)$$

and the constraints:

$$s \geq 0 \quad (1.1)$$

$$\frac{\beta y}{r_m} \geq m \quad (1.2)$$

$$m \geq 0 \quad (1.3)$$

Equation 1.1 is the liquidity constraint. Equation 1.2 is the payment-to-income constraint, which states that that mortgage payment as a percentage of income falls below some critical value, here $\beta$.\(^{19}\) Equation 1.3 restricts mortgage borrowing to be positive.

We assume the mortgage rate ($r_m$) and the interest rates earned on savings ($r_s$) are non-stochastic. We assume future income $y$ is known, house prices $h$ are constant across across

---

\(^{19}\)Fannie Mae currently restricts debt-to-income ratios to be 38% for manually underwritten loans or up to 45% for borrowers who hit very specific requirements. Given the graph of DTI in Figure 5, it’s clear that most borrowers hover exactly at this DTI limit of 36%, with a slight decrease as credit scores get larger. see https://www.fanniemae.com/content/guide/selling/b3/6/02.html
periods, and future wealth is given by

$$z = y + (1 + r_s)s + ph - (1 + r_m)m$$

(1.4)

Substituting 1.4 into $V$ and substituting in the current-period budget constraint, the consumer’s objective function is given by:

$$\max_{h,s,m} U[w - s - (ph - m), h] + \delta V[y + (1 + r_s)s + ph - (1 + r_m)m]$$  

(1.5)

subject to the constraints (1)-(3).

Letting the multipliers for these constraints to be denoted by $\lambda$, $\mu$, and $\theta$, the Kuhn-Tucker optimality conditions for the problem are given by:

$$s : -U_x + (1 + r_s)\delta V' + \lambda = 0$$

(1.6)

$$m : U_x - (1 + r_m)\delta V' - \mu + \theta = 0$$

(1.7)

$$h : -pU_x + U_h + p\delta V' = 0$$

(1.8)

along with the constraints (1)-(3) and the additional conditions:

$$\lambda \geq 0, \lambda s = 0$$

(1.9)

$$\mu \geq 0, \mu \frac{\beta y}{r_m} - m = 0$$

(1.10)

$$\theta \geq 0, \theta m = 0$$

(1.11)

Then the optimal house size is governed by Equation 1.8:

$$U_h/U_x = p[1 - \delta V'/U_x] = 0$$

and the choice between savings and mortgage is given by:

$$(1 + r_s)\delta V' + \lambda = (1 + r_m)\delta V' + \mu - \theta$$

(1.12)

The implications of these equations depend on the relative magnitudes of $r_s$ and $r_m$. Brueckner (1994) argues that the case when $r_s > r_m$ is most representative of the U.S.
economy, i.e. that pretax investment returns typically exceed the (pretax) mortgage rate. When this is the case, then 1.12 requires that

\[ \lambda < \mu - \theta \]

This constraint implies that we cannot have both \( s > 0 \) and \( \beta y / r_m > m > 0 \), since this would require \( \lambda = \mu = \theta = 0 \), violating the above. Then either constraint (2) or (3) needs to bind. Consider \( m = 0 \); then \( \theta > 0 \) and \( \mu = 0 \), which could not be possible since this implies \( \lambda < 0 \). Hence, it must be the case that \( m = \beta y / r_m \).\(^{20}\) This implies that, holding all else constant, an increase in \( r_m \) (for instance, as in across our FICO breakpoint) results in a discretely lower level of mortgage borrowing \( m \). Because we take \( h \) as given, this implies the LTV is also discretely lower under the FICO breakpoint than above.

1.4 Elasticity results and discussion

1.4.1 Variable discontinuities across FICO score

The best check for the validity of the regression discontinuity design is a visual one. Figure 1.7 shows the relevant outcome variables plotted against the FICO score for 2009. There are a few interesting trends to notice. First, mortgage rates do vary quite a lot across FICO scores, with low FICO borrowers obtaining mortgage rates (adjusted to no points) of over 7% in 2009, while mortgage rates were under 5% for the borrowers with the best FICO scores. To control for potential supply effects that may be present in low-FICO borrowers, I focus on FICO 680 and above. While the rate variation here is smaller – about 25 basis points across the 719/720 cutoff – I argue in Section 1.5.1 that the supply constraints across this threshold are negligible. Both the count of originations and the origination percent of potential borrowers exhibit striking cutoffs at FICO breakpoints, including the 720/740 cutoff (and less so, due to the small mortgage rate variation, the 739/740 cutoff) that is

\(^{20}\)Brueckner shows that when \( r_s \) is stochastic, any pair of \( m \) and \( s \), and not just the largest possible mortgage, become possibly optimal.
relevant to our analysis.

The characteristics of the loans vary discretely across the threshold as well. Origination amounts and loan-to-value ratios jump at each FICO threshold, becoming higher just above the breakpoint. This is consistent with a lower cost of borrowing makes larger loans more affordable. Appraisal amounts also jump at breakpoints, indicating that a lower cost of borrowing may induce an income effect (relatively richer, so more debt) in addition to the aforementioned substitution effect (debt relatively cheaper than consumption).

Table 1.4 shows the baseline propensity to get a mortgage, origination amount, LTV, and debt-to-income ratio. All numbers are per-week and reflect averages for the exact FICO score shown. The number of mortgages averages 20-50 for FICOs 680 to 760, with the number increasing as FICO increases. The propensity to get a mortgage increases with FICO score, starting from approximately 1.4 in 100,000 for FICO 620 and increasing to approximately 19 in 100,000 for FICO 760. Origination amounts and appraisal amounts of mortgages also increase with FICO. LTV is roughly constant across all FICO scores, and the debt to income ratio tends to fall with FICO score.
Origination amount tends to increase in FICO score, which is consistent with the idea that high-FICO borrowers are more likely to be richer. Interestingly, the LTV and DTI across breakpoints are relatively constant, and is not equal (on average for the population of borrowers) to the maximum LTV of 0.8. The constant LTV and DTI across breakpoints is encouraging for my method: to the extent that lenders have cited debt-to-income as one of the largest concerns and a reason they might reject mortgages, a smooth DTI ratio across FICO thresholds indicates that there isn’t necessarily stronger screening or rejection forces just below the cutoff.

1.4.2 Baseline specification

I run, for cutoffs $\Gamma \in 620, 640, 660, 680, 700, 720, 740, 760$:

$$Y_i = \beta_0 + \beta_1 1_{FICO_i \geq \Gamma} + f(FICO_i) + 1_{FICO_i \geq \Gamma} \times g(FICO_i) + \varepsilon_i$$ (1.13)

where $i$ indexes individual loans, the dependent variable $Y_i$ indicates whether loan $i$ is one of three outcome variables: a) the percent of the “potential borrower” population that obtained a loan (extensive margin); b) the origination amount of the mortgage (intensive margin); or c) the appraisal amount of the house being purchased; and both $f(FICO_i)$ and $g(FICO_i)$ are local polynomial regressions.

The RD is run using the rectangular kernel, but the results do not change qualitatively for different choices of specification.\footnote{This is as recommended by Imbens and Wooldridge (2007), which notes that more sophisticated kernels only make a difference when the results are not credible anyway since the sensitivity of the kernel likely implies too much sensitivity to the choice of bandwidth. Gelman and Imbens (2014) discusses potentially undesirable features of using higher-order polynomials in RD and instead recommend a linear or quadratic.}. Recall each FICO breakpoint is 20 points away (i.e. ceterus parablis, the same mortgage rate is given for all borrowers in FICO 680-699, and a different mortgage rate is given to borrowers with origination FICOs between 700-719). To avoid capturing multiple breakpoints in any given regression, I only use data for loans with FICO scores +/- 19 points from the FICO breakpoint (e.g. 701 to 739 for FICO threshold 720). The baseline range is chosen to be +/- 9 from the FICO breakpoint, but to show robustness
of the results to the choice in FICO range, I show also the result for the full potential range (+/- 19) and half of the baseline range (+/- 5). Standard errors are run by bootstrapping 10000 times, with clustering on the monthly level. All baseline results are run restricting to rate spreads of at least 5 basis points; since elasticities are measured with rate spreads in the denominator, this prevents the elasticity measure from becoming unreasonably large due to random variation in low-spread weeks. Untabulated robustness tests indicate that the results hold even without restrictions on rate spreads, although with more noise.

For each week of the data, I run this regression and collect a sequence of $\beta_1$. I then divide by the relevant difference in mortgage rates across the threshold to derive the semi-elasticity of mortgage demand. The estimation is run using interest rate level changes, i.e. a one percentage point change from 5 percent to 4 percent, rather than in percent changes (where a 1% change would correspond to a change in mortgage rates from 5 percent to 4.95 percent).

### 1.4.3 Elasticity measurements

Table 1.5 shows the base case regression discontinuity results, which constitute the main contribution of this paper. For the FICO cutoffs 660, 680, 700, and 720, the regression discontinuity is run for a baseline range of +/- 10 FICO points. The loan amount, appraisal amount, loan-to-value ratio, and mortgage propensity (extensive margin) results are shown, alongside the “base” level of those variables just above each discontinuity.

Later robustness tests (see Section 1.5.1) indicate that the FICO 700 results are the most valid, in the sense that they pass every robustness test, while FICO 680 borrowers may also be subject to screening due to a jump in securitization probability above the threshold. I include these results both because a) the securitization probability jump is fairly small and b) even if screening were at play, one would need a convincing story of how high differential screening across breakpoints corresponds systematically to the variation in the mortgage rate spread.

The first two rows show the intensive elasticity of demand, in units of dollars per percentage point decrease in mortgage rate. The results indicate that the intensive margin
response is large; origination amounts increase about $52k-$79k for FICO 680 and 700 borrowers for each percentage point change in mortgage rate. This is relative to a base amount of about $200k, amounting to an approximate 25% increase in the mortgage amount per 100 basis point change in interest rates.

The third row shows that the overall impact on the loan-to-value ratio is often statistically indistinguishable from zero. The only case when this is not true is for the cutoff 700, where the positive jump in the loan-to-value ratio is significantly different from zero. Mechanically, another way to think of this result is that the origination amount increased statistically significantly more than the appraisal amount rose across the threshold, per basis point of interest rate spread.

The last row shows the extensive margin estimate over the entire sample period, defined as the break in the propensity to get a loan divided by the absolute rate spread on a weekly level. The elasticity for FICO 720 borrowers is about twice that of FICO 700 borrowers, indicating that higher FICO borrowers are more sensitive to interest rates on the extensive margin. The results for FICO 740 are noisy, likely because the rate spread was historically low, and at times zero. The magnitudes suggest that, for a group of FICO 700 borrowers facing a 25 basis point drop in interest rates, the increase in individuals getting a mortgage at all will be about 9.5 per 100,000 potential borrowers.

These magnitudes are economically large, in light of the baseline propensity to obtain a mortgage as highlighted in Table 1.4. The estimates indicate that a 25 basis point decrease in interest rates induces a FICO 680 borrower to be 30% more likely to demand a loan, and a FICO 700 borrower to be 40% more likely to demand a loan.

The estimates for FICO 660 and FICO 680 are very similar. From FICO 680 to 700, the magnitude of the response is increasing: higher FICO borrowers seem more responsive to interest rates. This is true on both the intensive and extensive margins of adjustment. It is also true regardless of whether the responses are viewed as a percentage change from baseline or as a level difference in the size of loan demanded. The most straightforward interpretation is that higher-FICO individuals may be less liquidity-constrained, so that part
Table 1.5: Base RD results. Intensive and extensive response of borrowers across interest rate discontinuities. All numbers are per 100 basis points of rate spread. Restricted to rate gaps of 5 basis points or more. Mortgage propensity is defined as the number of individuals who get a mortgage per 100,000 individuals in the population per week. Base bandwidth is 10 FICO points, but the results are robust to choosing bandwidths of 5 or 19 FICO points. Source: NY Fed CCP/Equifax, Optimal Blue, McDash LLC, author’s calculations

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<td>700</td>
<td>720</td>
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<td>Origination amount</td>
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<td>52384.9***</td>
<td>78886.0***</td>
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<td>[35044.0,69725.8]</td>
<td>[60119.6,97652.4]</td>
<td>[-8994.4,67020.3]</td>
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<td>Appraisal amount</td>
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<td>46340.8***</td>
<td>63180.6***</td>
<td>-5841.7</td>
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<td>Base appraisal amount</td>
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<td>[15933.3,76748.3]</td>
<td>[36835.4,89525.7]</td>
<td>[-71197.7,59514.4]</td>
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<td>Loan-to-value ratio</td>
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<td>0.00148</td>
<td>0.0352***</td>
<td>0.0334</td>
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<tr>
<td>Base loan-to-value ratio</td>
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<td>[0.0140,0.0564]</td>
<td>[-0.0246,0.0913]</td>
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<td>Mortgage propensity</td>
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<td>21.78***</td>
<td>37.70***</td>
<td>29.25***</td>
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<tr>
<td>Base mortgage propensity</td>
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<td>[19.53,24.03]</td>
<td>[34.13,41.26]</td>
<td>[19.63,38.88]</td>
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</tbody>
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95% confidence intervals in brackets

\* p < 0.10, \** p < 0.05, \*** p < 0.01
of the extensive margin response may be individuals who would have otherwise bought the property in cash. While the increasing responsiveness does not hold for FICO 720, the estimates overall are a lot noisier due to smaller rate spreads throughout the sample.

### 1.4.4 Concavity with respect to mortgage rate changes

Does the response of borrowers to mortgage rate changes seem to be linear, in that a 100 basis point change in mortgage rate induces four times the response relative to a 25 basis point change in mortgage rate? The answer depends on exactly how consumer mortgage demand is modeled. If there were a large fixed cost to obtaining a mortgage, one might believe the response to a large mortgage rate change would be larger than a response to a small mortgage rate change. If the results are instead driven by discrete switching of borrowers into mortgages from cash when the mortgage rate falls below a certain point (for instance, if borrowers were willing to get a mortgage at 4% but prefer to pay cash when the mortgage rate hits 4.25%), then additional decreases in the mortgage rate may not induce too much extra demand.

To test the shape of the response to mortgage rate changes of different magnitudes, for each FICO, I estimate separate RDs for mortgage rate changes that are 5-20bp, 20-40bp, and 40-60bp. Figures 1.8 to 1.9 show the results. The graphs show that the largest change in demand per interest rate spread, both on the intensive and extensive margin, is induced by small (5-20bp) changes in interest rates. While the per-basis-point scaled responsiveness is decreasing in interest rate gaps, the aggregate responsiveness is increasing, as expected. To give a sense of magnitudes, for FICO 700, the first 5-20bp induces a change in mortgage propensity of 16 per 10,000 individuals per 100 basis points of rate spread, whereas 20-40 and 40-60bp of spread induce instead a change in mortgage propensity of 10 per 10,000 individuals. For the intensive margin, the first 5-20bp have an effective responsiveness of

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22For the extensive margin, the y-axis is the discontinuity in the borrower propensity per borrower per 100 basis points of rate spread; to compare to other numbers throughout this paper, multiply by 10,000. For the intensive margin, the numbers shown reflect the log change in the origination amount per 100 basis points of rate spread.
Figure 1.8: Extensive elasticity estimates, by size of mortgage rate spread. Markers denote point estimate and lines show 95% confidence interval from 1000 bootstraps. Source: author’s calculations, McDash LLC, Optimal Blue, New York Fed CCP / Equifax
Figure 1.9: Intensive elasticity estimates, by size of mortgage rate spread. Markers denote point estimate and lines show 95% confidence interval from 1000 bootstraps. Source: author’s calculations, McDash LLC, Optimal Blue, New York Fed CCP / Equifax.
an approximate 35% increase in the origination amount per 100 basis points of rate spread, whereas 40-60bp induce a 15% increase in origination amount per 100 basis points of rate spread.

1.4.5 Elasticities over Time

Tables 1.6 and 1.7 show the elasticity estimates, split into approximately two-year increments. The extensive elasticity estimates shown in Table 1.6 are largely stable over time, with some notable exceptions. For instance, for FICO 700, the RD for 2008-2009 was estimated to be about 19 individuals per 100,000 potential borrowers getting mortgages when the interest rate falls 100 basis points. The estimate for 2010-2011 is also approximately 19. The extensive elasticity jumps in a statistically significant manner to about 25 in 2012-2013; while this magnitude is larger, it is still near the upper end of the 95% confidence intervals for the earlier periods. In contrast, the estimates for FICO 720 jump discretely for 2012-2013 in both an economically and statistically significant manner. It is possible that these larger extensive margin reactions in the 2012-2013 period were driven by increased consumer willingness to begin investing in the housing market again as the housing bust felt like a further memory.

Table 1.7 shows the intensive elasticity estimates over time. For FICO 700, these estimates are again fairly constant over time. Because there are fewer observations, the FICO 720 estimates are noisier, and cannot be claimed to be statistically different. The FICO 680 estimates show increasing magnitudes from 2008-2009 to 2010-2012 and again to 2012-2013. As with the extensive elasticity estimates, this could be in part due to increasing willingness to invest in the housing market over time, or perhaps recovering income and employment situations as the economy recovered from the crisis.

Overall, these trends must be interpreted with caution given the noise of the data and the limited sample size of running the regressions partitioned across time. Still, the overall takeaway is that for our preferred specification of FICO 700, the extensive and intensive elasticity estimates appear to be relatively constant over time.
### Table 1.6: Extensive margin estimate, over time

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<tr>
<td></td>
<td>680</td>
<td>700</td>
<td>720</td>
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<tr>
<td>2008-2009</td>
<td>8.85***</td>
<td>19.23***</td>
<td>31.71***</td>
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<tr>
<td></td>
<td>[6.763,10.95]</td>
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<td>[26.93,36.49]</td>
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<tr>
<td>baseline propensity</td>
<td>14.58</td>
<td>19.89</td>
<td>25.42</td>
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<tr>
<td>2010-2011</td>
<td>16.54***</td>
<td>18.94***</td>
<td>28.07***</td>
</tr>
<tr>
<td></td>
<td>[13.56,19.53]</td>
<td>[15.16,22.71]</td>
<td>[21.94,34.20]</td>
</tr>
<tr>
<td>baseline propensity</td>
<td>12.99</td>
<td>16.54</td>
<td>19.97</td>
</tr>
<tr>
<td>2012-2013</td>
<td>27.41***</td>
<td>25.37***</td>
<td>50.17***</td>
</tr>
<tr>
<td></td>
<td>[23.88,30.95]</td>
<td>[21.93,28.80]</td>
<td>[44.11,56.23]</td>
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<tr>
<td>baseline propensity</td>
<td>14.97</td>
<td>20.10</td>
<td>24.86</td>
</tr>
<tr>
<td>2014</td>
<td>36.54***</td>
<td>23.05***</td>
<td>38.96***</td>
</tr>
<tr>
<td></td>
<td>[30.15,42.92]</td>
<td>[16.34,29.76]</td>
<td>[27.08,50.84]</td>
</tr>
<tr>
<td>baseline propensity</td>
<td>13.59</td>
<td>17.27</td>
<td>19.58</td>
</tr>
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### Table 1.7: Intensive margin estimate over time

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<tr>
<td></td>
<td>680</td>
<td>700</td>
<td>720</td>
</tr>
<tr>
<td>2008-2009</td>
<td>27574***</td>
<td>52738***</td>
<td>75739***</td>
</tr>
<tr>
<td></td>
<td>[15017,40131]</td>
<td>[24313,81162]</td>
<td>[44490,106988]</td>
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<tr>
<td>baseline orig. amt.</td>
<td>170789</td>
<td>187298</td>
<td>199988</td>
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<tr>
<td>2010-2011</td>
<td>50690***</td>
<td>52467***</td>
<td>97846***</td>
</tr>
<tr>
<td></td>
<td>[36316,65065]</td>
<td>[31928,73007]</td>
<td>[61645,134047]</td>
</tr>
<tr>
<td>baseline orig. amt.</td>
<td>162458</td>
<td>179793</td>
<td>192271</td>
</tr>
<tr>
<td>2012-2013</td>
<td>74425***</td>
<td>61089***</td>
<td>66775***</td>
</tr>
<tr>
<td></td>
<td>[50666,98184]</td>
<td>[41205,80972]</td>
<td>[37797,95753]</td>
</tr>
<tr>
<td>baseline orig. amt.</td>
<td>179613</td>
<td>195978</td>
<td>206218</td>
</tr>
<tr>
<td>2014</td>
<td>48079***</td>
<td>29350</td>
<td>62696*</td>
</tr>
<tr>
<td></td>
<td>[-9036,105191]</td>
<td>[-53582,112282]</td>
<td>[-22,125414]</td>
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<tr>
<td>baseline orig. amt.</td>
<td>101272</td>
<td>204410</td>
<td>209973</td>
</tr>
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1.4.6 Potential Channels

The observed magnitudes suggest that as debt becomes cheaper, individuals substitute away from other forms of saving or consumption and spend more on mortgages. This can be demonstrated using a simple heuristic: suppose for a moment that agents held fixed their desired mortgage payment and simply shifted the size of the house appraisal rather in response to interest rate changes. This approximation could proxy for a scenario in which individuals are credit constrained to only spend a fixed amount of money per period going forward.

As a back of the envelope for this rule of thumb, consider a $200,000 30 year fixed-rate mortgage at an interest rate of 5 percent. The monthly payment is $1074. Decreasing the interest rate to 4 percent leads to a monthly payment of $955, a $119 (or 11%) savings. Or, over the life of the loan, the borrower saves $42,773. Per the empirical estimates shown in Table 1.5, there is an additional $10-35k allocated to a higher origination amount than simply allocating the savings toward the loan would imply.

Empirically, borrowers increase their loan size and their appraisal amount by about the same amount, so that the LTV remains roughly constant but they are able to borrow more for a more expensive house. For FICO 700 borrowers and a $200k origination amount and $290k appraisal amount, this intensive margin adds up to approximately $80,000 higher origination and $116,000 larger appraisal amount. If borrowers had instead desired to keep their interest payment constant at $1074, the origination amount would instead have increased to $225,000. This implies borrowers are willing to borrow more at lower interest rates.

Since I measure local elasticities using cross-sectional variation, I abstract from general equilibrium effects. My exercise is meant to isolate the substitution effect from consumption or non-mortgage saving to mortgage debt in the face of relatively cheaper mortgage debt, all else equal. There is still a Hicksian elasticity (income effect) in play, however. In reality, mortgage rates often fall due to easy monetary policy, which has further implications on the stock market, house prices, and overall income.
1.4.7 Alternative Explanations

One might worry that the results are due to lender supply rationing rather than price-rationing. Given that securitizations and default rates are consistent across breakpoints, this concern would be consistent with lender screening on default rates and tolerating a set threshold for defaults that is consistent across thresholds. One could then interpret the jump in the extensive margin as reflecting the fact that fewer low-FICO borrowers qualify for the default cutoff. The only reason to believe this might be discrete is that the higher interest rate causes these borrowers to default more. Similarly, one could interpret the intensive margin jump as lenders being more tolerant of higher origination volumes from higher-credit score borrowers.

My results are inconsistent with these possible concerns. Recall that the empirical results suggest a roughly constant elasticity for any given FICO score over time, meaning that the change in loan demand tends to change by the same factor as the interest rate across a credit score gap changes. There are two main institutional details that support the idea that lenders are not changing screening in lockstep with rate changes, which would be necessary to argue that the effects I measure are supply-side rather than demand-driven. First, LLPAs change discretely, and the reason the rate gap changes is the change in the valuation of the upfront cost of the LLPA, driven in part by the mortgage stack. It is unclear why these mechanisms should induce a roughly constant response from lenders. Second, LLPAs are imposed by Fannie/Freddie and go to the GSEs, so the nature of lender rationing would have to exactly move in line with the LLPAs to obtain consistent elasticity measurements over time. That is, higher LLPAs (higher rate spreads) would have to induce greater relative screening below any given threshold. While LLPAs are typically raised to protect Fannie and Freddie against perceived default risk, this default risk should not directly affect lender behavior, since the lenders only assume “putback risk” on the loans.

Ideally, one could test whether lenders are rationing supply by examining borrower characteristics for applications and for accepted loans. If the characteristics across the cutoff are discontinuous, the change in observed loan count and size might be attributed
to differential screening across the cutoff. Unfortunately, the data available do not contain much information about selection. HMDA mortgage applications are not linked to FICO score, and most data sets do not contain additional demographic or income information linked to specific mortgages.

1.5 RD Validity and Empirical Robustness

The interpretation of discrete jumps in originations and defaults at certain FICO score thresholds has been the subject of some academic debate. Keys et al. (2010) and Keys et al. (2012) argue that the discontinuity in default rates from FICO 619 to FICO 620 can be attributed to moral hazard induced by the increased likelihood of FICO 620 loans to be securitized by the GSEs. Bubb and Kaufman (2014) instead argue that the cutoffs are driven by lender screening, as evidenced by the discontinuous number and default rate of loans at these same credit score cutoffs, so that the exclusion restriction of using this cutoff as an instrument for securitization is not valid. For the empirical approach of this paper, I use higher FICO scores than those used in this previous literature. I show that for these cutoffs, there does not appear to be evidence of differential securitization or default trends, indicating that there is not differential lender screening across these thresholds. This result is key for interpreting my other measurements as the elasticity of demand for interest rates.

1.5.1 Testing for supply side factors: RD tests on defaults and securitizations

One potential concern on interpreting the regression discontinuity results is whether the jumps in origination amount across mortgage rate breakpoints is driven by supply-side factors (such as lender rationing and screening) rather than demand. In this section, I show that there does not appear to be evidence that lenders screen differentially across our cutoffs, and argue they do not have incentive to screen differentially. This provides further support that the regression discontinuity is isolating the demand elasticity of borrowers to interest rates.

Figure 1.10 illustrates these trends. The left panel shows default rates (where default is
Figure 1.10: Default and foreclosure trends across breakpoints. Sample is all conventional 30-year fixed rate purchase mortgages between January 2008 and December 2015. A loan is considered in default if it has ever been 61 days delinquent within 36 months of origination. A loan is considered to be in foreclosure if the foreclosure process has ever been started within 36 months of origination. I test whether a significant discontinuity exists at the FICO breakpoints in Table 1.8. Source: McDash LLC, author’s calculations.

defined as the loan ever having been 61 days delinquent within 36 months of origination) by FICO at origination. The right graph shows foreclosure rates (where a “foreclosure” is whether the foreclosure process has ever been initiated within 36 months of origination) across FICO at origination. If there were differential screening across breakpoints, one might expect a jump upward in the default rate just above any given cutoff, since differential screening implies the lenders may have more carefully screened those just below but the borrowers on each side of the threshold are otherwise essentially identical. One factor pushing the bias in the other direction is the fact that lower FICO borrowers also face higher interest rates (which may induce more default). In untabulated results, I show that even when the rate gap is small across the threshold, there is no evidence of differential screening (in the form of higher defaults just above the FICO threshold).

Table 1.8 shows the results for a regression discontinuity to measure breakpoints in default rates at the various cutoffs. The coefficients for the discontinuity at the first two cutoffs – 619/620 and 639/640 – are positive and significant, with economically meaningful magnitudes, indicating that there is likely differential screening across these breakpoints. While FICO 619 and FICO 620 borrowers have essentially identical default risk \textit{ex-ante}, “bad”
borrowers are more likely to get approved at FICO 620 given lender screening rules-of-thumb that causes more intense screening below cutoffs. Hence, there is a discrete jump upwards in the default risk – i.e. better FICO score individuals just above the cutoff default more than those individuals just below.

Promisingly, these default discontinuities disappear after the 620 and 640 breakpoints. The results for the higher FICO breakpoints are statistically insignificant, and the point estimates are economically close to zero. This holds regardless of the bandwidths tested. These results indicate that there is no evidence of differential lender screening across breakpoints 660 and higher.

Table 1.8 also shows the results for the discontinuity in securitization rates across breakpoints. At FICO breakpoints up to and including 680, there is evidence that there is increased securitization just above the cutoff. This may induce differential lender screening: since otherwise identical borrowers are more likely to be securitized at 680 than at 679, the lenders may have an incentive to screen 679 borrowers more carefully, as there is a greater

---

**Table 1.8: Discontinuities in supply-side propensities.** Each number listed is the regression discontinuity for the FICO listed for each variable separately. A loan is considered securitized if it is ever bought in the first 36 months after origination. Default is defined as ever having been 61 days delinquent or more at any point 36 months after origination. Source: McDash LLC and New York Fed / Equifax; author’s calculations.

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<td>Discontinuity in P(securitization)</td>
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<td>Discontinuity in P(default)</td>
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</table>

95% confidence intervals in brackets

* p < 0.10, ** p < 0.05, *** p < 0.01
chance that the loan will be held in portfolio and therefore that the lenders will be directly exposed to default risk. These trends indicate that for the purposes of my analysis, only FICO breakpoints 700 and above can be used.

For robustness, I rerun this analysis for an earlier time period. Because my mortgage rate data are limited, I do not use this time period for my demand elasticity measurement. However, the results indicate that even in earlier periods used by previous literature, there do not appear to be default or securitization cutoffs at higher FICO scores.\textsuperscript{23}

1.5.2 Smoothness across thresholds for FHA

This paper estimates the impact of conventional mortgage rates on conventional mortgage loans. One potential concern about this identification strategy is that the propensity to obtain FHA loans and FHA loan sizes might also respond to the mortgage rate differentials across these cutoffs. To test this, I estimate a regression discontinuity in the count of FHA mortgages over each threshold. If there were a substantial breakpoint in the propensity to get an FHA loan at my cutoffs of interest, then my estimates would not be valid: some individuals might still obtain mortgages but under the FHA program instead of Fannie/Freddie, but I would count these borrowers as selected out of mortgages on the extensive margin.

My estimates suggest that FHA switching is not a major concern in my setting. Table 1.9 shows the RD exercise performed on the propensity of borrowers to get an FHA loan. There is no change across thresholds to get FHA loans: the estimates are close to zero, with the 720 breakpoint indicating that being above 720 FICO amounts to a change in 0.42 individuals per 100,000 getting an FHA mortgage per week. This is small relative to the total of 10.4 (per 100,000) individuals getting a conventional loan per week and small relative to the estimated discontinuity of 9.5 individuals (per 100,000) per 25 basis point of rate change. Hence, while FHA switching might add some noise to the general estimates, the RD exercise

\textsuperscript{23}In Bubb and Kaufman (2014), the sample of loans are those originated January 2003-2007. I repeat their analysis and find comparable results (Appendix Figure A.2). I then extend their analysis, and the results for the defaults of higher FICO scores are shown in Appendix Figure A.4. There are no discontinuities at higher FICO scores, suggesting there is no differential screening across FICO breakpoints. This is in contrast to Appendix Figure A.2.
is still valid.\textsuperscript{24}

1.5.3 Testing “search-and-wait” behavior

Another potential concern for the regression discontinuity validity is that borrowers query for their credit score multiple times, only receiving a mortgage if their credit score is above the desired threshold. If this were true, it would mean that my method does not pick up an extensive margin of mortgage borrowing, but rather the same borrowers “timing” their loans to attempt to get the best possible mortgage rate.

In this subsection, I show that borrowers do not seem to time their mortgages to their credit score. I justify this in a few ways. First, I discuss that why this sort of timing would be difficult, if not impossible, given how the mortgage market is structured. Second, I show that credit scores move somewhat randomly before acquisition of a mortgage. Finally, I study shopping behavior using mortgage inquiries in my credit bureau data.

First, it is difficult, if not impossible, for borrowers to acquire real-time data on credit scores. The Fair Credit Reporting Act (FCRA) grants consumers free access once each year

\textsuperscript{24}Given that FHA mortgage insurance premia have changed over this sample, it is important also to test the smoothness across time. The reason this could be a concern is that the tradeoff between taking a conforming vs. an FHA loan could change over time as the rate spreads between the two vary. When FHA loans are much more expensive than conforming loans, as they have been historically, borrowers may only resort to FHA when they cannot afford a down payment, and this may not vary discontinuously across the FICO breakpoints we consider. In contrast, if FHA loans are less expensive for some FICO borrowers but not others, this may vary with the FICO-induced breakpoint in mortgage pricing. Untabulated results indicate that there are no significant FHA breakpoints even breaking the sample into periods of two years each.
to their credit report from each major credit bureau, although take-up seems to be low; the CFPB estimates that only 10 percent of the eligible population receives a free credit report each year.\textsuperscript{25} Even though some credit cards offer “free FICO” reports, the credit score displayed tends to be at least a couple weeks lagged, and is therefore not incredibly useful for individuals trying to time their mortgage purchases. Moreover, previous studies have found that mortgage shopping hardly occurs. A recent CFPB report finds that about 77 percent of purchase mortgage-borrowers apply to only one lender, and are therefore unlikely to be querying their credit score by visiting loan officers multiple times.\textsuperscript{26}

If credit scores systematically moved upward before a mortgage, then we would worry that some borrowers query their credit score, attempt to manipulate it by closing accounts or reducing other loan balances, and then re-query their credit score, repeating the process until their credit score is high enough to take advantage of the discretely lower mortgage rate. I show that borrowers’ credit scores do not systematically increase before mortgages are originated, indicating that at large, manipulation does not happen. In Figure 1.11, Panel A shows the initial FICO time at the start of the search against the origination FICO score. Panel B shows a similar graph, using instead median credit score both at start of search and origination (which reflects the fact that lenders use the median of 3 credit scores). Both graphs are roughly linear. There is no breakpoint at any given FICO score, indicative that there is no differential mortgage timing that causes bunching at higher credit score breakpoints; rather, the distribution of credit scores at origination is as smooth as the credit scores at the start of the mortgage search.

To study shopping behavior, I examine the number of queries for mortgages for each borrower up to 6 months before the mortgage was originated. The number of mortgage inquiries is smooth across credit scores at origination, as seen in Panel C of Figure 1.11. This provides evidence that individuals just below the cutoff are not inclined to continue inquiring about their credit score to facilitate mortgage timing. The number of months

\textsuperscript{25}See Consumer Financial Protection Bureau (2015a)

\textsuperscript{26}See Consumer Financial Protection Bureau (2015b)
Figure 1.11: Mortgage shopping behavior across credit scores. All panels aggregate the baseline dataset, i.e. individual conforming purchase loan data from October 2008 to June 2015. Panel A shows the FICO score at origination (taken as a mean across loans) compared to the FICO score when mortgage shopping started, and Panel B shows the median credit score at origination (again the mean across loans) compared to the median credit score at the time of initial mortgage search. Panel C shows the number of mortgage inquiries in the 6 months previous to origination versus the credit score at origination. The number of cumulative searches shows no discontinuity across mortgage cutoffs. Panel D shows the number of months searched on average before the mortgage was originated, with the 95% confidence intervals shaded in grey. Source: McDash LLC, NY Fed CCP/Equifax, author’s calculations
searched across FICO score at origination is shown in Panel D of Figure 1.11, with 95% confidence intervals shaded in grey. The number of months searched is roughly smooth across the breakpoints I consider. If anything, the number of months searched is higher just below a given cutoff than just above. This is potential evidence of failed manipulation: one could imagine that a borrower has a fixed number of months before she must buy a house, and she buys if her FICO score falls above a desired threshold or at her deadline. The fact that there is a slight uptick of the number of months searched under the FICO thresholds indicates that these individuals may not have been able to wait sufficiently long before originating a mortgage.\footnote{Consider the expected stopping time of a Brownian motion with drift. The decision rule of the agent is to stop at \( \min \{ \bar{T}, T_{\text{stop}} \} \). We can solve for the expected stopping time \( T_{\text{stop}} \). But there is noise in the process, and the presence of a strict deadline causes the distribution of realized stopping times to be truncated on the right by \( \bar{T} \). In this case, conditional on realizing the desired FICO score, the average actual stopping time is less than \( T \), whereas conditional on being below the cutoff, the actual stopping time is exactly \( T \). This rough sketch shows why we might expect the average shopping time for mortgages to be higher just under a FICO pricing cutoff.}

### 1.5.4 Attempted manipulation of credit score

One might worry that manipulation of credit scores could invalidate my regression discontinuity. In this section, I explain both that because of institutional structure, this is theoretically impossible, but even if manipulation could occur, under some fairly loose assumptions the results would still be valid.

In theory, it should be impossible to manipulate credit scores. The credit score agencies change their credit scoring algorithms over time, and these algorithms are never revealed to the public. Still, individuals on online forums speculate that they can take certain actions, such as carrying less debt and closing extra tradelines, to improve their credit score.

Even if individuals are aware of credit score thresholds and attempt to manipulate their scores, my regression discontinuity strategy is still valid and is still as good as randomized as long as there is continuous noise in the ability of individuals to affect their credit score (“partial manipulation”, rather than “complete manipulation”).\footnote{This was shown in Lee (2008). Formally, each individual is assigned a FICO score \( V \), which is influenced partially by (a) the individual’s choices and characteristics, and (b) by random chance. Treatment (in this case, a}
formulae are “black boxes” to the public, with uncertainty regarding how any given chosen action, such as closing a credit account or paying off debt, might affect one’s credit score, it seems likely that the assumptions necessary for “as good as randomized” to hold.29

The noisiness of credit scores can be seen in Figure 1.12. The distribution of the 6-month-lagged FICO scores for borrowers with a 699 or 700 FICO score at origination is quite wide, with many borrowers falling below 680 or above 720. Moreover, the distributions of previous credit scores for borrowers who ultimately originate at FICO 699 and 700 are virtually indistinguishable. The histogram looks similarly noisy even for one-month lagged FICO score.30

1.5.5 Continuity of characteristics in underlying population

Since credit scores are assigned by credit bureaus, one might worry that there is a mechanical breakpoint in individual characteristics at the FICO scores I study. In this section, I discuss trends in individual-level credit data across credit scores and show that the underlying population is continuous across a variety of credit variables.

I run regression discontinuities using a similar methodology to my base results, except that the population is now the entire Equifax sample rather than restricted to mortgage borrowers. To transform the Vantage credit scores provided by Equifax to FICO scores, I use the merged Equifax-McDash LLC data to derive the historical relationship between Equifax lower mortgage rate) is given to an individual if and only if $V$ is greater than the known FICO threshold $v_0$. Lee (2008) shows that if, conditional on the individual’s choices and characteristics, the probability density of $V$ is continuous – even if this density function of $V$ varies across individuals – in the neighborhood of $V = v_0$, variation in the treatment status is as good as randomized by an experiment, and satisfies the minimal assumptions for RDDs. McCrary (2008) formalizes an econometric test based on this argument to test for a discontinuity in the running variable. This relies on manipulation to be monotonic, meaning that manipulation happens only in one direction, which is intuitive in our setting. This test would not apply to our count of actual loans since this is a choice variable that responds to mortgage rate changes. Moreover, the test relies on a continuous forcing variable, whereas the underlying potential borrower FICO scores are discrete.

29The CFPB held focus groups and found that “many consumers said they were not sure how to improve their scores and were confused by conflicting advice about which actions to take. See Consumer Financial Protection Bureau (2015a).

30The noise in lagged FICO scores means that a fuzzy RD – that is, trying to instrument for FICO at origination using previous FICO scores – has a weak first stage and cannot be performed.
Figure 1.12: FICO 6 months previous to origination, conditional on FICO at origination being 699 or 700. Only about 3.5% of borrowers who originate loans at FICO 700 were at FICO 700 six months before origination; the rest of the borrowers are distributed both above and below the cutoff with quite a bit of noise. Source: Author’s calculations and New York Fed CCP / Equifax.

score and FICO score and use this adjustment so that the RD can be performed across FICO thresholds. Untabulated results indicate that using raw Equifax-provided credit scores does not change the qualitative results.

Table 1.10 shows the results of these RDs for a select set of credit variables. The base bankcard balance increases over credit scores, but I cannot reject that the bankcard balance is smooth across credit score cutoffs (i.e. the 95% confidence intervals of the regression discontinuity comfortably contain 0). Car debt decreases over credit scores, but again the results indicate we cannot reject a smooth distribution of car debt across credit scores. Credit utilization, measured as the total balance held by an individual divided by the total credit available to that individual, tends to fall as credit scores increase, in line with the typical intuition that richer and higher-credit individuals are less likely to be credit constrained.

The results indicate that the underlying population is not substantially different at the FICO breakpoints used for the elasticity measurement. This provides further support for the validity of the regression discontinuity.
Table 1.10: Select credit variables, RD on full population. $+/- 10$ FICO points is shown, although the results are qualitatively similar $+/- 20$ and $+/- 5$ FICO points. The Equifax credit score is adjusted using historical relationships to FICO scores as described in the main text. Credit utilization measured as the total balance held by an individual divided by the total credit available to that individual. Source: New York Fed CCP / Equifax, author’s calculations.

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95% confidence intervals in brackets
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

1.6 Conclusion

In this paper, I have developed a novel methodology to measure the demand elasticity of purchase mortgages to interest rates. My estimates suggest that individuals who are buying a new home are sensitive to interest rates both on the extensive (choosing whether to get a mortgage) and intensive (the size of the mortgage) margins. The magnitude of the estimates is large, indicating that a 25 basis point decrease in interest rates corresponds to a 50% increase in the likelihood of a potential borrower to demand a mortgage and an increase in loan size of approximately $15k. I show further evidence that borrowers with high FICOs are more sensitive to interest rate changes than those with smaller (but still high) FICO scores, elasticities are approximately constant over time, and the marginal responsiveness to interest rates is decreasing.

The large responsiveness of borrowers to interest rates has policy implications. For instance, if policymakers wanted to encourage homeownership, it may be too blunt of a tool to lower the risk-free rate, since low-FICO borrowers are often subject to additional fees or higher interest rates in all borrowing markets they engage in. Rather, one could imagine a
government subsidy to cover the LLPAs which induce the interest rate spreads in my paper. While this would be controversial for political reasons, it may well induce a greater marginal responsiveness of borrowing per dollar than (say) the outright purchase of mortgage backed securities by the Federal Reserve. This is all speculative, and would benefit from a more rigorous framework, which is beyond the scope of this paper. Moreover, it is important to remember that while this paper has focused mainly on high FICO scores due to the identification strategy, but determining the impact of constrained supply (lender screening) versus decreased demand from mortgage borrowers for the lower FICO individuals is also of importance.

Finally, there are implications for my estimate beyond those I developed in the paper. For instance, under certain assumptions, one could theoretically back out the elasticity of intertemporal substitution (EIS). Also, while I have established the large magnitude of demand responsiveness, I have not investigated the drivers of the responsiveness. By calibrating a simple model, one could also investigate whether the quantities found in this paper are consistent with a frictionless world, or whether credit constraints (e.g. a binding payment-to-income constraint) are an important driver to the demand response observed. It may also be possible to examine further micro data on cash purchases or loan applications to further understand the underlying drivers of demand.
Chapter 2

The Time-Varying Price of Financial Intermediation

2.1 Introduction

Mortgage lending is one of the main activities of the US financial intermediation sector and a principal driver of its growth in recent decades (Greenwood and Scharfstein, 2013). In recent years, the intermediary in most cases directly connects borrowers with capital market investors (through the market for mortgage-backed securities, or MBS), rather than funding loans from deposits or other funding sources. So a priori one might expect that the price of this service should be fairly low and stable. We instead show that over the period 2008 to 2014, it was highly volatile. We then explore the drivers of this variation and study its implications for the passthrough of monetary policy, specifically the Federal Reserve’s

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1 Co-authored with Paul Willen and Andreas Fuster. We thank John Campbell, Andy Davidson, Fernando Ferreira, Sam Hanson, Sean Hundtofte, Dwight Jaffee, Adi Sunderam, and Stijn Van Nieuwerburgh, and seminar audiences at Brandeis, the Homer Hoyt Institute, FRB St. Louis, FRB New York, the Board of Governors, and the NBER Summer Institute for helpful comments and suggestions. The views expressed in this paper are solely those of the authors and not necessarily those of the Federal Reserve Banks of Boston or New York, or the Federal Reserve System.

2 Over our sample period (2008-2014), about 80% of new mortgage loans are securitized through the “agency” MBS market, where the government-backed agencies Fannie Mae, Freddie Mac and Ginnie Mae insure the timely payment of principal and interest payments to investors.
large-scale asset purchase programs, colloquially known as “quantitative easing” (QE).

Our first contribution is to develop a new methodology to measure the price of intermediation, which we define as the payment made to the intermediary for the service of linking the borrower and the ultimate supplier of funds for the loan. This payment covers costs associated with originating, underwriting and servicing the loan and also may include profits. One way one can think of the role of the intermediary in mortgage origination is as a dealer who buys a loan (meaning the right to future coupon and principal payments) from the borrower (in the “primary” market), and sells it in the “secondary” (MBS) market to investors from around the world. The intermediary’s dollar margin, or the price of intermediation, is then defined as the difference between the value of the loan in the secondary market and what the intermediary pays to the borrower. This latter payment includes not only the loan amount (or principal), but also an additional upfront transfer known as “rebate” (if positive from the point of view of the borrower) or “discount points” (if negative). The rebate depends on the loan’s note rate and typically changes daily for a given note rate.

The two central inputs for our analysis are thus the secondary market value of a mortgage and the rebate paid by the intermediary to the borrower. Measuring the price of a loan in the MBS market is relatively straightforward, though we use two different methods to value the part of the cash flow associated with the servicing of the mortgage.\(^3\) Cleanly measuring rebates is much more challenging, since the “rate sheets” on which they are quoted are in general not publicly disclosed. A key innovation in the paper is that we use a new administrative dataset that documents rebates on a daily basis as a function of the note rate and detailed characteristics of the borrower and the loan. The data come from a company called Optimal Blue, an industry-leading provider of real-time data to loan officers.

We use these data for several complementary analyses. To begin, we study the high-frequency (daily) passthrough of MBS price changes to rebates over the period 2008-2014,

\(^3\)Our baseline measure values all cash flows based on MBS market prices; an alternative measure relies on “base servicing multiples” from an industry source to assess the value of the 25 basis points annual compensation for the right and obligation to service the mortgage.
first focusing on six major monetary policy announcements (mostly QE-related) and then looking across all days in our sample. Next, we study how the price of intermediation evolved at lower (monthly) frequency, explore potential drivers of the variation, and study the implied costs to borrowers. Finally, we clarify the relationship between our price of intermediation and a commonly used measure that instead compares mortgage rates to yields in the MBS market.

Our main findings are the following: The passthrough of MBS price changes to the primary mortgage market following QE announcements was generally large, though appears to be affected by the level of demand for mortgages (measured by daily applications for new loans) at the time of the announcement. At times when demand was strong, such as around the expansion of “QE1” in March 2009, passthrough was relatively weaker and the price of intermediation increased.

More generally, we find that at the daily frequency, rebates move very closely with prices in the MBS market. We find that, on average, 92% of changes in MBS market prices are passed through to the primary market. We also find evidence for asymmetry: while MBS market price decreases are on average completely passed through to the primary market, MBS price increases yield a smaller passthrough of about 0.8. The latter coefficient also varies with the level of demand: when demand for new loans is higher, intermediaries pass through less of MBS price increases to the primary market.

Our results on high frequency passthrough are in stark contrast to other consumer markets. Ausubel (1991), notably, showed that prices in the credit card market did not seem to respond at all to changes in the cost of funds for banks. More recent work showed that Ausubel’s finding was not unique to the time period he studied and casual empiricism confirms that from the start of the Great Recession to the present, credit card interest rates have fallen only two percentage points whereas the Fed Funds rates has fallen five percentage points and delinquency rates on credit cards have fallen two percentage points.4

4Calem et al. (2006) write that, “The pattern of rate movements since 1991 also suggests that credit card interest rates have remained sticky and that spreads continue to vary countercyclically.” According to Federal Reserve Release G.19, the interest rate on credit cards on which borrowers were paying interest was 15.24
Evidence from deposit rates paints a similar picture. Driscoll and Judson (2013) shows that depository institutions change interest rates on short term Certificates of Deposit roughly every six to seven weeks and that the coefficient on the Fed Funds rate in a regression of changes in CD rates is only 0.4. In contrast, we find that lenders in the mortgage market change rates at least once a day and a comparable regression generates a coefficient of 0.92.

Despite the strong daily passthrough, we show that the price of intermediation is highly variable over time. In particular, it strongly increases with current mortgage application volume: at monthly frequency, a one standard deviation increase in new mortgage applications is associated with a 30-35 basis point increase in the price of intermediation relative to an average price in our sample of 142 basis points. We view this as evidence consistent with significant capacity constraints in the mortgage industry, for which we also present direct evidence based on the processing time of new loan applications.

We also document a significant upward trend in the price of intermediation over the period from 2009 to 2014; using our baseline specification, this amounts to 30 basis points per year. This trend is not explained by a change in interest rate volatility (a driver of hedging costs of intermediaries) or a change in market concentration. It is partly explained by an increase in per-worker labor costs in the real estate credit sector, though of course it is difficult to know which way the causality goes. Even after controlling for labor costs, however, a positive trend remains, bearing out anecdotal evidence of an increased legal and regulatory burden leading to increased costs over this period. Consistent with this interpretation, we show that an important part of the upward trend appears to be due to a decrease in lenders’ valuation of mortgage servicing rights (relative to the value of the cash flows in the MBS market), which may reflect increased costs of servicing loans and the changed treatment of servicing rights under revised capital regulations.

We find that the variation and the upward trend in the price of intermediation has had substantial costs to mortgage borrowers. Specifically, over 2009-2014, had the price of

percent in the Q3, 2007 and 13.35 percent in Q2, 2016. According to the New York Fed Quarterly Report on Household Debt and Credit, 9.34 percent of credit card debt was past due in Q3, 2007 as compared to 7.17 percent in Q2, 2016.
intermediation been insensitive to application volume and had there not been an upward trend, US borrowers collectively would have received roughly an additional $140 billion (in present value terms), holding the volume and timing of originations constant. Another exercise we can do is to translate the increase in the price of intermediation into its effect on interest rates for borrowers, holding the upfront cost to the borrower constant. We find that over extended times during our sample period, mortgage rates would have been 30-40 basis points lower under the counterfactual described above.

Our work relates to various strands of existing research. Most broadly, we contribute to the voluminous literature studying the effects of monetary policy and financial market conditions on the real economy through the credit channel (e.g. Bernanke et al., 1999; Bernanke and Gertler, 1995; Kashyap and Stein, 2000). Specifically, we focus on the link between financial markets (which in turn may be affected by monetary policy) and borrowing rates faced by households. Recent contributions with a similar focus include Gertler and Karadi (2015) and Gilchrist et al. (2015). While other work has emphasized time-varying risk-premia, for instance in corporate bonds (Gilchrist and Zakrajsek, 2012), we focus specifically on changes in rates due to time-varying margins of intermediaries. Evidence suggests that rates in turn affect the real economy; for instance, Walentin (2014) finds that mortgage spreads have significant explanatory power for several macro variables.5

Related to our sample period and event studies, a growing literature has studied the effects of QE on lending rates and quantities. Most directly, this paper builds on Fuster and Willen (2010) who looked at QE1 announcements in more detail, based on an earlier version of the rate sheet data we use here. Hancock and Passmore (2011, 2015) also study the impact of unconventional monetary policy on primary mortgage rates, while Stroebel and Taylor (2012), Krishnamurthy and Vissing-Jörgensen (2011, 2013) and Boyarchenko et al. (2015) focus primarily on MBS market spreads. The effects of QE announcements on the quantity of mortgage originations (especially refinancings) are studied by Fuster and Willen (2010),

5Walentin defines mortgage spreads as the gap between headline mortgage rates and long-term government bond yields.
Beraja et al. (2015) and Di Maggio et al. (2016), focusing on heterogeneity across borrower types, regions, and market segments, respectively.

In the banking literature, Hannan and Berger (1991), Neumark and Sharpe (1992) and Drechsler et al. (2015), among others, have studied the adjustment of deposit rates to shocks, and link it to market power. In the mortgage market, Scharfstein and Sunderam (2013) study heterogeneity across counties in the sensitivity of rates and refinancing to changes in MBS yields over 1994-2011, finding less passthrough in more concentrated markets. We study whether changes in concentration could explain the increase in intermediation prices that we document, but since mortgage lending concentration fell substantially over 2010-2014, this does not appear to be a promising explanation of the patterns in our data.

Related to our focus on capacity constraints in the mortgage market, Sharpe and Sherlund (2016) present evidence consistent with limited capacity affecting the types of loans that lenders choose to originate. Fuster et al. (2013), who focus on longer-term trends in intermediary margins (and did not use the high-quality daily rate sheet data used here) also highlight capacity constraints as a potentially important explanation of temporarily high margins. Other work has focused on the capacity constraints of mortgage servicers (who may be the same entity as the originators we study) and how these constraints have affected modification activity during the crisis (e.g. Cordell et al., 2009; Maturana, 2015).

Finally, studying the market for financial intermediation in mortgages is also interesting from an industrial organization perspective. Our analysis parallels others studying how product prices react to changes in input prices—for instance, how the price of gasoline reacts to the price of crude oil (Borenstein et al., 1997; Bachmeier and Griffin, 2003). We do find some asymmetry in the passthrough, with positive MBS price changes being reflected in YSPs more slowly than negative changes, in line with existing findings of similar asymmetries in many markets (e.g. Peltzman, 2000; Driscoll and Judson, 2013).

The remainder of the paper proceeds as follows: in Section 2.2, we discuss the market for financial intermediation and our concepts of interest through a simple model. We then turn to the question of how to measure the theoretical concepts in the data in Section 2.3.
Section 2.4 presents our event study of major monetary policy announcements. In Section 2.5, we study the daily passthrough over the entire sample period, while in Section 2.6, we focus on long-term variation in the price of intermediation. We then explore the implications of our estimated models in Section 2.7, while Section 2.8 concludes.

2.2 Financial Intermediation in the Mortgage Market

In this section we provide a brief overview of intermediation in the mortgage market through the lens of a simple model; see e.g. Fuster et al. (2013) for a more extensive discussion of the institutional details.

2.2.1 A Simple Model

Consider a simple model of the market for financial intermediation in mortgages, where we define financial intermediation as the service of matching a borrower in the primary market with an investor in the secondary market. We start with a lender who makes a loan to a borrower with a fixed interest rate \( r_n \). Following industry parlance, we refer to \( r_n \) as the “note rate” of the loan. A central feature of the mortgage market is that, in addition to providing the borrower with the principal on the loan, the intermediary also either receives an additional upfront payment from the borrower, referred to as the borrower “paying (discount) points,” or pays a “rebate” to the borrower to cover closing costs and other expenses. This upfront payment, which goes by many different names (Yield Spread Premium, Service Release Premium, (negative) discount points) plays a central role in all mortgage transactions but is often not explicitly disclosed to the borrower who just sees the points/rebate in the form of changed closing costs.

The size of that rebate, which we denote \( YSP(r_n) \), depends on the note rate — a higher note rate is more valuable (since it generates higher future cash flows) and thus commands a higher \( YSP \).\(^6\) One useful way to think about this transaction is that in originating a mortgage,

\(^6\)If the borrower pays discount points, this corresponds to the intermediary paying a negative rebate, \( YSP(r_n) < 0. \)
the intermediary *buys* the mortgage from the borrower by paying the principal plus the rebate. That is, the price paid for a mortgage with $100 principal and note rate $r^n$ is:

$$p^n_{YSP} = 100 + YSP(r^n).$$

After the intermediary buys the loans from the borrower, it turns around and sells it to investors. In general, intermediaries can sell loans to many different types of investors but over the period we study, about 80% of new mortgage lending was funded through “agency” MBS guaranteed by the government-sponsored enterprises (GSEs) Fannie Mae and Freddie Mac or the government agency Ginnie Mae; only about 20% of loans were kept on bank balance sheets.\(^7\) Our discussion will focus on a loan sold through a Fannie Mae MBS; the mechanics for Freddie Mac or Ginnie Mae are very similar.

To sell loans in the secondary market, the intermediary typically starts by putting together a pool of loans and then exchanges the pool with Fannie Mae for an MBS backed by those loans.\(^8\) The intermediary pays a monthly premium called a guarantee fee (g-fee) and a one-time upfront fee called the “Loan-Level Price Adjustment” (LLPA) to Fannie Mae, in exchange for which Fannie Mae creates the security and ensures timely payment of principal and interest. After the swap with Fannie Mae, the intermediary holds a tradeable MBS that will pay cash flows to its holder based on the payments from the underlying mortgages. It can then sell the MBS to an investor (such as a pension fund or a central bank) in the secondary market.

The process of closing, packaging the loan into an MBS and delivering it to an investor takes several weeks but, fortunately for the intermediary, there is a highly liquid forward market, the so-called “To Be Announced” or TBA market, for GSE MBS. More or less immediately after agreeing to terms, or “locking,” the loan with the borrower, the intermediary

---


\(^{8}\)It is also possible to sell individual loans to a GSE directly through their “Cash Window.” The GSEs pool these loans themselves, and then market the issued MBS.
can sell the loan forward in the TBA market. We define

\[ p_{TBA}^n \]

to be the price of a loan in the TBA market (per $100 principal) net of anticipated payments to Fannie Mae associated with the sale, securitization and insurance of the loan. Since we study the market for intermediation, and not the market for mortgages per se, we take \( p_{TBA}^n \) as exogenously given.

We then define the market price of intermediation \( \phi^n \) of a loan with note rate \( r^n \) as:

\[ \phi^n \equiv p_{TBA}^n - p_{YSP}^n \]  \hspace{1cm} (2.1)

Our empirical analysis will investigate how the price of intermediation changes over time, and how it is affected by the level of demand. To get some intuition, consider a profit-maximizing and, for simplicity, price-taking intermediary who originates mortgages. We assume that they make \( q^n \) loans of note rate \( r^n \):

\[ \max_{q^n} \phi^n \cdot q^n - C(q^n) \]

where \( C(\cdot) \) includes the costs to the intermediary of underwriting, originating and servicing loans (as discussed in the next subsection) and delivering the resulting MBS to an investor. Trivially, the first-order condition is

\[ C'(q^n) = \phi^n \]  \hspace{1cm} (2.2)

Equation (2.2) implies the usual condition that price equals marginal cost which would, in a perfectly competitive market with free entry, imply zero economic profit in equilibrium. It is important to stress that this does not mean that we should not observe profits in the mortgage market or that an increase in demand for intermediation will not increase returns for intermediaries. In particular, marginal cost includes payments to all factors of production. If we think of intermediaries as owning capital, either physical like computer systems or non-physical like human or reputation capital, then an increase in demand for intermediation
will lead to increases in profits for intermediaries as measured by accountants.

Figure 2.1 graphically shows the equilibrium in the market for intermediation. In the standard supply-and-demand representation of a market, the quantity $q$ on the $x$-axis is the number of mortgages originated and the price $\phi$ on the $y$-axis is the price of intermediation. If we assume increasing marginal costs, equation (2.2) implies that supply is upward sloping in $q$. Looking at the demand side, households demand fewer mortgages as $\phi$ goes up. To see why, note that holding $p^n_T$ constant, any increase in $\phi$ reduces the rebate paid to the borrower for a given note rate $r^n$.

One goal of this paper is to understand how changes in the secondary market price translate into the the primary market. Figure 2.1 shows that the effect of a change in $p^n_T$ on $\phi$ and $q$ depends on the shape of the supply curve, which in turn depends on intermediaries’ marginal costs.

As depicted in the top panel, if the marginal cost of originating mortgages is increasing, then an increase in $p^n_T$ will lead to an increase in $\phi$, and thus passthrue to primary market prices ($p_Y$) will be incomplete. As shown in the bottom panel, if instead the marginal cost is constant, the supply curve is flat and changes in TBA prices will completely pass through to YSPs ($\phi$ remains constant). Also, the loan quantity response to a change in TBA prices is larger in that case. Of course one can imagine intermediate cases, such as kinked supply curve that is flat up to some “normal capacity” level and then starts to slope upwards. Then, passthrough would be complete at relatively low levels of $q$, but diminish once $q$ is to the right of the kink.

Our discussion here has for simplicity considered a single note rate. In reality, intermediaries typically offer loans with many different note rates, $n = 1, \ldots, N$, which in turn differ in their secondary and primary market values. Then, the first-order condition (2.2) will hold for all $n$. If the marginal costs of producing different note rates are equal, this would in turn imply that $\phi^n$ should be the same for all $n$.

Also, we emphasize that $\phi$ is not equivalent to the origination-related transaction costs and fees the borrower has to pay. In particular, as we will discuss below, a borrower typically
Supply and Demand for Intermediation

Figure 2.1: The Market for Financial Intermediation
works with a loan officer or broker that either gets paid out of the YSP or requires a separate payment. Also, there are additional fees, for instance for an appraisal or title search, that are outside the transaction that we focus on.

### 2.2.2 The Intermediary Cost Function $C(q^u)$

What are the costs to the intermediary? The intermediary plays two functions in the life of the loan, underwriting/originating the loan, and then servicing the loan once it has been made.\(^9\) We discuss each in turn.

The first component of origination costs are the direct costs associated with the process of underwriting the loan. An intermediary must employ loan officers to work with borrowers, underwriters to review loan applications, a compliance department to make sure that the loan officers and underwriters are fulfilling their legal and contractual obligations, and so on. Additional costs include rent, information technology expenses, advertising and other administrative costs.

The second component of origination costs involve various forms of risk management. In particular, mortgage originators actively engage in “pipeline hedging,” meaning that they hedge financial risks between the time a borrower “locks” a rate/YSP combination and the time the loan closes and is delivered to an MBS investor, which typically takes somewhere between 30 and 90 days. The main risk is that the fraction of loans that are actually originated is lower than expected.\(^10\) This tends to occur primarily when rates fall between the time of lock and origination, since many borrowers may either try to renegotiate or go to a different intermediary altogether. Such an outcome is costly for originators if they forward-sold the loan in the MBS market, since an inability to meet that commitment will require them to buy back part of their committed volume at a higher price (since rates

---

\(^9\)In practice, the entity servicing the loan is not always the same as the one that originated the loan. However, since the intermediary that originally owns the “mortgage servicing right” (MSR) gets compensated when transferring it (there is a relatively active market in which MSRs are traded), this does not affect our discussion.

\(^10\)There is also the risk that a higher-than-expected fraction of loans end up being originated. In expectation, a positive fraction of loans “fall out” due to idiosyncratic events, such as the property appraisal not coming in sufficiently high or the borrower being unable to produce required documentation.
To hedge this risk, originators typically either use “mortgage options” (options on TBA contracts) or swaptions. The cost of the hedge will be higher when the implied interest rate volatility is higher, and in our empirical analysis we will proxy for this with an index of implied Treasury option volatility.

Another risk management cost is due to the possibility that the intermediary will be forced to buy back a loan that the guaranteeing agency determines to be in violation of its underwriting guidelines. The volume of such “putbacks” became very large for the loan vintages that performed worst during the crisis. However, for new loans, it can be mitigated through careful underwriting. Also related in part to putback risk, there is a cost of capital, since intermediaries that want to sell loans to the guaranteeing agencies are required to maintain a certain net worth (as a cushion against future liabilities).

In addition to underwriting the loan, the second main task of the intermediary is to service the loan, which consists of collecting payments from the borrowers after the loan is made, and in case the borrower becomes delinquent, working out a loss mitigation strategy and/or initiate foreclosure. Servicing generates costs but can also generate income. Servicers receive “float income” (coming from a delay between when payments are received from borrowers and when they are passed on to investors). In addition, the servicer also gains an opportunity to cross-sell financial products and has the inside track to refinance the loan.

Formally, we can decompose the cost of intermediation into one-time origination costs, \( C_o \), and per-period servicing costs, \( C_s \). The present value (PV) of the costs of intermediation is then:

\[
C(q^n) = C_o(q^n) + PV(C_s(q^n)).
\] (2.3)

In addition to the timing, there is also a fundamental difference in the aggregate cost function for underwriting versus servicing. As we discuss in detail later, the demand for underwriting fluctuates enormously. A drop in interest rates can lead to massive waves of new loan applications which can tax the limited resources of the industry. A similar problem

\[11\]This risk could be avoided by not selling the loan forward until it has been originated. However, this creates an alternative risk, namely that prices in the MBS market move between the time of the rate lock and the time of the sale. This risk, like the risk of fallout, is primarily due to interest rate movements.
does not occur with servicing since refinancing typically has no effect on the aggregate number of loans being serviced. As a result, we would expect \( C_0' \) to be upward sloping but we would not expect \( C_s' \) to be. Thus, if we assume that the per-period cost of servicing a loan is a constant \( c_s \), we can then write the marginal cost of producing and servicing a loan as\(^{12}\)

\[
C'(q^n) = C_0'(q^n) + PV(c_s).
\]  

(2.4)

**The Valuation of Servicing**

One important institutional detail in GSE MBS is how the servicer gets compensated. For as long as a loan is open, a servicer receives a monthly payment equal to 25 basis points (annual) of the mortgage amount. This payment is taken out of the borrower’s monthly payment (and is thus part of the note rate). As discussed above, the servicer additionally receives other income (or potential benefits), but also incurs costs. Our baseline calculation of \( \phi \) does not separately measure these additional costs/benefits to the servicer, and simply values the 25 basis points of servicing based on the value of the cash flow in the MBS market. We can write (using the superscript “\( n - 0.25 \)” to mean a note rate of \( r^n - 0.25 \)):

\[
\phi^n = p^n_{TBA} - p^n_{YSP}
\]

\[
= p^{n-0.25}_{TBA} + (p^n_{TBA} - p^{n-0.25}_{TBA}) - p^n_{YSP}
\]

\[
= p^{n-0.25}_{TBA} + 0.25 \cdot \frac{p^n_{TBA} - p^{n-0.25}_{TBA}}{0.25} - p^n_{YSP}
\]

\[
= p^{n-0.25}_{TBA} + 0.25 \cdot \text{mult}_{\text{MBS}}^n p^n_{YSP}
\]  

(2.5)

where \( \text{mult}_{\text{MBS}}^n \) is a valuation multiple that transforms an interest rate strip (here, worth 25 basis points) into a present value.

In the case above, this valuation multiple is based on MBS prices for different note rates.

\(^{12}\)Note that \( c_s \) can change across loans originated at different times, as our empirical analysis will suggest that it has. The assumption here is only that the marginal cost is independent of the quantity of originations at a given time.
However, in our empirical analysis, we will also make use of an alternative multiple to value base servicing, provided by a firm called MIAC (Mortgage Industry Advisory Corporation) that specializes in the valuation of and market-making for mortgage servicing rights. These multiples will lead to an alternative measure of intermediary margins, $\pi^n$:

$$\pi^n = p_{TBA}^{n-0.25} + 0.25 \cdot \text{mult}_{MIAC}^n - p_{YSP}^n$$  (2.6)

$\pi$ is different from $\phi$ in that it incorporates the additional benefits from servicing, but also the per-period costs. Thus, based on equations (2.2) and (2.4) we should have that $\phi$ equals $C'_s(q^n) + PV(c_s)$ (where $c_s$ is the net per-period cost of servicing) while $\pi$ equals $C'_o(q^n)$ (the origination costs and profits).\textsuperscript{13} The difference between the $\phi$ and $\pi$ is thus equal to the present value of the net cost of servicing.

### 2.3 Measurement

In this section, we describe our approach to calculating the components of the price of intermediation $\phi$, defined in equation (2.1). First, we discuss how to measure $p_{YSP}^n$, including how we choose $r^n$, the note rate of the mortgage. We then turn to the question of how to measure $p_{TBA}^n$, the price of a given mortgage in the secondary market.

#### 2.3.1 Measuring the Primary Market Price

Lenders publish daily rate sheets which are, essentially, a menu of combinations of note rates and associated yield spread premia (YSPs). The YSP is a payment made by the lender which is shared by the borrower and the loan officer; it can also be negative, meaning the borrower has to “pay points.” Figure 2.2 shows an example of a rate sheet. The upper left panel shows that if the borrower commits to close a 30-year fixed-rate mortgage within 30 days with a note rate of 4.625%, the lender will pay the borrower 70 cents per hundred

\textsuperscript{13}$\pi$ is close to the measure of “originator profits and unmeasured costs” (or OPUC) of Fuster \textit{et al.} (2013), with the difference that here we will not explicitly calculate the “best execution” MBS coupon, and that we do not include origination points in the calculation. On the other hand, our measurement below uses better quality and higher frequency data than Fuster \textit{et al.} (2013).
dollars of principal. If instead the borrower chooses a 4.25% rate, she will have to pay the lender 130 cents. The rest of the rate sheet covers other products (like adjustable-rate mortgages) and “adjustments” which are changes in the YSP to reflect the fact that, for example, the property is a condominium or the borrower has a low credit score.

Some background on the structure of the mortgage market helps here. Following industry convention, we refer to the individual who works directly with the borrower as a loan officer or LO. The party we called “intermediary” in our discussion above, i.e. the entity that provides the funds to the borrower and then sells the loan in the secondary market, is (somewhat confusingly) referred to as the investor. The main breakdown of the market is between retail or single-investor LOs and wholesale or multi-investor LOs. Multi-investor LOs can be further broken down into correspondent LOs who underwrite and fund the loan before selling it to the investor and broker LOs who link the borrower to the investor who then underwrites and funds the loan.\footnote{The use of multi-investor LOs has fluctuated over time, falling from a peak of over 60 percent in 2006 to 40 percent in 2014. See “Mortgage Brokers See Slight Gain in Market Share During 4Q14; Retail Lost Some Ground in 2014,” Inside Mortgage Finance, February 27, 2015.}

Our rate sheet data come from a company called Optimal Blue (formerly known as
LoanSifter) which provides data on rates and YSPs to multi-investor LOs. Optimal Blue either digitizes rate sheets like the one in Figure 2.2 or accesses investor websites to create an online database of rates and YSPs. Optimal Blue then provides LOs with a search engine that allows the LO to enter the characteristics of the loan such as the loan-to-value (LTV) ratio, FICO, and loan amount. Importantly, the offers in Optimal Blue are essentially binding on the investor. If the borrower selects an offer and the LO delivers a loan with the specified characteristics, the investor has an obligation to fund it at the chosen rate/YSP combination (assuming the borrower fulfills the underwriting guidelines). Investors typically issue the first rate sheet of the day around 10am and then frequently revise it over the course of the day.\(^{15}\) Our data only includes a single snapshot taken at the end of the day, meaning we have the last rate sheet issued on any given day.

Each LO has access to a subset of lenders with which the LO has an agreement, and offers for an identical loan may differ across loan officers for a given lender. We obtain offers either for a generic LO that was set up specifically for us (for data from October 2008 - September 2009) or for five different representative loan officers (since September 2009).\(^{16,17}\)

Further information about the Optimal Blue dataset can be found in Table 2.1. The number of lenders over which Optimal Blue searches fluctuates in our sample. Part of this reflects the entry and exit of lenders from the multi-investor market; for example, Bank of America exited in 2011.\(^{18}\) In addition, since our searches since 2009 are based on the profiles of actual loan officers, any change in the set of investors with whom a specific loan officer has a relationship may lead to a change in the number of offers in our sample. We do not know the identities of individual lenders, but know that essentially all the largest lenders

\(^{15}\) Investors generally adjust their rate sheets on at least a daily level. Of the 35.4k rate sheets captured in our sample, only 2.3k (about 6.5%) show no change from the previous day.

\(^{16}\) For the period since September 2009, we average a given lender’s offers across the LOs the lender has a relationship with.

\(^{17}\) Over the entire sample period of more than six years, there are 49 days missing, either due to missing backups/queries or due to obviously inconsistent data.

Table 2.1: Characteristics of the proprietary lender ratesheet data from Optimal Blue used for our analysis.

The rate/point offers depend on borrower- and loan-level characteristics, such as the FICO score and loan type. Our base case is listed above. The second part of the table shows descriptive statistics on the rates and points on ratesheets, both within day (across lenders), across days (taking the mean of lenders for any given day), and pooled (across both lenders and days).

<table>
<thead>
<tr>
<th>Loan-level characteristics for baseline scenario</th>
<th>Base case</th>
<th>Base case</th>
</tr>
</thead>
<tbody>
<tr>
<td>Loan amount</td>
<td>300,000</td>
<td>Prepayment penalty</td>
</tr>
<tr>
<td>Loan-to-value ratio (LTV)</td>
<td>80</td>
<td>Lock period</td>
</tr>
<tr>
<td>FICO</td>
<td>750</td>
<td>Owner-occupied or investment</td>
</tr>
<tr>
<td>Program</td>
<td>Conforming</td>
<td>State</td>
</tr>
<tr>
<td>Loan type</td>
<td>Fixed</td>
<td>MSA</td>
</tr>
<tr>
<td>Term</td>
<td>30 year</td>
<td></td>
</tr>
</tbody>
</table>

| Rate sheet information                        |          |           |          |          |          |          |
| unique lenders                                | 63       | mean      | SD       | p10      | p50      | p90      |
| lenders per day                               | 21.7     | 5.6       | 13       | 21       | 28       |
| offers per ratesheet                          | 22.9     | 18.5      | 9        | 16       | 48       |

| Points and rates                              |          | mean      | SD       | p10      | p50      | p90      |
| Within day                                    |          |           |          |          |          |          |
| points offered                                | 101.2    | 1.8       | 98.5     | 101.5    | 103.3    |
| rates offered                                 | 4.54     | 0.41      | 3.99     | 4.54     | 5.09     |

| Across days                                   |          |           |          |          |          |          |
| points offered                                | 101.2    | 1         | 99.9     | 101.3    | 102.4    |
| rates offered                                 | 4.53     | 0.57      | 3.78     | 4.52     | 5.25     |

| Pooled                                        |          |           |          |          |          |          |
| points offered                                | 101.2    | 2.2       | 98.2     | 101.5    | 103.7    |
| rates offered                                 | 4.55     | 0.71      | 3.63     | 4.50     | 5.50     |
are in the Optimal Blue data.\textsuperscript{19}

Our baseline scenario involves a fixed-rate mortgage on an owner-occupied property located in Los Angeles, CA, a borrower with a FICO of 750, a term of 30 years, a loan amount of $300,000, a loan-to-value ratio of 80, no prepayment penalty and a 30-day lock period. We consider alternative scenarios as well, and find that the qualitative results remain unchanged.

\textbf{Tracking a mortgage note rate over time}

In principle, we could choose a single note rate and follow that note rate over our entire sample period. Unfortunately, in reality, the set of quoted note rates at a point in time is quite narrow and changes often as interest rates evolve, since there is no market for loans with either very high or very low YSPs (high YSPs are unattractive to lenders due to the prepayment option; low YSPs are unattractive to borrowers because they require high upfront payments). As shown in Table 2.1, our data from Optimal Blue is consistent with these facts – the mean points across ratesheets for our entire sample is approximately 101, with a within-day standard deviation of 1.8. The within-day range of rates offered is also reasonably narrow and is typically contained within a range of two percentage points.

To address the problem of time-varying sets of note rates, we derive a constant-YSP note rate, which we argue provides a reasonable index of mortgage rates for our analysis. Our main analysis uses “Rate101”, the note rate that yields a YSP of +1 point (or $p_{YSP} = 101$), which is anecdotally a typical YSP that borrowers choose. We construct Rate101 for each rate sheet by interpolating between different offers and then use the daily median value across our sample of rate sheets as our baseline.\textsuperscript{20}

The top panel of Figure 2.3 shows the evolution of Rate101 over our sample. Rate101 started above 6 percent in 2008, prior to the monetary policy actions that started in late

\textsuperscript{19}We do have numeric identifiers for individual lenders, but do not make use of those in our analysis.

\textsuperscript{20}The interpolation is required because, as Figure 2.2 shows, YSPs are quoted in decimals but note rates are generally quoted in 1/8 of a percentage point. In this example (for the 30-day lock), we would linearly interpolate between 4.625 and 4.750 to produce a precise rate that corresponds to a YSP of 1 (in this case 4.641).
Figure 2.3: Rate101 (top) and the differences against Rate102, Rate100, and the Freddie Mac Primary Mortgage Market Survey series for 30-year fixed-rate mortgages (bottom), all weekly averages.
November of that year, and reached its low point near the end of 2012 at close to 3 percent.
The bottom panel shows how Rate101 compares to two alternative choices, Rate100 (for a
YSP of 0) and Rate102 (for a YSP of +2), and also to the widely-quoted Freddie Mac Primary
Mortgage Market Survey rate. The figure shows that over 2010-2014, the rate change per 1
point in YSP was quite stable around 20 basis points, and that the Freddie Mac rate was on
average quite close to our Rate101 (thereby validating our choice of +1 as a “typical” YSP).
Earlier in our sample, however, the effect on the note rate of a change in YSP was much
larger: at times, a borrower could get a 100 basis point lower mortgage rate by accepting a
1-point lower rebate. This in turn made it attractive to borrowers to get relatively lower
YSPs (i.e. 0 instead of +1); this is reflected in the Freddie Mac survey rate, which is closer to
Rate100 over this early period.

Rate101 changes from one day to the next, but to study daily passthrough we will want
to hold the note rate constant over time. Thus, we introduce the notation

\[ p_{YSP}^{Rate101,t}(s), \]

which means the time-s primary market price of a loan with a note rate of time-t Rate101.
By definition, \( p_{YSP}^{Rate101,t}(t) = 101 \). We define \( p_{TBA}^{Rate101,t}(s) \) similarly.

### 2.3.2 Measuring the Value of a Mortgage in the Secondary Market

The main secondary market for mortgages is called the To-Be-Announced or TBA market.
The TBA market is a forward market for mortgage-backed securities (MBS) guaranteed by
Fannie Mae, Freddie Mac and Ginnie Mae, and is one of the largest fixed income markets in
the world (Vickery and Wright, 2013). In this market, buyers (such as mutual funds, pension
funds, foreign investors, and, in recent years, the Fed) promise to buy a pool of mortgages

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21 The Freddie Mac rate is based on a weekly survey of about 125 lenders, asking them for their “most
popular” rate and points combination on first-lien prime conventional conforming home purchase mortgages
with a loan-to-value ratio of 80 percent. We focus on the series for 30-year fixed-rate mortgages.

22 This was due to a narrowing of MBS price differences across coupons, as also discussed in Fuster and
Willen (2010).
meeting certain specified characteristics at a specific date in the future. The majority of newly produced agency MBS pools are traded in this market.\textsuperscript{23} Agency MBS are typically only traded in coupon increments of 50 basis points (e.g. 3.5\%, 4\%, etc.)

As already mentioned earlier, the guaranteeing agency, in our case Fannie Mae, charges an ongoing insurance premium or guarantee fee (“g-fee”) as well as an upfront premium depending on loan characteristics, known as “loan level price adjustment” (LLPA). The exact values of g-fees are not disclosed, but we know that they vary over our sample. Up to 2008, the typical g-fee was roughly 22 bps, meaning that Fannie charged an annualized fee of 0.22 percent of the unpaid principal balance of a loan every month.\textsuperscript{24} In 2012, two 10 basis point increases were announced, on January 1 (to 32 bps) and on September 1 (to 42 bps). Through the rest of our sample period, the ongoing g-fee is still assumed to be at 42 bps. The upfront LLPA for the base-case loan characteristics only changes once over our sample period, from 25 bps prior to December 23, 2010 to 50 bps.\textsuperscript{25}  

In our baseline calculation for $\phi$, we assume that the value of a mortgage with note rate $\text{Rate}_{101}$ in the secondary market is simply given by the interpolated TBA market price of an MBS with coupon $\text{Rate}_{101} - g\text{fee}$, and subtracting the upfront LLPA. For instance, if $\text{Rate}_{101} = 4.56$, $g\text{fee} = 0.32$, and $LLPA = 0.25$, then our the secondary market value equals:

$$p_{TBA}^{\text{Rate}_{101}}(s) = p_{TBA}^4(s) + (24/50) \ast (p_{TBA}^{4.5}(s) - p_{TBA}^4(s)) - 0.25,$$

that is, we interpolate between the prices of the 4 and 4.5\% coupons. Our calculation above implicitly presumes that a loan always gets securitized in a coupon below $\text{Rate}_{101} - g\text{fee}$, whereas in reality originators have the option to securitize a loan in any coupon rate at or

\textsuperscript{23}The remainder are pools that either do not meet the criteria for the TBA market or are so-called “spec pools,” groups of loans with certain characteristics that are desirable to investors (for example, an investor might want low credit score loans because of their more attractive prepayment properties.)

\textsuperscript{24}The value of 22 bps is obtained from Fannie Mae 10Ks; we take an average of the average guarantee fee over 2005-2008.

\textsuperscript{25}This value includes the 25 bps “adverse market delivery charge” that the GSEs started charging in March 2008; see the announcement at https://www.fanniemae.com/content/announcement/0721.pdf. Fannie Mae’s current LLPA matrix is available at https://www.fanniemae.com/content/pricing/llpa-matrix.pdf.
below $\text{Rate}101 - 0.25$. Fuster et al. (2013) provide a detailed discussion of the decision into which coupon to pool; what is important for us here is that the differences across these options are typically small.\footnote{26}

### 2.3.3 Data Sources

The MBS price data is from J.P. Morgan and, for simplicity, we assume that all loans are sold to Fannie Mae. For our baseline analysis, we normalize all prices to be 45-days-to-settlement using a weighted combination of the 1-, 2-, and 3-months-out contracts.\footnote{27} This is the relevant metric if the time between rate lock (prior to loan origination) and delivery in an MBS trade is 45 days, which is close to the approximate average lag from application to origination in the HMDA data. Different normalizations do not materially affect our results since the gaps between the prices are generally stable.

To measure time-series variation in demand, we use new loan applications from the confidential version of the Home Mortgage Disclosure Act (HMDA) dataset. The HMDA dataset captures a large share (roughly 90\%) of mortgage applications and originations. The confidential version of the data contains exact application and action (i.e. accept or reject) dates, which allows us to count applications on a daily level. We include all first-lien, single-family loans in our measure, including applications for refinancing and purchase loans. The available data covers 2008 through October 2014.\footnote{28} In our lower-frequency analysis in Section 2.6, we use total monthly originations, normalized by the number of

\footnote{26} We choose to ignore the pooling decision because it would require us to make assumptions about “buy down” multiples set by Fannie Mae that are not publicly disclosed.

\footnote{27} These contracts are sometimes referred to, respectively, as “front”, “back”, and “double back”. The following illustrates our weighting: on “notification day” in the TBA market, the front-month time-to-notification is 0 days, the back month is approximately 30 days, and the double back is approximately 60 days. In this case we use $1/2 \ast p_{\text{back}} + 1/2 \ast p_{\text{doubleback}}$. The following day, the front-month time-to-notification is approximately 30 days, back is 60 days, and double back is 90 days. In this case we use $1/2 \ast p_{\text{front}} + 1/2 \ast p_{\text{back}}$. This methodology ensures that there are no spurious jumps in MBS prices on the monthly notification days.

\footnote{28} To be included in the HMDA data for a given year, an application needs to be processed within that year. Applications submitted towards the end of year $t$ are thus frequently included in the HMDA file for year $t + 1$ only. Since we do not have the 2015 HMDA data yet, including October-December 2014 would lead us to understate application volumes for these months.
business days in a given month.

We also use the HMDA data to measure lender concentration, by calculating the market share of the top four lenders (following Scharfstein and Sunderam, 2013) at a monthly frequency. This measure is specific to the MSA in question, which is Los Angeles in our baseline case (since we are looking at rate/YSP offers for Los Angeles), although the overall trends in market concentration are similar across the country during the period we study.

As a measure of labor costs, we use real estate credit payrolls, divided by real estate credit employment. Both series are from the Bureau of Labor Statistics and available at a monthly frequency. To measure the volatility of interest rates, which may affect originators’ hedging costs, we use the monthly average Merrill Lynch Option Volatility Expectations (MOVE) index, an index of the normalized implied volatility on 1-month Treasury options, weighted on the 2, 5, 10, and 30 year contracts.

Finally, as discussed in Section 2.2.2, for our alternative measure of intermediary margins \(\pi\) we use base servicing valuation multiples provided to us by the Mortgage Industry Advisory Corporation (MIAC). We have monthly data from the start of our data in October 2008 until September 2014; we assume that the value in October 2014 is the same as September 2014. For the valuation of the remaining interest strip (after g-fee and base servicing are deducted from the coupon), we interpolate between the TBA prices of the surrounding coupons, as we do in our baseline calculation.

2.4 Event Studies: QE Announcements

In this section, we use the concepts derived above to explore the effect of announcements about the Federal Reserve’s large-scale asset purchase program (and one other unconventional monetary policy measure, date-based forward guidance) over the period 2008 to 2013. We do this first because the results are of inherent interest: an explicit purpose of asset purchases (or quantitative easing, QE) was to drive down the cost of mortgage credit for consumers. But, more broadly, the monetary policy announcements provide a sort of laboratory to understand the transmission of shocks in the secondary mortgage market to
primary market. The six events we focus on are:


2. **QE1 Expansion**: March 18, 2009. FOMC announced the program would be expanded: purchases of agency MBS and agency debt increased by $750B; purchases of Treasury securities increased by $300B.

3. **Forward Guidance**: August 9, 2011. FOMC changed statement language to “exceptionally low levels for the federal funds rate at least through mid-2013,” from “exceptionally low levels for the federal funds rate for an extended period.”

4. “QE3”: September 13, 2012. Open-ended commitment to purchase $40B agency MBS per month until labor market improved “substantially.”

5. **Taper Tantrum**: June 19, 2013. Then-Fed Chairman Bernanke’s press conference: “If the incoming data are broadly consistent with this forecast, the committee currently anticipates that it would be appropriate to moderate the monthly pace of purchases later this year.”

6. **Non Taper**: September 18, 2013. Contrary to market expectations, FOMC opts not to start reducing MBS purchases.

Our choice of events is, by its nature, somewhat arbitrary but our goal was to find news that surprised markets and led to significant shifts in the bond market, as all of these did.29 As an example of a date that did not meet our criteria, the announcement of “QE2” on November 3, 2010 had little effect on bond markets because anticipation of QE2 had led to a substantial rally over the previous three months. The Taper Tantrum is the only event with an MBS price decrease among the six events that we study.

---

29To enter our sample, the date had to be among either the 25 days in our sample with the biggest increases or among the 25 days with the biggest decreases in the yield on the current coupon MBS (from J.P. Morgan) and coincide with a major announcement regarding Federal Reserve policy.
Figure 2.4: Event studies of major monetary policy (QE) announcements over our sample period. Top lines show the TBA and YSP prices holding the rate fixed at Rate101 (Rate100 in 2008-2009) of the day prior to the announcement. Middle line shows the passthrough of the TBA price change to YSP. Bottom line shows daily application counts as measured by HMDA.
Figure 2.4 shows the evolution of key variables for each event. We start our discussion with the announcement of QE3 in September 2012 (the bottom left panel). On September 12, 2012, Rate101, the median note rate on a mortgage with a one percent rebate, was 3.375 percent. We calculate that $p_{TBA}$, the secondary market price, of the Rate101 loan on September 12 was 102.7 meaning that after funding the loan and paying the 1 percent rebate, the intermediary margin was 1.7 dollars per hundred dollars of principal. The announcement of QE3 the following day led to an increase in $p_{TBA}$ to 103.8. Had intermediaries kept rebates the same, the margin on the loan with a note rate of 3.375 would have gone up to 2.8 dollars per hundred dollars of principal. However, we calculate that the rebate on that loan also went up after the announcement, from 1 percent to 1.6 percent. Overall, the secondary market price $p_{TBA}$ went up by 1.1 percent and the primary market prices $p_{YSP}$ went up by 0.6 percent meaning that about 55 percent of the price increase was passed through to borrowers. The bottom left panel of Figure 2.4 shows that $p_{TBA}$ drifted down over the next few days but $p_{YSP}$ stayed more or less the same so effective passthrough was somewhat higher at longer horizons.

Looking across the six events now, several features of the data are worth noting. First, the high frequency relationship between $p_{TBA}$ and $p_{YSP}$ is quite close. Almost everywhere, increases in the secondary market price lead to increases in the primary market price. This occurs even when the changes in prices are very small. It is important to stress that there is nothing mechanical about this relationship in the data as the two time series come from completely different data sources: $p_{TBA}$ is generated from data from global financial markets and $p_{YSP}$ comes from offers to loan officers working with individual borrowers.

The second notable feature of Figure 2.4 is that passthrough appears to vary significantly across the different events. Borrowers received less than 50 percent of the effects of the QE1 Expansion announcement in March 2009 and, at some horizons, much less. In contrast, the effects of the initial announcement of QE in November 2008, the Taper Tantrum in June

---

30 For the first two events, we use Rate100 instead of Rate101 because Rate100 was more representative of the note rates borrowers were choosing at that time (see earlier discussion of Figure 2.3).
2013 and the Non-Taper in September 2013 were passed on to borrowers almost entirely. What can explain these differences? In Section 2.2.1 above, we argued that the degree of passthrough depends on the shape of the supply curve. Recall that an increase in prices in the secondary market, all else equal, leads to an increase in the demand for intermediation and that a higher slope of the cost curve implies lower passthrough, as depicted in Figure 2.1. To explore this effect, we add the daily volume of new loan applications to each figure. As noted already, passthrough was very high for the initial QE1 announcement but much lower for the QE1 Expansion four months later. Consistent with the idea that volume matters, we see a large difference in volume around the announcement. Indeed, at 37,000 applications per day, volume on November 24, 2008 was at a historically low level, so there was likely some capacity slack that allowed for passthrough of increased MBS prices to borrowers. In contrast, the day before the announcement of the QE1 Expansion, there were 63,000 applications and that number spiked to over 100,000 following the announcement; consistent with the idea of intermediaries facing convex costs in quantity, passthrough was lower. June and September of 2013 are also instructive. In the former case, bond prices fell dramatically and, not surprisingly, demand did not increase and passthrough was high. In September of 2013, bond prices rose but from a low level induced by the original taper tantrum, meaning that even after the increase, refinancing was not that appealing to borrowers.

A third feature of Figure 2.4 is that the price of intermediation $\phi$ appears to rise over time. If we compare the original announcement of QE with the Non-Taper, passthrough was higher in the latter, as already noted, but the gap between intermediaries’ revenue ($p_{TBA}$) and what they pay the borrower for the loan ($p_{YSP}$) is much higher in the latter. This increase in $\phi$ could, according to the theory, result from higher volume, but the data appears to reject that — application volume in September 2013 was very similar to application volume before the QE1 announcement, but $\phi$ was much higher.

In the next two sections, we will consider questions raised here econometrically. How big is passthrough? Does volume systematically affect passthrough? Is passthrough higher for decreases in prices versus increases? Did the price of intermediation increase over time?
What accounts for that increase?

2.5 High-Frequency Passthrough

The first question we are interested in is to what extent changes in MBS prices from one day to the next are reflected in YSPs offered on ratesheets. To investigate this, we regress the daily change in the YSP for a given rate on the change in the MBS market value of a mortgage with this note rate.

Specifically, we start with the Rate101 for date \( t \). We calculate \( p_{Rate101t}^{TBA}(t) \) for that day, while \( p_{YSP}^{Rate101t}(t) = 101 \) by definition. We then move one day forward and calculate \( p_{Rate101t}^{TBA}(t+1) \) and \( p_{YSP}^{Rate101t}(t+1) \) which no longer necessarily equals 101. To illustrate, consider the following example:

<table>
<thead>
<tr>
<th></th>
<th>3/31/2010</th>
<th>4/01/2010</th>
</tr>
</thead>
<tbody>
<tr>
<td>Primary Market</td>
<td></td>
<td></td>
</tr>
<tr>
<td>( p_{Rate101t}^{TBA} )</td>
<td>101.00</td>
<td>101.66</td>
</tr>
<tr>
<td>( p_{YSP}^{Rate101t} )</td>
<td>101.97</td>
<td>101.66</td>
</tr>
</tbody>
</table>

\( y_t = -0.31 \)

In this case, the passthrough is almost complete (0.31/0.33, or 93.9%).

The top panel of Figure 2.5 shows a scatter plot of daily changes in the primary market value of a Rate101 loan against the change in its secondary market value. From the figure, it is clear that there is a very strong relationship between price changes in the primary and secondary market, though the passthrough appears slightly stronger for negative changes than positive changes.

Table 2.2 shows the results from simple linear regressions to quantify the amount of passthrough. In column (1), we see that the average passthrough coefficient is 0.92, and that 88% of the variation in YSP changes is explained by variation in MBS price changes. We find that the passthrough of price decreases appears to be stronger than the passthrough
Figure 2.5: Top panel shows scatterplot of daily first differences of YSPs and MBS prices. Bottom panel shows coefficients of first difference regression by year. Top panel: Grey dots show every data point (for the full sample period, October 2008 - October 2014) while black dots show averages by deciles of \( p_{TBA} \) ("binscatter"). Diagonal line is the 45-degree line, where points would lie with perfect passthrough. Both the YSP and MBS series are for Rate101, as discussed in Section 2.5. These data underlie the regressions in Table 2.2. Bottom panel shows coefficients of first difference regression by year: \( \Delta \text{YSP} = \beta_0 + \beta_+ \Delta p_{TBA}^+ + \beta_- \Delta p_{TBA}^- \) is run by year, and the coefficients are plotted on the graph alongside bars that indicate the annual new mortgage applications as calculated using the HMDA data. Source: Optimal Blue; J.P. Morgan Markets; HMDA; authors’ calculations.
Table 2.2: Regressions of $\Delta p_{TY}^{\text{Rate101}}$ on $\Delta p_{TBA}^{\text{Rate101}}$ at daily frequency. “Applications” is the daily HMDA application volume from the previous day. $\Delta p_{TBA}^{+}$ indicates the magnitude of the day-over-day change in TBA price for positive changes only, and $\Delta p_{TBA}^{-}$ corresponds to the negative changes. Columns 4 and 5 also include a price change lagged by one business day. All prices are normalized to the same rate (“Rate101”).

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\Delta p_{TBA,t}$</td>
<td>0.915***</td>
<td>(0.014)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\Delta p_{TBA,t}^+$</td>
<td>0.795***</td>
<td>0.790***</td>
<td>0.793***</td>
<td>0.788***</td>
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</tr>
<tr>
<td></td>
<td>(0.023)</td>
<td>(0.024)</td>
<td>(0.023)</td>
<td>(0.023)</td>
<td></td>
</tr>
<tr>
<td>$\Delta p_{TBA,t}^-$</td>
<td>1.021***</td>
<td>1.027***</td>
<td>1.022***</td>
<td>1.026***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.022)</td>
<td>(0.022)</td>
<td>(0.022)</td>
<td>(0.022)</td>
<td></td>
</tr>
<tr>
<td>$\Delta p_{TBA,t-1}^+$</td>
<td>0.078***</td>
<td></td>
<td></td>
<td>0.080***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.020)</td>
<td></td>
<td></td>
<td>(0.019)</td>
<td></td>
</tr>
<tr>
<td>$\Delta p_{TBA,t-1}^-$</td>
<td>0.012</td>
<td>0.007</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.023)</td>
<td>(0.023)</td>
<td></td>
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<td></td>
</tr>
<tr>
<td>$\Delta p_{TBA}^+ \times \text{Applications}$</td>
<td>-0.064***</td>
<td>-0.069***</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.019)</td>
<td>(0.023)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\Delta p_{TBA}^- \times \text{Applications}$</td>
<td>0.009</td>
<td>0.015</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.018)</td>
<td>(0.021)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\Delta p_{TBA,t-1}^+ \times \text{Applications}$</td>
<td>-0.023</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.017)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\Delta p_{TBA,t-1}^- \times \text{Applications}$</td>
<td>-0.039*</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.021)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Constant</td>
<td>-0.001</td>
<td>0.022***</td>
<td>0.016***</td>
<td>0.022***</td>
<td>0.015***</td>
</tr>
<tr>
<td></td>
<td>(0.002)</td>
<td>(0.004)</td>
<td>(0.005)</td>
<td>(0.004)</td>
<td>(0.005)</td>
</tr>
<tr>
<td>Adj. $R^2$</td>
<td>0.88</td>
<td>0.89</td>
<td>0.89</td>
<td>0.89</td>
<td>0.89</td>
</tr>
<tr>
<td>Observations</td>
<td>1431</td>
<td>1431</td>
<td>1431</td>
<td>1431</td>
<td>1431</td>
</tr>
</tbody>
</table>

Robust standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
of price increases (column (2)). Notably, the asymmetry of passthrough is statistically and economically significant, with price decreases being passed through approximately 100% within this one-day window. Price increases, in contrast, are only passed through about 80% on the first day.\textsuperscript{31} In column (3), we add the price change from the previous day, and find that there is some additional passthrough of lagged positive (but not negative) changes, so that over two days, approximately 87% of MBS price increases are reflected in primary market YSPs. (In untabulated results, we find that the effects for further lagged MBS price changes are statistically indistinguishable from zero.)

While the daily passthrough is very strong on average, in the remaining two columns we explore a potential driver of time variation in this passthrough, namely the level of demand following the discussion in Section 2.2. Specifically, we interact the changes in the MBS value with the standardized level of new applications from HMDA, so that the coefficient on the interaction term corresponds to the effect on daily passthrough of a one-standard deviation increase in (one-day-lagged) application volume. Column (4) shows that indeed, a higher level of applications lowers the passthrough of MBS price increases to YSPs. For instance, the coefficients imply that if applications are two standard deviations above average, only 66% ($= 0.791 - 2 \times 0.064$) of a price increase are passed through. The final column shows that this interaction effect remains unchanged if we add the lagged price change as well.

The bottom panel of Figure 2.5 graphically illustrates how differences in application volume at a lower frequency are related to variation over time in the passthrough coefficients. It plots the coefficients from regression (2) from Table 2.2, but estimated separately year-by-year (except that we pool the 2.5 months of data from 2008 with 2009). The figure shows that for MBS price increases, the estimated passthrough was lowest in 2012, when applications were at their highest levels. Passthrough then increased over the following two years, as application volumes dropped; in 2014, the year with the lowest mortgage demand

\textsuperscript{31}Figure 2.5 suggests potential non-linearity in the relation between secondary and primary price changes. In untabulated regressions, we find that adding quadratic MBS price changes results in a significant negative (but relatively small) coefficient for price declines, and an insignificant positive coefficient for price increases. None of the other results in this section are qualitatively altered by adding squared price changes to the regressions.
in our sample, passthrough of positive price changes exceeds 0.9. The passthrough of price decreases (the upper line) is fairly stable and close to 1, except in 2013 when it goes up to 1.1.

In Appendix A.7, we discuss an alternative methodology where changes in mortgage rates are regressed on changes in MBS yields (on the so-called “current coupon,” which is the market benchmark), at the daily, weekly, or monthly frequency. With Rate101, we obtain similar daily passthrough to what we found in this section. Perhaps surprisingly, the passthrough coefficients exhibit a slight decrease when we look at longer horizons (esp. monthly); the reasons for this will be further discussed in Section 2.7.1. Finally, we find much stronger passthrough using our Rate101 rather than the commonly used Freddie Mac rate, suggesting less (non-random) measurement error in our rate measure.

The take-away from these regressions is that at high frequencies, primary market prices strongly respond to the secondary market. In a sense, this should not be surprising given that lenders issue new rate sheets every day and sometimes more than once a day. But it is in contrast with findings of infrequent adjustments in other consumer finance markets, where rates offered to consumers only react slowly to changes in monetary policy and market rates (e.g. Driscoll and Judson, 2013).

Although these high-frequency regressions suggest a direct and strong link from MBS prices to the primary market, the result that increases in MBS prices result in incomplete passthrough leaves open the possibility of lower frequency movements in the price of intermediation, which we turn to next.

### 2.6 Evolution of the Price of Intermediation Over Time

Figure 2.6 shows the evolution of our baseline estimate of the price of intermediation at the daily frequency. This cost is calculated as the secondary market value of the Rate101 loan \( p_{TR}^{Rate101} \) (net of payments to Fannie Mae) less the primary market value \( p_{YSP}^{Rate101} \) which is, by definition, 101:
Figure 2.6: As explained in Section 2.6, \( \phi \) is our baseline estimate of the price of intermediation and \( \pi \) is our alternative measure of intermediary margins where the 25 basis points of servicing cash flow are valued by a separate multiplier, rather than implicitly by MBS prices. Lower panels show monthly average \( \phi \) plotted against applications per business day and average processing time (from HMDA); implied interest rate volatility (MOVE); payroll per employee in real estate credit (from the BLS); and mortgage market concentration (from HMDA).
We estimate that over the whole sample, the price of intermediation averaged 142 basis points. The standard deviation was large (61 basis points), as evidenced by the fact that our estimated values range from 0 to 300 basis points.

As explained earlier, we also calculate an alternative measure of intermediation margins \( \pi \), where the 25 basis points of servicing cash flow are valued using a separate multiplier (from MIAC) that takes into account other costs/benefits of servicing (while our calculation of \( \phi \) implicitly values the servicing as if it was just a 25 bp interest strip).

Figure 2.6 shows that the time series of \( \phi \) displays a somewhat less pronounced upward trend than \( \pi \). There are two main reasons for this: first, MIAC servicing multiples did not fall in early 2009, unlike the market-implied value of a 25 bp interest strip. Second, toward the end of the sample, servicing multiples fell relative to MBS-price-implied valuations. Following our discussion in Section 2.2.2, this implies that the present value of net servicing costs increased over our sample period, something we will come back to later.

2.6.1 Determinants of Variation in the Price of Intermediation

We now turn to potential drivers of the variation in the price of intermediation. Figure 2.6 plots time series of four key variables that proxy for either the costs of intermediaries or their ability to earn excess profits:

1. New application counts from the HMDA data;
2. Interest rate volatility as measured by the Merrill Lynch MOVE index;
3. The payroll per employee in real estate credit, from the BLS;
4. Market concentration, as measured by the market share of the top 4 lenders in the Los Angeles MSA in the HMDA data.

Applications proxy for potentially increasing marginal costs, or increased pricing power due to limited origination capacity, as discussed earlier. Indeed, we observe a strong positive
correlation between $\phi$ and application volume. Higher interest rate volatility increases the cost of hedging the origination pipeline, so we would expect it to correlate positively with $\phi$. However, the chart shows that the main variation in rate volatility was due to a decrease following the height of the crisis; since then, the MOVE has remained relatively flat and does not seem to be a main driver of the evolution of $\phi$. Employee payroll is likewise an important component of origination costs, and indeed has seen an upward trend over this period, consistent with the increase in $\phi$. Finally, market concentration has decreased over this time, suggesting that, at least when measured based on market shares in the HMDA data, changes in concentration cannot explain the rise in $\phi$.

To analyze this more formally, we begin by regressing $\phi$ on these variables, at the monthly frequency, both in levels and changes. We furthermore add Rate101 as an additional control variable, to ensure that the correlations we document are not driven by the downward trend in rates over the time period we document. In the levels regressions, we also add a linear time trend, to test whether there appears to be an increase in the price of intermediation that is not accounted for by our explanatory variables. All explanatory variables except Rate101 are normalized to have a mean of zero and a standard deviation of one.

Table 2.3 shows that an increase in new application volume is strongly positively associated with a higher price of intermediation, both in levels and changes, and whether or not other explanatory variables are included. In levels, adding the linear time trend substantially increases the coefficient on applications in column (2), and the time trend and applications jointly explain 85 percent of the variation in $\phi$ (while the time trend alone would explain 52 percent). The tight fit is illustrated by the chart below the table. In terms of magnitude of the effect, a one-standard deviation increase in applications is associated with a 36 basis point increase in $\phi$. When we add other controls, or conduct the regression in monthly changes, the magnitude of the effect is reduced only slightly (to around 28 basis points).

The regression in changes is shown in Table 2.4.

Table 2.5 separately analyzes the effects of applications and the other controls on the
Table 2.3: Understanding time-variation in the price of intermediation – regression in levels. The definition of \( \phi \) and the explanatory variables can be found in Section 2.3. All explanatory variables except for the time trend (where the unit is calendar month) have been standardized over the relevant sample, so that the coefficients can be interpreted as the effect of one standard deviation of the relevant variable on the price of intermediation.

Regression Results

<table>
<thead>
<tr>
<th></th>
<th>( \phi ), OLS</th>
<th></th>
<th>( \phi ), IV</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
<td>(3)</td>
</tr>
<tr>
<td>Applications</td>
<td>0.203 ( ^* )</td>
<td>0.360 ( ^*** )</td>
<td>0.289 ( ^*** )</td>
</tr>
<tr>
<td></td>
<td>(0.111)</td>
<td>(0.042)</td>
<td>(0.062)</td>
</tr>
<tr>
<td>Time Trend</td>
<td>0.026 ( ^*** )</td>
<td>0.015 ( ^* )</td>
<td>0.017 ( ^** )</td>
</tr>
<tr>
<td></td>
<td>(0.002)</td>
<td>(0.008)</td>
<td>(0.007)</td>
</tr>
<tr>
<td>Volatility</td>
<td>-0.026</td>
<td>-0.090</td>
<td>-0.017</td>
</tr>
<tr>
<td></td>
<td>(0.072)</td>
<td>(0.075)</td>
<td>(0.068)</td>
</tr>
<tr>
<td>Lender Conc.</td>
<td>0.073</td>
<td>0.071</td>
<td>0.102</td>
</tr>
<tr>
<td></td>
<td>(0.073)</td>
<td>(0.080)</td>
<td>(0.086)</td>
</tr>
<tr>
<td>R.E. Payroll</td>
<td>0.197 ( ^*** )</td>
<td>0.188 ( ^*** )</td>
<td>0.179 ( ^*** )</td>
</tr>
<tr>
<td></td>
<td>(0.050)</td>
<td>(0.059)</td>
<td>(0.065)</td>
</tr>
<tr>
<td>Rate101</td>
<td>-0.173</td>
<td>-0.129</td>
<td>-0.129</td>
</tr>
<tr>
<td></td>
<td>(0.117)</td>
<td>(0.148)</td>
<td>(0.148)</td>
</tr>
<tr>
<td>Constant</td>
<td>1.398 ( ^*** )</td>
<td>-14.490 ( ^*** )</td>
<td>-6.841 ( ^*** )</td>
</tr>
<tr>
<td></td>
<td>(0.123)</td>
<td>(1.311)</td>
<td>(5.005)</td>
</tr>
</tbody>
</table>

Newey-West standard errors in parentheses

\( ^* p < 0.10, ^** p < 0.05, ^*** p < 0.01 \)

Predicted vs. Actual, Specification (2)
Table 2.4: Understanding time-variation in the price of intermediation – regression in monthly differences. The definition of $\phi$ and $\pi$, as well as the explanatory variables, can be found in Section 2.3.

Regression Results

<table>
<thead>
<tr>
<th></th>
<th>$\Delta \phi$, OLS</th>
<th></th>
<th>$\Delta \phi$, IV</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
<td>(3)</td>
<td>(4)</td>
</tr>
<tr>
<td>$\Delta$ Applications</td>
<td>0.261***</td>
<td>0.277***</td>
<td>0.252***</td>
<td>0.317***</td>
</tr>
<tr>
<td></td>
<td>(0.056)</td>
<td>(0.081)</td>
<td>(0.063)</td>
<td>(0.051)</td>
</tr>
<tr>
<td>$\Delta$ Volatility</td>
<td>-0.023</td>
<td>-0.006</td>
<td>0.073</td>
<td>0.058</td>
</tr>
<tr>
<td></td>
<td>(0.085)</td>
<td>(0.080)</td>
<td>(0.080)</td>
<td>(0.087)</td>
</tr>
<tr>
<td>$\Delta$ Concentration</td>
<td>-0.063</td>
<td>-0.049</td>
<td>-0.010</td>
<td>-0.008</td>
</tr>
<tr>
<td></td>
<td>(0.075)</td>
<td>(0.079)</td>
<td>(0.089)</td>
<td>(0.073)</td>
</tr>
<tr>
<td>$\Delta$ R.E. Payroll</td>
<td>0.027</td>
<td>0.026</td>
<td>0.021</td>
<td>0.022</td>
</tr>
<tr>
<td></td>
<td>(0.055)</td>
<td>(0.052)</td>
<td>(0.076)</td>
<td>(0.057)</td>
</tr>
<tr>
<td>$\Delta$ Rate101</td>
<td>0.166</td>
<td>0.558***</td>
<td>(0.208)</td>
<td>(0.176)</td>
</tr>
<tr>
<td>Constant</td>
<td>0.028</td>
<td>0.030</td>
<td>0.026</td>
<td>0.028</td>
</tr>
<tr>
<td></td>
<td>(0.020)</td>
<td>(0.025)</td>
<td>(0.021)</td>
<td>(0.019)</td>
</tr>
<tr>
<td>Obs.</td>
<td>72</td>
<td>72</td>
<td>72</td>
<td>72</td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.41</td>
<td>0.38</td>
<td>0.38</td>
<td>0.39</td>
</tr>
<tr>
<td>F stat</td>
<td>30</td>
<td>33</td>
<td>82</td>
<td>30</td>
</tr>
</tbody>
</table>

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
Decomposing the Price of Intermediation

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
<th>(6)</th>
</tr>
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<tbody>
<tr>
<td>Applications</td>
<td>0.334***</td>
<td>0.404***</td>
<td>0.403***</td>
<td>-0.131</td>
<td>-0.027</td>
<td>0.003</td>
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<tr>
<td></td>
<td>(0.088)</td>
<td>(0.067)</td>
<td>(0.070)</td>
<td>(0.085)</td>
<td>(0.047)</td>
<td>(0.046)</td>
</tr>
<tr>
<td>Time Trend</td>
<td>0.010***</td>
<td>0.009</td>
<td>0.015***</td>
<td>0.016**</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.003)</td>
<td>(0.009)</td>
<td>(0.003)</td>
<td>(0.008)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Volatility</td>
<td>0.174**</td>
<td></td>
<td>-0.200***</td>
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<tr>
<td></td>
<td>(0.074)</td>
<td></td>
<td>(0.058)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Concentration</td>
<td>0.070</td>
<td>0.076</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.100)</td>
<td>(0.077)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>R.E. Payroll</td>
<td>0.280***</td>
<td></td>
<td>-0.131**</td>
<td></td>
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<td></td>
</tr>
<tr>
<td></td>
<td>(0.068)</td>
<td></td>
<td>(0.056)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Constant</td>
<td>1.132***</td>
<td>-5.291***</td>
<td>-4.196</td>
<td>0.265***</td>
<td>-9.339***</td>
<td>-9.981***</td>
</tr>
<tr>
<td></td>
<td>(0.079)</td>
<td>(1.886)</td>
<td>(5.376)</td>
<td>(0.085)</td>
<td>(1.744)</td>
<td>(4.723)</td>
</tr>
</tbody>
</table>

|                   |       |       |       |       |       |       |
| Obs.              | 73    | 73    | 73    | 73    | 73    | 73    |
| F-stat            | 97    | 95    | 37    | 97    | 95    | 37    |

Newey-West standard errors in parentheses
* p < 0.10, ** p < 0.05, *** p < 0.01

<table>
<thead>
<tr>
<th></th>
<th>Δ π</th>
<th></th>
<th>Δ (φ − π)</th>
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</thead>
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<tr>
<td>Δ Applications</td>
<td>0.349***</td>
<td>0.458***</td>
<td>-0.080**</td>
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<tr>
<td></td>
<td>(0.071)</td>
<td>(0.064)</td>
<td>(0.034)</td>
</tr>
<tr>
<td>Δ Volatility</td>
<td>0.231***</td>
<td></td>
<td>-0.173***</td>
</tr>
<tr>
<td></td>
<td>(0.082)</td>
<td></td>
<td>(0.044)</td>
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<tr>
<td>Δ Concentration</td>
<td>0.020</td>
<td>-0.028</td>
<td></td>
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<tr>
<td></td>
<td>(0.088)</td>
<td></td>
<td>(0.039)</td>
</tr>
<tr>
<td>Δ R.E. Payroll</td>
<td>0.051</td>
<td></td>
<td>-0.029</td>
</tr>
<tr>
<td></td>
<td>(0.079)</td>
<td></td>
<td>(0.034)</td>
</tr>
<tr>
<td>Constant</td>
<td>0.012</td>
<td>0.024</td>
<td>0.016</td>
</tr>
<tr>
<td></td>
<td>(0.025)</td>
<td>(0.025)</td>
<td>(0.012)</td>
</tr>
</tbody>
</table>

|                   |       |       |       |
| Obs.              | 72    | 72    | 72    |
| F-stat            | 30    | 82    | 86    |

Standard errors in parentheses
* p < 0.10, ** p < 0.05, *** p < 0.01
two components of \( \phi \), the origination costs \( (\pi) \) and the present value (PV) of servicing costs \( (\phi - \pi) \). The top part of the table shows that applications are very strongly positively correlated with \( \pi \), consistent with origination costs or profits increasing with demand. In contrast, the PV of servicing costs displays a negative correlation with applications. This finding is likely driven by the fact that mortgages originated at a time of high application volume tend to have a shorter expected life span (precisely because \( \phi \), or alternatively the gap between the mortgage note rate and MBS yields, is high at those times, and expected to decrease in the future).\(^{32}\)

Interest rate volatility is positively related to origination costs, as would be expected given that the cost of hedging increase when volatility is high. The lack of statistical significance may indicate that our proxy for hedging costs is too crude, or that hedging costs were not a significant driver of origination costs over this period. In contrast, volatility is significantly negatively related to \( \phi - \pi \). The explanation is similar to the one for applications: when volatility is high, this decreases the expected life span of a mortgage (since the borrowers’ prepayment option becomes more likely to be in-the-money going forward) and thus the expected PV of servicing costs decreases. The two offsetting effects explain why overall, \( \phi \) is not significantly related to volatility.

The measure of payroll per employee in the real estate credit sector, which trended upward over the sample period, is positively related to \( \pi \), suggesting that an increase in the labor cost involved in the origination process could be an important part of the upward trend in the price of intermediation. In monthly changes, payroll is not significantly related to \( \pi \), but month-to-month changes likely contain significant noise. Surprisingly, the correlation between payroll and the PV of servicing costs is slightly negative, though only statistically significant in levels.

There is no evidence that changes in market concentration affected either component of intermediation prices over this period—which is not surprising, given that concentration

\(^{32}\)Indeed, in unreported results, we find that adding the “primary-secondary spread” as a regressor brings the coefficient on applications in the \( \phi - \pi \) regression much closer to zero and eliminates its statistical significance.
trended down over this time (so regressing $\phi$ or $\pi$ on concentration alone actually yields a negative and significant coefficient). Finally, the level of rates is not significantly related with $\phi$. Looking at the two components separately, in levels the PV of servicing costs is significantly lower when rates are high, again consistent with expected life being shorter. However, this relationship loses significance in monthly changes.

Figure 2.7 shows that our measure of $\phi$ evolves similarly if we change the assumed note rate (to Rate100 or Rate102), the assumed FICO score (to 680 instead of 750), the MSA (New York instead of Los Angeles) or the loan size ($150,000 instead of $300,000). As a consequence, regressions with $\phi$, $\pi$, or $\phi - \pi$ series based on these alternative assumptions yield results very similar to those shown in Tables 2.3 and 2.5. These findings provide “robustness checks” with respect to our assumptions on loan characteristics, but below we will also discuss what they mean for the interpretation of the results.

### 2.6.2 Additional Evidence and Interpretation

We view the strong positive correlation between $\phi$ and application volume documented above as highly suggestive of limited capacity in mortgage originations. To the extent that $\phi$ (or $\pi$) includes profits (or high rents for the factors of production), why does capacity not expand so that profits get competed away? Lenders may be reluctant to add additional capacity if they think the increase in volume is relatively short-lived, as is often the case with refinancing booms. Furthermore, new entry into the mortgage intermediation business is far from costless; for instance, an intermediary has to fulfill a number of requirements (such as a minimum net worth) to be able to securitize mortgages through the GSEs.

To further support our interpretation, we present evidence based on processing times of mortgage applications according to the HMDA data. The second panel in Figure 2.6 shows, at the monthly frequency, the number of new mortgage applications plotted against the median processing time of applications submitted in that month (i.e. the number of days between the application date and the “action” date, when either the loan closes, or the application is denied or withdrawn).
The figure shows that when the number of new mortgage applications increases, it takes longer to process additional applications. The correlation between the two series in levels is 0.38; in changes it is 0.64. The variation in processing times can be substantial: for instance, it jumps from below 25 days to about 40 days following the November 2008 Fed announcement. This evidence suggests that indeed, the capacity of mortgage originators to process applications is limited. A regression analysis, shown in Table 2.6, confirms the significance of this relation: a one-standard deviation increase in monthly applications is associated with about a 3-day increase in processing time. It also shows that conditional on application volume, there was a significant upward trend in processing time over this
Table 2.6: Regression of HMDA processing delays on the loan demand. The dependent variable, delay, is defined as the number of days between loan application and action (accept, withdraw, or deny). We measure loan demand using the count of loan applications from HMDA. Monthly regression using data from January 2008 to September 2014. Applications normalized per business day, then standardized. Newey-West robust standard errors shown for Columns (1) and (2); robust standard errors shown for Columns (3) and (4). Column (2) contains calendar-month fixed effects to control for potential seasonality.

<table>
<thead>
<tr>
<th></th>
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<th>(4)</th>
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<td></td>
<td>Delay</td>
<td>Delay</td>
<td>Δ Delay</td>
<td>Δ Delay</td>
</tr>
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<td>Std. New Applications</td>
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<td>3.543***</td>
<td></td>
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<td></td>
<td>(0.782)</td>
<td>(0.730)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Time Trend</td>
<td>0.139***</td>
<td>0.141***</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.0412)</td>
<td>(0.0395)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Δ Std. New Applications</td>
<td>2.385***</td>
<td></td>
<td>2.955***</td>
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</tr>
<tr>
<td></td>
<td>(0.470)</td>
<td></td>
<td>(0.325)</td>
<td></td>
</tr>
<tr>
<td>Dec. Indicator</td>
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<td>-51.83**</td>
<td></td>
<td>0.344**</td>
</tr>
<tr>
<td></td>
<td>(25.73)</td>
<td>(25.02)</td>
<td>(0.205)</td>
<td>(0.148)</td>
</tr>
<tr>
<td>Jan. Indicator</td>
<td></td>
<td>-3.659***</td>
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<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>(1.050)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Constant</td>
<td>-51.83**</td>
<td></td>
<td>0.344**</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(25.02)</td>
<td>(0.148)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Month FEs</td>
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<td>yes</td>
<td>no</td>
<td>no</td>
</tr>
<tr>
<td>Adj. R²</td>
<td>0.45</td>
<td>0.44</td>
<td>0.39</td>
<td>0.60</td>
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<tr>
<td>Observations</td>
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<td>81</td>
<td>80</td>
<td>80</td>
</tr>
</tbody>
</table>

Standard errors shown in parentheses.

* p < 0.10, ** p < 0.05, *** p < 0.01

time period. This is consistent with evidence from industry surveys that indicates that the labor intensity of underwriting has increased substantially since 2008.

This leads to the question of how to interpret the positive time trend in $\phi$. An important component of this trend comes from the relative decrease in the effective value of servicing rights based on the MIAC multiples relative to their MBS-price-implied value—which is what is driving the difference between $\phi$ and $\pi$. In other words, net servicing costs seem to have increased over 2008-2014. This is consistent with evidence on an increase in the direct costs of servicing over this period (see for instance Figure 1 in Goodman 2016) and also the increased regulatory cost of holding mortgage servicing rights for banks under Basel III (see Hendricks et al. 2016 for a thorough discussion). Consistent with the latter channel, there

---

33 Calendar months are also important in explaining variation in processing time; in particular, processing times (for given application volume) tend to increase in December. The last column in the table shows that once we add indicators for December and January to the regression in changes, the adjusted $R^2$ increases dramatically and the constant becomes significant (indicative of the positive time trend).

34 See https://www.mba.org/Documents/Research/ChartoftheWeek%2007102015.pdf.
has been a significant shift of servicing activity from banks to non-banks over the period since 2010.\textsuperscript{35}

But even after accounting for the effect of servicing valuations, there remains a positive time trend in $\pi$ as long as we do not control for payroll (see column (2) of Table 2.5). This could be due to the increased labor intensity of underwriting noted above, or the need for more qualified people doing it—an explanation consistent with the positive correlation with payroll (though an alternative interpretation could be that employees in the real estate credit sector simply earn higher rents when the profitability of originations increases).

There are a number of potential explanations that seem less consistent with our evidence. One such explanation is that the positive relationship between $\phi$ ($\pi$) and applications, and/or the positive trend in $\phi$, are due to changes in the expected life span of the originated loans. If there is a constant per-period cost of an open loan (e.g. due to the liability/putback risk, discussed below), variation in the expected life span would translate into differences in $\pi$ (as originators want to be compensated upfront if expected lifetime costs increase).

We already noted above that the PV of servicing costs, $\phi - \pi$, is significantly related to changes in expected life due to changes in interest rate volatility, and perhaps also due to changes in rates. However, the strong correlation between origination costs $\pi$ and applications is not affected by adding these variables to the regression (if anything, the opposite is the case). We have also collected direct proxies for the expected lifespan of newly originated mortgages and find that they are not positively related to $\phi$—see Appendix A.9 for details.

Other evidence also does not point toward an important role for anticipated per-period costs (other than those already captured in the servicing valuation) in the increase in $\phi$. One such cost is related to potential legal liabilities. In the wake of the crisis, the GSEs have aggressively enforced “representations and warranties,” forcing many entities that had sold mortgages to them to buy back (mostly delinquent) mortgages where some flaw in the

\textsuperscript{35}According to Kaul and Goodman (2016), the share of single-family mortgages (in terms of remaining balances) serviced by non-banks increased from 6% in 2010 to 31% in 2015.
underwriting or documentation was found. This “putback risk” has commonly been cited as a reason behind the tighter lending standards in recent years, since lenders want to avoid this risk on new loans going forward.\textsuperscript{36}

If increased expected putback costs were priced in directly by intermediaries, we would expect that $\phi$ would have increased more on some types of loans than others. In particular, this theory would suggest that riskier loans should have seen a larger increase in $\phi$ (since they are more likely to lead to a delinquency followed by a repurchase and a credit loss).\textsuperscript{37} Furthermore, loans with a longer expected life span should have seen a larger increase in $\phi$, since they will remain a potential liability for longer. However, as shown in Figure 2.7, $\phi$ did not increase more for FICO 680 loans than for FICO 750 (if anything, the contrary), even though the former have higher delinquency risk. Also, there is no evidence that smaller loan sizes (150k vs. 300k), which are associated with slower prepayment speeds, command a higher $\phi$ for the same note rate.\textsuperscript{38}

There is some divergence across $\phi$ for note rates Rate102 vs. Rate100 in 2012, with $\phi$ being higher for lower note rates (with longer expected life). But the difference remains relatively small compared to the overall increase in $\phi$ over the sample period, and reverts back to zero in 2013/early 2014. That said, it is plausible that the increased aversion to putbacks was a significant driver of the upward trend in origination costs (for instance due to the need for more qualified underwriting personnel, and more time spent on each loan, as discussed above).

Finally, as noted above, our measure of $\phi$ is almost unchanged if instead of Los Angeles,

\textsuperscript{36}For instance, the Federal Reserve’s Senior Loan Officer Opinion Survey in April 2013 found that “Three-fourths of banks also cited the risk of putback of delinquent mortgages by the GSEs as an important factor restraining their current ability or willingness to approve home-purchase loans, and (...) a large fraction of banks reported an increase in the importance of this factor over the past year.” See http://www.federalreserve.gov/boarddocs/snloansurvey/201305/default.htm.

\textsuperscript{37}Goodman and Zhu (2013) show that the incidence of putbacks is substantially higher for low-FICO loans, and also provide additional discussion of putback patterns in recent years.

\textsuperscript{38}It is somewhat puzzling that $\phi$ does not vary much with loan size, given that we think of origination costs as having a substantial fixed component (and thus might expect a larger proportional charge for smaller loan sizes). However, we have verified on lender rate sheets that most of them have at most small adjustments for small loan sizes. It is still possible that borrowers with small loans will typically pay proportionally more upfront (or take a higher note rate) to cover fixed costs of loan origination that are not captured in our measure.
we use New York as the MSA in our rate sheet search. This is the case even though market concentration (as measured in HMDA) was somewhat higher in LA over 2008-2009 but then fell quite steeply and has been lower than in New York since 2012. This again means that we do not find evidence suggesting that market concentration (or changes therein) explains the pattern in intermediation costs that we document.\footnote{Similarly, at the national level, concentration in mortgage lending has been decreasing over our sample period. According to data from Inside Mortgage Finance, the market share of the top 10 lenders in the US overall was 75.7\% in 2010 before declining to 63\% in 2012 and 45.4\% in 2014. Also, the weighted-average county-level “Top 4” share shown in Figure 1 of Scharfstein and Sunderam (2013) fell from over 0.38 in 2010 to below 0.3 in 2013 and 2014, and is thus close to its longer-term average for the period since 1994.} However, our findings are not necessarily inconsistent with those of Scharfstein and Sunderam (2013) — they simply mean that at least over the period since 2008, the effects of concentration did not occur at the level we study (i.e. intermediary rate sheets) but could instead occur through the split of the rebate between LO and borrower.

### 2.7 Economic Implications

In this section, we first clarify the relationship between our measure of the price of intermediation and a commonly used alternative measure, the spread between primary market rates and secondary market yields. We then explore the relevance of our calculations to households by using our estimates of the price of intermediation to measure how much households spent on intermediation during the period we study. This calculation has particular policy relevance since, as already discussed, the mortgage market was a key element in the transmission of monetary policy. We then do several counterfactual exercises to decompose household expenditures.

#### 2.7.1 The Primary-Secondary Spread

Traditionally, market analysts have measured the price of intermediation by computing the difference between rates paid by borrowers and the yields on mortgage-backed securities. In contrast, we look at the difference between the price of a mortgage with a given note rate...
in the secondary market and the funds provided to the borrower, including any rebate. To understand the difference between the two approaches, consider an intermediary similar to that in Section 2.2.1 that makes a loan with note rate \( r^n \) and pays the borrower \( p^n_{YSP} \). However, rather than selling the loan directly, the intermediary raises \( p^n_{YSP} \) in the secondary market by issuing debt tied to the payments on the mortgage. Define \( y^n \) to be the implied coupon on this debt defined by:

\[
p^n_{YSP} = PV(\text{principalpayments}(n)) + y^n \text{mult}_{MBS}^n
\tag{2.8}
\]

where \( \text{mult}_{MBS}^n \) is a valuation multiple similar to the one defined in Section 2.2.2. Similarly, we can write that

\[
p^n_{TBA} = PV(\text{principalpayments}(n)) + r^n \text{mult}_{MBS}^n
\tag{2.9}
\]

Equations (2.8) and (2.9) generate a relationship between the price of intermediation measured as the difference in prices and as the spread between rates in the primary market and implied coupon in the secondary market.

\[
\phi^n = p^n_{TBA} - p^n_{YSP} = (r^n - y^n) \text{mult}_{MBS}^n
\tag{2.10}
\]

In other words, the one-time payment to the intermediary, \( \phi^n \) equals the present value of an interest strip that pays the difference between what the borrower pays to the intermediary \( (r^n) \) and what the intermediary pays to investors \( (y^n) \).

\( r^n - y^n \) is similar to what market participants normally refer to as the “primary-secondary spread.”\(^{40}\) Rearranging equation (2.10) as

\[
\frac{\phi^n}{\text{mult}_{MBS}^n} = r^n - y^n
\tag{2.11}
\]

\(^{40}\)Analysts typically define the primary-secondary spread as the difference between an index of primary market rates like the 30-year fixed rate index from the Freddie Mac Primary Mortgage Market Survey and compare it with the yield on an MBS trading at par. This measure would only be equivalent to ours if the rebate on the Freddie Mac loans was 0 which is typically not the case. Since the rebates are usually positive, the primary-secondary spread overstates the rate spread. Even if intermediation were free, a positive rebate would imply a positive spread between the note rate and yield on a loan trading at par.
and taking differences over time shows that changes in rates reflect three factors:

\[
\left(1 \Delta \text{Secondary Market Cost of Funds}\right) \left(2 \Delta \text{Price of Intermediation}\right) \left(3 \Delta \text{MBS Multiplier}\right)
\]

\[
r^n(t') - r^n(t) = y^n(t') - y^n(t) + \frac{\phi^n(t') - \phi^n(t)}{\text{mult}_{\text{MBS}}^n(t')} - \frac{(r^n(t) - y^n(t)) \text{mult}_{\text{MBS}}^n(t') - \text{mult}_{\text{MBS}}^n(t)}{\text{mult}_{\text{MBS}}^n(t')}
\]

(2.12)

In contrast, changes in the primary market price only reflect two factors:

\[
p^n_{\text{YSP}}(t') - p^n_{\text{YSP}}(t) = p^n_{\text{TBA}}(t') - p^n_{\text{TBA}}(t) - \left(\phi(t') - \phi(t)\right)
\]

(2.13)

Comparing equations (2.12) and (2.13) illustrates the challenge of using rates to measure changes in the price of intermediation. Changes in the value of the interest strip can change rates even when there is no change in the price of intermediation. Intuitively, suppose that market expectations of prepayments go down, leading the MBS multiplier to go up. Equation (2.12) illustrates that even if the cost of funds and the price of intermediation stay the same (meaning terms (1) and (2) are zero), the primary market rate will fall, leading one to conclude, incorrectly, that the price of intermediation has fallen. The reason for the fall in rates is simply that the price of intermediation is now spread out over a longer period.

The top left panel of Figure 2.8 illustrates the relationship between the rate spread, \(r - y\) and the price of intermediation, \(\phi\). At some points in our sample, the rate spread and \(\phi\) tell similar stories. For example, in 2012, both \(\phi\) and the rate spread almost double, a fact that is not surprising given that the multiplier, shown in the bottom part of the panel, is relatively stable. But at other points, rate spread and \(\phi\) give different accounts. For example, in late 2008 and early 2009, the rate spread spikes and then drops dramatically. The decline does not show up in \(\phi\), which remains within a relatively narrow band. The difference, of course, is the multiplier which rises from one at the end of 2008 to nearly six at the beginning of 2010. Intuitively, as the multiplier went up, the rate spread required to maintain a stable price of intermediation fell roughly by a factor of six. It is important to point out that the strong time trend we documented in Section 2.6.1 does not show up in the rate spread. The
Figure 2.8: *Primary-secondary spread and QE passthrough analysis. See Section 2.7.1.*
difference between the trends in the two series is, of course, explained by the multiplier. The rising multiplier ensured that the increase in the price of intermediation translated into a much smaller increase in rates. Put differently, if the multiplier had remained constant over this period, the rate spread would have widened much more dramatically than it did.

In the other three panels of Figure 2.8, we revisit three of the QE-related event studies described in Section 2.4 to see if the rate spread and $\phi$ yield different interpretations of the data. The top left panel shows the time around the initial announcement of QE in November of 2008. The lines labelled $p_{TBA}$, $p_{YSP}$ and price passthrough are identical to the corresponding lines in Figure 2.4. However, the bottom part of the panel now shows Rate101 ($r^n$) and the implied coupon ($y^n$) and a corresponding measure of passthrough in rates. To understand the differences, focus on the announcement of QE3 in September of 2012 (the bottom left panel in Figure 2.8). On the day prior to the announcement, a loan paying a one percent rebate offered a rate of 3.47 percent – in other words, $Rate_{101} = 3.47$. We then calculate the cost of funds in the TBA market to be $y^n = 3.08$ percent meaning that the primary-secondary spread is 41 basis points. What happens to the primary-secondary spread after the announcement? According to the Optimal Blue data, Rate101 falls by 10 basis points to 3.37 percent but the secondary market price of the Rate101 loan falls by 23 basis points to 2.85 percent. In other words, passthrough is 10/23 or 43 percent. In contrast, the one-day price changes imply 55 percent passthrough. What accounts for the difference? As equation (2.12) shows, it must be that the interest strip multiplier went down. The point here is that the big shock to the level of prices in the secondary market also affects relative prices in the secondary market and those relative prices determine the interest strip multiplier. Indeed, at the time, many commentators looked at the rate spread and concluded that passthrough was exceptionally low.\(^4\) Our measure shows much higher levels of passthrough and, in fact, the gap between the two measures widened significantly over the next few days before narrowing. The other two events in Figure 2.8 show much smaller divergence between the two measures.

2.7.2 Expenditure on Intermediation

Over the 73 month period we cover in the paper, American households refinanced 6.5 trillion dollars of mortgages and used 3.8 trillion dollars of new mortgage debt to purchase homes.\textsuperscript{42} According to our estimates, households implicitly paid 155 billion dollars to financial intermediaries for their services in these transactions (99 billion dollars for the refinances and 56 billion dollars for the purchase mortgages), or about 25 billion per year on average. We arrive at this estimate by using our monthly average estimates of $\phi$ from Section 2.6.1 and multiplying them by the dollar amount of monthly originations.\textsuperscript{43} One obvious question is how large a number this is. To give some perspective, note that according the Bureau of Economic Analysis, the cumulative reduction in household mortgage interest payments over the relevant period was around 760 billion dollars.\textsuperscript{44} As another comparison, Hurst et al. (2016) find that the GSE policy of uniform mortgage rates across locations (rather than letting rates vary with credit risk) implied a redistribution across US regions of 14.5 billion dollars (in NPV terms) over the 2007-9 period, or roughly 5 billion per year.

The top panel of Figure 2.9 shows our estimate of the time series of monthly expenditures, which range from less than one billion dollars in some months to between five and six billion per month at the peak in the summer and fall of 2012. To understand the evolution of costs, we consider some counterfactual experiments. As we showed in Section 2.6.1, two variables, application volume and at time trend, account for most of the variation in the price of intermediation, $\phi$, and so one important question is how much of the variation in intermediation expenditures is explained by these two factors. In the bottom panel of

\textsuperscript{42}These figures are based on HMDA data, and may thus slightly understate the actual total, since about 10% of loans are not covered in HMDA.

\textsuperscript{43}This therefore assumes that other types of mortgages, such as FHA loans or loans held on bank balance sheets, incur the same price of intermediation.

\textsuperscript{44}See “Mortgage Interest Paid, Owner- and Tenant-Occupied Residential Housing” at http://www.bea.gov/national/supplementary.htm. The 760 billion dollar figure equals the difference between the sum of all interest paid from 2009-2014 if interest payments were fixed at the 2008Q4 level and actual interest payments. This number includes reductions in interest payments due to lower interest rates (due to refinancing of fixed-rate mortgages and automatic adjustments of adjustable-rate mortgages) and reductions in payments due to lower outstanding principal resulting from foreclosures and other debt reduction.
Figure 2.9: Counterfactual expenditure on intermediation and Rate101 under different assumptions. See Section 2.7.2 and 2.7.3 for relevant discussion.
Figure 2.9, we use our regression estimates to calculate predicted values of $\phi$ under three sets of assumptions: (1) $\phi$ does not react to applications; (2) the time trend was zero; and (3) the combination of (1) and (2). In each case, we assume that the level of $\phi$ at the beginning of our sample period was at its actual level. We then use those estimates to calculate counterfactual expenditures on intermediation displayed in the top panel, holding the volume of new loan originations fixed at its actual level.

The line labeled “No effect of apps” shows that if $\phi$ had not responded to application volume, this would have lowered expenditure on intermediation by about 50 billion dollars to 106 billion. If, on the other hand, we let $\phi$ vary with applications as it did but there was no increasing time trend, expenditures would have fallen by over 90 billion dollars. And finally, the combination of the two counterfactual assumptions would have wiped out most of the expenditure, reducing it to only 13 billion over the 73 months of our sample.

The economic interpretation of these numbers is somewhat nuanced. As mentioned above, 99 billion dollars or two-thirds of the expenditure on intermediation involved refinances of existing mortgages. This is important because one of the channels through which the Federal Reserve QE policies transmits to households was by allowing them to refinance into lower interest rate mortgages. Although the benefits to households obviously outweighed the costs, our results show that these costs were substantial. One can interpret the 99 billion figure as one of the costs of having a mortgage market that is dominated by fixed-rate mortgages, since mortgagors need to refinance to benefit from lower rates. In an economy where most borrowers have adjustable-rate mortgages instead, the transmission of interest rates to household cash flow requires no action by financial intermediaries.

Interpretation of the other counterfactuals is less stark but interesting nevertheless. In particular, our results show that the upward trend in the price of intermediation documented in Section 2.6.1 resulted in a nearly three-fold increase in expenditure on intermediation during this period. Capacity constraints also led to substantial increases in expenditures on intermediation, highlighting the limits of the sector as a channel for policy.

A natural question is whether it is reasonable to assume in our counterfactuals that $\phi$
in October 2008 is a reasonable “reference level,” given that it is substantially lower than what we observe over the rest of our sample period. While we do not have the Optimal Blue data going back further, it turns out that a similar calculation based on the Freddie Mac survey rate implies that φ was roughly constant at this low level over 2006-2008 — see Chart 2 in Fuster et al. (2013). Thus, it is not the case that the starting point of our φ series is “unusual” relative to historical values.

It is important to stress that we are not making any welfare statements here. What the numbers above reflect is a transfer of the surplus generated by lower rates (higher MBS prices) from households to intermediaries, taking the volume of loan originations as fixed. This is not to say that the high price of intermediation could not have welfare effects. In particular, had φ remained at its lower original level, this would have led to additional mortgage originations that would have generated surplus for both borrowers and intermediaries. Thus, if for instance post-crisis regulations led to the positive time trend in φ, then one can argue that there was in fact a deadweight loss. That said, these regulations may of course also have offsetting benefits, such as fewer mortgage defaults, that would have to be weighed in a full welfare analysis.

2.7.3 Counterfactual Mortgage Rates with Alternative φ

In the previous section, we studied how expenditures on intermediation would have differed under various counterfactual assumptions about the evolution of φ. In this section, using the above insights, we transform these counterfactual φ into counterfactual Rate101 series. This provides an alternative (and perhaps more easily interpretable) way of assessing the effect that the increased φ had on borrowers over our sample period.

These counterfactual Rate101 series are shown in the bottom panel of Figure 2.9. The

---

45 There is a difference in levels between the chart in Fuster et al. (2013) and our φ because here we subtract 101 from $p_{TBA}$ while there it was only 100. There are also small differences in assumed g-fees between the two calculations, but these only have minor effects on the evolution of the series.

46 A full discussion of the strength of this channel requires a model of borrower behavior and is beyond the scope of this paper.
figure shows that the costs of intermediation did have a significant effect on the interest rates faced by borrowers. Our experiment of setting the sensitivity of the price of intermediation to applications to zero would have reduced rates by 10 basis points on average and as much as 88 basis points in January 2009. Eliminating the time trend would have reduced Rate101 by 16 basis points on average and by 29 basis points by the end of the sample. The combination of the two counterfactual experiments would have implied a decrease in Rate101 of 30-40 basis points over an extended period in 2012-13.

2.8 Conclusion

Over the period 2000-2014, residential mortgage originations in the US have averaged about 2.2 trillion dollars per year.\textsuperscript{47} Given the size of the market, even relatively small changes in the price of intermediation, defined as the difference between the value of a mortgage’s cash flows to investors in the MBS market and what a borrower receives, add up to significant changes in implicit borrower expenditures. In this paper, we have systematically studied how the price of intermediation has evolved over 2008-2014, a period during which monetary policy and other macroeconomic and financial factors led to record low interest rates.

We find a significant upward trend in this price that appears driven by increased net costs of mortgage servicing and potentially the increased labor intensity of mortgage underwriting due to new regulations and lenders being more averse to liability risk. In addition, there are substantial fluctuations around this trend that are closely related to the level of demand for new mortgages; this is strongly suggestive of capacity constraints in mortgage originations. We estimate that the upward trend and the sensitivity to demand together increased expenditures on intermediation by about 140 billion dollars over the 73 months in our sample, holding origination volumes constant.

Capacity constraints have affected the passthrough of monetary policy. Even though we show that offers to borrowers in the primary mortgage market generally respond very

\textsuperscript{47}Source: Inside Mortgage Finance, Mortgage Market Statistical Annual.
quickly to MBS price changes, we also find that the passthrough of MBS price increases is subdued when application volumes are high. This implies that policy actions that increase MBS prices, for instance an announcement of increased asset purchases, will pass through less strongly if demand for mortgages was already strong. Put differently, in such a situation, intermediaries may absorb a large chunk of the increase in MBS values, rather than passing it on to borrowers. Thus, intermediation frictions are important for policy makers to consider when designing policy actions that primarily target the mortgage market.

Finally, it is important to emphasize that expenditures on intermediation in the mortgage market could potentially be much lower under a different institutional setup. Most of the variation in mortgage demand, and in the price of intermediation, in recent years was due to the refinancing of fixed-rate mortgages. Refinancing in most cases requires a full re-underwriting of the mortgage even though the reduction in the monthly payment will generally lead to a reduced credit risk relative to the outstanding loan.\textsuperscript{48} Making the process more streamlined would not only save borrowers time, but potentially also substantial amounts of money.

\textsuperscript{48}Credit risk may not be lower if the borrower withdraws equity in a cash-out refinance.
Chapter 3

The Reaction of the U.S. Government
to Debt: Past and Present

3.1 Introduction

How do governments react to debt? Are they largely passive, letting times of high growth
decrease the overall debt/GDP ratio, or do they tend to react responsibly, decreasing expendi-
ditures in times of high debt? This paper estimates a historical fiscal reaction function to
investigate whether governments have tended to be fiscally prudent.

Some economists in recent years have warned of the vicious cycle between debt and
growth (Buttiglione et al. (2014), Reinhart and Rogoff). One mechanism underlying this
relationship is that, in periods of high debt, governments may be forced to pull back on
expenditure on infrastructure and other growth-enhancing investments. Particularly in times
of economic stress, when the government multiplier tends to be high, this fiscal prudence
contributes to a slowdown of economic growth. The vicious cycle could be triggered if the
cutback in government expenditure actually results in an increase in the government stock
of debt relative to GDP, perhaps both because GDP decreases (with a constant stock of debt)
and revenues decrease sufficiently to offset the expenditure cutbacks. This could result in a
period of high debt again and a vicious cycle of debt-growth.
This paper strives to quantify if, and how, the U.S. government has historically responded to debt levels. Understanding the government reaction function, and desire for “fiscal space” – that is, unused debt-carrying capacity – is one key to understanding the mechanism of the debt-growth nexus.\footnote{While the government has no explicit “debt limit”, there is an implicit limit to how much debt that lenders are willing to let the government hold at a reasonable price. The natural next question is then, of course, what is a “reasonable” price? There is no single answer here; this notion of “fiscal space” is hard to measure, but the general intuition is that governments want to leave some slack by not running egregiously high debts in order to maintain the ability to borrow at relatively low rates.} It is also important in understanding whether historically, the government has acted responsibly by proactively managing expenditures, or whether the relatively prudent history in the U.S. is the outcome of more passive measures, such as revenue adjustments, inflation, and growth rates that drive down the debt/GDP ratio.

The first section briefly surveys relevant literature. It is followed by an overview of the data and methods used. The third section presents results: first, showing the change in fiscal reaction over time; second, quantifying nonlinearities in the fiscal reaction to debt, also over varying time periods; third, exploring whether the government has been responsive to private-sector debt and leverage. The last section proposes directions for further research and concludes.

### 3.2 Literature

Most baseline fiscal reaction function estimations use Bohn (1998) as a guide. Bohn runs the regression

\[ s_t = \rho d_t + \alpha_0 + \alpha_G GVAR_t + \alpha_Y YVAR_t + \epsilon_t \]  

(3.1)

where \( s_t \) is the surplus/GNP ratio, \( d_t \) is the debt/GNP ratio, \( GVAR_t \) is some measure of expenditure deviation from trend, and \( YVAR_t \) is the output deviation from trend.\footnote{Bohn (1998) uses the GVAR and YVAR variables given in Barro (1979), but Bohn (2008) instead uses the deviation of military expenditure from its trend value (as estimated by a rolling regression that accounts for two lagged values of military expenditure) and the deviation of output from its Hodrick-Prescott–filtered series.}

The regression is motivated by Barro’s (1979) tax-smoothing model. Given that the deadweight loss of taxation may be an increasing function of the size of taxes, an optimizing
government may choose to smooth tax rates over time. In this simple smoothing model, the primary surplus at any point in time should only depend on the level of temporary government spending and a measure of output fluctuation. Bohn extends this by asking whether governments additionally respond to the level of debt, giving rise to Equation 3.1. Bohn finds that the government does tend to respond to debt, with a coefficient on debt of about 0.10, implying that a one percentage point increase in debt/GDP corresponds to an increase in the primary surplus of about 10 basis points.

Recent papers such as Mendoza and Ostry (2008) and Mauro et al. (2015) extend the framework to cross-country panel data. The papers conclude that most countries exhibit fiscal prudence, with a positive reaction of the primary surplus to levels of debt, although the results vary across countries. Mauro et al. (2015) in particular demonstrate that fiscal reactions have varied across time even within a country by calculating each government’s response using a rolling specification; many countries that have been fiscally prudent when considering the whole sample have also experienced pockets of unsustainable trends in expenditures and debt.

Naturally, this is an oversimplification of the actual decision function of the government, for at least three reasons. First, governments may respond stronger to debt as the level of debt increases, particularly if the costs of debt overhang increase in the level of debt. Moreover, the relevant debt consideration may be how far the economy is from its time-varying debt capacity. Debt capacity itself is an elusive concept: it may depend on intangibles such as government reputation, expected economic growth, and the risk appetite of those who hold debt. Lastly, the timing of government expenditure decisions may not coincide with the exact timing of output deviations used as a control: even in good times, if the government were presented with a high-return investment project, it might feel more compelled to spend. The timing of strong government expenditure opportunities is not captured in the model and could shift expenditures from one year to another, making it harder to detect prudence even if, in the long-run, it exists.
3.3 Data and Methods

3.3.1 Data

Data on U.S. government revenues, expenditures, military expenditures, and debt are from Henning Bohn and are available from his website. For data from 1792-1970, he uses the Historical Statistics of the United States. For more recent data, he aggregates the data from the Budget of the United States and the National Income Accounts. The original source of his military data is unclear, but I was able to acquire similar numbers using the Correlates of War database, available publicly online.

I additionally use data on sector-level debt. This data is available back to 1945 from the Federal Reserve (FRED). I also use leverage data from Schularick and Taylor (2012), which has the benefit of going back to 1900. Schularick and Taylor construct the data themselves using annual data for aggregate bank loans and the total balance sheet size of the banking sector. They define leverage as the total bank loans (defined as end-of-year outstanding domestic currency lending to domestic households and nonfinancial corporations, not including lending within the financial system), divided by bank assets, which are defined as the year-end sum of all balance sheet assets of banks with national residency, excluding foreign currency assets.³ For the U.S., the key source was the Federal Reserve’s All Bank Statistics, although details on other data sources used are included in their appendix.

3.3.2 Methods

I use a Hodrick-Prescott filter to detrend output, and “output deviation” is measured as the fraction deviation of actual output from this trend. Following Bohn (2008), I measure unanticipated expenditures by calculating an AR(2) regression of military expenditures (as a fraction of GDP) to capture an “expenditure trend”, and then measure an “expenditure deviation” as the fraction deviation from this trend. These de-trended series match those

³“Banks” are defined as monetary financial institutions, including savings banks, postal banks, credit unions, mortgage associations, and building societies, but excluding brokerage houses, finance companies, insurance firms, and other financial institutions.
used in Bohn (2008).

The regression specification is a standard OLS with heteroskedasticity-robust standard errors.

3.4 Results

![Figure 3.1: U.S. primary surplus and debt, 1792-2012.](image)

3.4.1 Reaction across time

Table 3.1 demonstrates that the behavior of the government over the past 60 years differs significantly from the rest of the sample. The structural break in the time series was chosen using a Supremum Wald structural break test, which is a fairly standard structural break methodology that (as its name suggests) chooses the highest possible Wald test statistic evaluated at each potential structural break over the sample.

Over the entire history, from 1792-2012, the coefficient on debt is about 0.10, indicating that an increase in debt levels of one percentage point of GDP corresponded to an increase in the primary surplus of 10 basis points (also as a percent of GDP). This relationship also
Table 3.1: U.S. primary surplus (dependent variable) against debt, output deviation, and expenditure deviation across time

<table>
<thead>
<tr>
<th></th>
<th>(1) 1792 to 2012</th>
<th>(2) 1792 to 1950</th>
<th>(3) 1950 to 2012</th>
</tr>
</thead>
<tbody>
<tr>
<td>debt</td>
<td>0.0948**</td>
<td>0.0977**</td>
<td>0.0164</td>
</tr>
<tr>
<td></td>
<td>(0.0165)</td>
<td>(0.0156)</td>
<td>(0.0341)</td>
</tr>
<tr>
<td>output deviation</td>
<td>7.120</td>
<td>13.00**</td>
<td>36.15**</td>
</tr>
<tr>
<td></td>
<td>(4.610)</td>
<td>(3.996)</td>
<td>(12.91)</td>
</tr>
<tr>
<td>expenditure deviation</td>
<td>-77.78**</td>
<td>-95.35**</td>
<td>9.086</td>
</tr>
<tr>
<td></td>
<td>(8.481)</td>
<td>(5.911)</td>
<td>(13.30)</td>
</tr>
<tr>
<td>constant</td>
<td>-2.758**</td>
<td>-3.513**</td>
<td>-1.117</td>
</tr>
<tr>
<td></td>
<td>(0.425)</td>
<td>(0.339)</td>
<td>(1.012)</td>
</tr>
<tr>
<td>Observations</td>
<td>220</td>
<td>158</td>
<td>63</td>
</tr>
<tr>
<td>Adjusted $R^2$</td>
<td>0.597</td>
<td>0.839</td>
<td>0.076</td>
</tr>
</tbody>
</table>

Standard errors in parentheses

$^+ p < 0.10, ^* p < 0.05, ^{**} p < 0.01$

holds for the period 1792-1950 (cutting out the last 62 years of the sample); however, for 1950-2012, the fiscal reaction to debt is reduced, with a one percentage point increase in debt (relative to GDP) corresponding to less than 2 basis points in increased primary surplus. Moreover, this result is not statistically significant.

The interpretation of the control variables is as follows: for the full sample, a one percentage point increase in output from its trend corresponds to an increase of 7 basis points in the primary surplus.$^4$ Each specification of Table 3.1 has a positive coefficient on the output deviation, suggesting that governments tend to run larger surpluses when output is high. This is intuitive: governments may want to maintain a fiscal buffer in order to raise expenditures when times are bad, which they might in turn facilitate by running fiscal surpluses when times are good.

The expenditure deviation term enters with a negative coefficient for the first two columns. This is in line with intuition as well. A positive expenditure deviation occurs

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$^4$Note that the output deviation and expenditure deviation variables are measured as fraction deviations from their trend; e.g. 0.03 rather than 3%.
Table 3.2: U.S. primary surplus (dependent variable) against debt, output deviation, and expenditure deviation across time

<table>
<thead>
<tr>
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<th>(1)</th>
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<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
<th>(6)</th>
</tr>
</thead>
<tbody>
<tr>
<td>debt</td>
<td>0.0948** (0.0165)</td>
<td>-0.0139 (0.0378)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>output deviation</td>
<td>7.120 (4.610)</td>
<td>8.384* (4.060)</td>
<td>44.17** (14.13)</td>
<td>50.55** (13.44)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>expenditure deviation</td>
<td>-77.78** (8.481)</td>
<td>-79.87** (7.623)</td>
<td>10.76 (13.45)</td>
<td>-20.75* (10.10)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>pre-break debt</td>
<td>0.0756** (0.0170)</td>
<td>0.0951** (0.0153)</td>
<td>0.0456* (0.0208)</td>
<td>0.0646** (0.0181)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>post-break debt</td>
<td>0.122** (0.0229)</td>
<td>0.0638** (0.0213)</td>
<td>-0.0322 (0.0259)</td>
<td>0.0571** (0.0136)</td>
<td></td>
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</tr>
<tr>
<td>pre-break output deviation</td>
<td>11.91** (4.102)</td>
<td></td>
<td>18.95* (7.345)</td>
<td></td>
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<tr>
<td>post-break output deviation</td>
<td>48.18** (15.11)</td>
<td></td>
<td>99.96** (6.126)</td>
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<td></td>
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<tr>
<td>pre-break mil. exp. surprise</td>
<td>-93.34** (6.037)</td>
<td></td>
<td>-9.476 (8.909)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>post-break mil. exp. surprise</td>
<td>8.122 (14.16)</td>
<td></td>
<td>-421.6** (15.16)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>constant</td>
<td>-2.758** (0.425)</td>
<td>-2.810** (0.427)</td>
<td>-3.323** (0.341)</td>
<td>-0.0405 (1.089)</td>
<td>-0.700 (0.720)</td>
<td>-2.029** (0.513)</td>
</tr>
</tbody>
</table>

Observations                        220     220     220     61     61     61
Adjusted $R^2$                       0.597   0.629   0.750   0.114  0.337  0.811

Standard errors in parentheses

$^+ p < 0.10$, $^* p < 0.05$, $^{**} p < 0.01$
when expenditures are larger than trend. In our current specification, following Bohn (2008), we proxy these expenditure surprises by using military expenditures (over GDP), hence these deviations pick up changes in military buildup typically surrounding wars (see Figure 3.2). The result is intuitive since a positive expenditure deviation signifies a need for unanticipated spending, which increases the expenditures of the government without an offsetting increase in revenue. Hence positive unanticipated military expenditures have a negative overall impact on primary surpluses.

![Figure 3.2: Military surprises and U.S. government debt.](image)

Why was the fiscal reaction to debt in the last six decades different? Part of the explanation lies in outliers in the post-Great Recession fallout. Whereas primary surpluses in the 1950-2007 period averaged 0.33, primary surpluses in the post-2007 period averaged -6, reflecting how, in the aftermath of the crisis, the government raised expenditures to stimulate the economy. Even removing these outliers, however, the result holds that the government has been much less responsive to debt in recent years.

On a larger scale, one might speculate that, over the past several decades, the government has felt less of a need to build such a large fiscal buffer, which would drive the result that recently, primary surpluses have not been as reactive to debt. Perhaps, as World War II faded into distant memory, the U.S. government began to feel less at risk, relative to the early 1900s when the Great Depression and World War I made disaster feel inevitable. If governments do perceive the risk of rare disasters to fall, then their perceived need to build
Table 3.3: U.S. revenue or expenditure (dependent variable) against debt, output deviation, and expenditure deviation across time

<table>
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<td></td>
</tr>
<tr>
<td>debt</td>
<td>0.190**</td>
<td>0.115**</td>
<td>-0.0274*</td>
<td>0.127**</td>
<td>0.0419**</td>
<td>-0.0403</td>
</tr>
<tr>
<td>(0.0253)</td>
<td>(0.00765)</td>
<td>(0.0117)</td>
<td>(0.0297)</td>
<td>(0.0143)</td>
<td>(0.0289)</td>
<td></td>
</tr>
<tr>
<td>output deviation</td>
<td>-2.968</td>
<td>2.804</td>
<td>19.79**</td>
<td>-10.34</td>
<td>-10.11**</td>
<td>-18.86</td>
</tr>
<tr>
<td>(7.614)</td>
<td>(2.221)</td>
<td>(5.882)</td>
<td>(6.559)</td>
<td>(3.719)</td>
<td>(12.85)</td>
<td></td>
</tr>
<tr>
<td>expenditure deviation</td>
<td>36.99**</td>
<td>23.60**</td>
<td>0.380</td>
<td>112.7**</td>
<td>116.7**</td>
<td>-24.02*</td>
</tr>
<tr>
<td>constant</td>
<td>3.113**</td>
<td>1.998**</td>
<td>18.94**</td>
<td>6.102**</td>
<td>5.643**</td>
<td>22.48**</td>
</tr>
<tr>
<td>(0.616)</td>
<td>(0.188)</td>
<td>(0.424)</td>
<td>(0.639)</td>
<td>(0.338)</td>
<td>(1.031)</td>
<td></td>
</tr>
<tr>
<td>Observations</td>
<td>220</td>
<td>158</td>
<td>63</td>
<td>220</td>
<td>158</td>
<td>63</td>
</tr>
<tr>
<td>Adjusted $R^2$</td>
<td>0.592</td>
<td>0.908</td>
<td>0.232</td>
<td>0.731</td>
<td>0.943</td>
<td>0.203</td>
</tr>
</tbody>
</table>

Standard errors in parentheses

* $p < 0.10$, * $p < 0.05$, ** $p < 0.01$

...a buffer stock as precautionary spending may also be reduced, and this may be reflected in a lower fiscal reaction to debt. There remains further work to be done here, as is discussed in the last section of this piece.

Table 3.3 shows how revenues and expenditures react in an otherwise identical regression to that in Table 3.1. The regressions indicate some interesting patterns. Focusing on the early period, from 1792-1950, revenues increased drastically as debt levels rose (Column 2); expenditures also rose, albeit to a lesser extent (Column 5). Hence, primary surpluses tended to rise when debt levels were high despite increasing expenditures, since revenues increased significantly more. In the last 6 decades of the period, from 1950 to 2012, expenditures tended to decrease as debt increased (Column 6); revenues decreased less than expenditures, hence the slightly positive overall reaction of primary surplus to debt.

This observation, however simple, is intriguing. It implies that high debt levels in recent years were associated with pullbacks in expenditure, whereas in historical periods, high debt corresponded to increases in expenditure. This may be in part due to persistence of spending. Governments that spent freely were also those that ran up large amounts of debt; hence perhaps a more appropriate interpretation is that debt and expenditure tended to...
co-move over longer periods, rather than expenditures increasing in reaction to high debt. Still, in recent years, the result may be indicative of hitting the limits of potential government debt carrying capacity. If the U.S. government were near its debt limit, there may be social and political pressure to cut expenditure (see, for instance, the media hype surrounding the budget sequestration of 2013), and this may have contributed to the observation that expenditures tended to be lower when debt levels were higher in recent years.

3.4.2 Nonlinearity in reaction function

The idea that governments are adverse to particularly high levels of debt might lead to reaction functions that are nonlinear. That is, perhaps governments are responsive to debt mainly at high levels, when building a buffer stock is a more relevant concern. Furthermore, particularly high debt may correspond to a significant dampening of economic growth; Reinhart and Rogoff present summary statistics that suggest that growth performance has worsened significantly for countries with more than 90% debt/GDP.

To test whether the U.S. government reaction function has historically been nonlinear, I add a quadratic term to the regression. Since debt is always positive, a highly positive coefficient on the debt squared term would reflect a strong response of the government to high levels of debt.

Table 3.4 shows the results. Debt is measured as a percentage of GDP, so 100% debt/GDP would correspond to 10000% in the “debt sq” row; hence the magnitudes of the quadratic coefficients appear small despite having a potentially meaningful impact. For instance, the overall differential effect of having 90% debt/GDP instead of 60% debt/GDP, all else equal, would be given by 5.85 percentage point increase in the primary surplus/GDP ratio for the period 1792-1950. A comparable 90% versus 60% debt/GDP comparison would result instead in a 0.75 percentage point increase in the primary surplus for the more recent period.

\[ \begin{align*}
5^{5} & \text{Using the coefficients from the regression tables, } (90 - 60) \times (-0.00593) + ((90)^2 - (60)^2) \times (0.00134). \\
6^{6} & \text{ }(90 - 60) \times 0.00207 + (90^2 - 60^2) \times 0.000152
\end{align*} \]
Table 3.4: U.S. primary surplus (dependent variable) against debt, debt squared, output deviation, and expenditure deviation across time

<table>
<thead>
<tr>
<th></th>
<th>(1) 1792 to 2012</th>
<th>(2) 1792 to 1950</th>
<th>(3) 1950 to 2012</th>
</tr>
</thead>
<tbody>
<tr>
<td>debt</td>
<td>0.0756**</td>
<td>-0.00593</td>
<td>0.00207</td>
</tr>
<tr>
<td></td>
<td>(0.0194)</td>
<td>(0.0197)</td>
<td>(0.131)</td>
</tr>
<tr>
<td>debt sq.</td>
<td>0.000265</td>
<td>0.00134**</td>
<td>0.000152</td>
</tr>
<tr>
<td></td>
<td>(0.000209)</td>
<td>(0.000210)</td>
<td>(0.00147)</td>
</tr>
<tr>
<td>output dev.</td>
<td>7.089</td>
<td>13.99**</td>
<td>36.48*</td>
</tr>
<tr>
<td></td>
<td>(4.569)</td>
<td>(3.284)</td>
<td>(13.91)</td>
</tr>
<tr>
<td>expenditure</td>
<td>-78.22**</td>
<td>-99.96**</td>
<td>8.973</td>
</tr>
<tr>
<td></td>
<td>(8.543)</td>
<td>(4.839)</td>
<td>(13.40)</td>
</tr>
<tr>
<td>constant</td>
<td>-2.565**</td>
<td>-2.691**</td>
<td>-0.804</td>
</tr>
<tr>
<td></td>
<td>(0.374)</td>
<td>(0.261)</td>
<td>(2.597)</td>
</tr>
<tr>
<td>Observations</td>
<td>220</td>
<td>158</td>
<td>63</td>
</tr>
<tr>
<td>Adjusted $R^2$</td>
<td>0.597</td>
<td>0.881</td>
<td>0.061</td>
</tr>
</tbody>
</table>

Standard errors in parentheses

$^+ p < 0.10, ^* p < 0.05, ^{**} p < 0.01$

debt/GDP, all else equal, would be given by an 8.26 percentage point increase in the primary surplus/GDP ratio for the period 1792-1950.\(^7\) For the 1950-2012 period, this would instead be 1.02 percentage point increase.\(^8\) In short, the recent period only saw a 0.25 percentage point increase in the primary surplus response to debt rising to increased levels, whereas the more historical period displayed a more convex response to debt, with a 2.41 percentage point increase in the response of the primary surplus to a 90-to-120% debt/GDP change relative to the 60-to-90% change.

These illustrations show how the response to the primary surplus to high debt levels in the pre-1950 part of the sample was much larger than in more recent years. This gives additional color to the result discussed in the previous subsection, which indicated that the government had been more fiscally prudent in earlier periods; this appears to be primarily

\(^7\)(120 – 90) * (-0.00593) + ((120)^2 – (90)^2) * (0.00134).

\(^8\)(120 – 90) * 0.00207 + (120^2 – 90^2) * 0.000152
Table 3.5: U.S. revenue or expenditure (dependent variable) against debt, debt squared, output deviation, and expenditure deviation across time

<table>
<thead>
<tr>
<th></th>
<th>Revenue 1792 to 2012</th>
<th>Revenue 1792 to 1950</th>
<th>Revenue 1950 to 2012</th>
<th>Expenditure 1792 to 2012</th>
<th>Expenditure 1792 to 1950</th>
<th>Expenditure 1950 to 2012</th>
</tr>
</thead>
<tbody>
<tr>
<td>debt</td>
<td>0.389**</td>
<td>0.0762**</td>
<td>0.0355</td>
<td>0.383**</td>
<td>0.126**</td>
<td>0.102</td>
</tr>
<tr>
<td>(0.0320)</td>
<td>(0.0123)</td>
<td>(0.0483)</td>
<td>(0.0318)</td>
<td>(0.0318)</td>
<td>(0.0168)</td>
<td>(0.0110)</td>
</tr>
<tr>
<td>debt sq.</td>
<td>-0.00276**</td>
<td>0.000508**</td>
<td>-0.000667</td>
<td>-0.00355**</td>
<td>-0.00108**</td>
<td>-0.00151</td>
</tr>
<tr>
<td>(0.000359)</td>
<td>(0.000169)</td>
<td>(0.000454)</td>
<td>(0.000338)</td>
<td>(0.000162)</td>
<td>(0.000126)</td>
<td></td>
</tr>
<tr>
<td>output deviation</td>
<td>-2.638</td>
<td>3.180</td>
<td>18.36**</td>
<td>-9.919^</td>
<td>-10.91**</td>
<td>-22.10^</td>
</tr>
<tr>
<td>(7.452)</td>
<td>(2.147)</td>
<td>(5.990)</td>
<td>(5.785)</td>
<td>(3.211)</td>
<td>(12.00)</td>
<td></td>
</tr>
<tr>
<td>expenditure deviation</td>
<td>41.59**</td>
<td>21.86**</td>
<td>0.871</td>
<td>118.6**</td>
<td>120.4**</td>
<td>-22.91^</td>
</tr>
<tr>
<td>(12.40)</td>
<td>(3.472)</td>
<td>(5.895)</td>
<td>(8.078)</td>
<td>(4.812)</td>
<td>(10.45)</td>
<td></td>
</tr>
<tr>
<td>constant</td>
<td>1.108^</td>
<td>2.308**</td>
<td>17.57**</td>
<td>3.523**</td>
<td>4.981**</td>
<td>19.39**</td>
</tr>
<tr>
<td>(0.503)</td>
<td>(0.162)</td>
<td>(1.084)</td>
<td>(0.430)</td>
<td>(0.282)</td>
<td>(2.282)</td>
<td></td>
</tr>
<tr>
<td>Observations</td>
<td>220</td>
<td>158</td>
<td>63</td>
<td>220</td>
<td>158</td>
<td>63</td>
</tr>
<tr>
<td>Adjusted $R^2$</td>
<td>0.664</td>
<td>0.918</td>
<td>0.234</td>
<td>0.803</td>
<td>0.954</td>
<td>0.215</td>
</tr>
</tbody>
</table>

Standard errors in parentheses

$^+ p < 0.10, ^* p < 0.05, ^{**} p < 0.01$

Driven by the strong reaction to high levels of debt in the earlier period versus a more subdued response in the more recent period.

Table 3.5 decomposes the estimate from Table 3.4 into the revenue and expenditure components. Over the full sample, the coefficient on the quadratic debt term for expenditures (column 4) is larger in magnitude than the coefficient on the quadratic debt term for revenues (column 1), although both are negative. This indicates that, at higher levels of debt, the fall in expenditures tends to dominate the fall in revenues. Interestingly, the behavior of revenues seems to be different in the subsample before 1950, when the high debt levels tended to both increase revenues and decrease expenditures (columns 2 and 5), and in the period post-1950, when high debt levels instead tended to decrease both components of the primary surplus, although the result is not statistically significant (columns 3 and 6).

The lack of statistical significance for that the coefficients for the 1950-2012 period on debt and debt squared in Table 3.4 and Table 3.5 is somewhat concerning, but perhaps not surprising given that the subsample is relatively short and also contains the most recent years, in which government behavior has not necessarily been prudent in the recovery
from the Great Recession. The pre-1950 behavior – with both higher revenues and lower expenditures during times of high debt – offers strong support of the idea that the U.S. government has been historically active in maintaining fiscal prudence.

3.4.3 Reaction to sector-level debt

In this section, I examine the period from 1955-2012 to investigate whether the U.S. government reacted to debt buildups not only in the government sector, but also in the household, corporate, and financial sectors. This could be one explanation for the statistical insignificance of fiscal reaction to government debt during this period, if the government’s primary surplus adjustments were instead tuned to private sector debt levels.

Figure 3.3: U.S. debt by sector

Figure 3.3 illustrates the trends of debt in these sectors, with each series normalized so that its 2008 value equals 100. Over the relevant period, the debt in all of these sectors increased, albeit non-monotonically and at different rates. Nonfinancial corporate debt increased after the crisis while financial institutions and household deleveraged. Overall, nonfinancial corporate debt appears more cyclical than the household and financial debt levels.

Table 3.6 examines the reaction of the primary surplus to the levels and changes of each sector’s debt for 1955-2012. When measured separately, the primary surplus is increasing in the changes in debt (columns 3, 5, 7) but decreasing in the levels of debt (columns 2,
### Table 3.6: U.S. primary surplus (dependent variable) against debt, output deviation, and expenditure deviation across sectors

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
<th>(6)</th>
<th>(7)</th>
</tr>
</thead>
<tbody>
<tr>
<td>debt</td>
<td>-0.0137</td>
<td>0.0628*</td>
<td>0.00952</td>
<td>0.0667*</td>
<td>-0.0209</td>
<td>0.0540</td>
<td>0.0263</td>
</tr>
<tr>
<td></td>
<td>(0.0419)</td>
<td>(0.0337)</td>
<td>(0.0274)</td>
<td>(0.0265)</td>
<td>(0.0421)</td>
<td>(0.0374)</td>
<td>(0.0180)</td>
</tr>
<tr>
<td>output deviation</td>
<td>46.02**</td>
<td>52.68**</td>
<td>39.70**</td>
<td>49.03**</td>
<td>39.25**</td>
<td>49.39**</td>
<td>11.57</td>
</tr>
<tr>
<td>expenditure deviation</td>
<td>11.29</td>
<td>-59.06**</td>
<td>14.78</td>
<td>-99.38**</td>
<td>10.53</td>
<td>-56.83**</td>
<td>31.06**</td>
</tr>
<tr>
<td>household level</td>
<td>0.454**</td>
<td>0.167</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.165)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>household change</td>
<td>-0.121**</td>
<td>0.167</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.0271)</td>
<td>(0.128)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>nonfinancial level</td>
<td>-0.198**</td>
<td>0.167</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.0380)</td>
<td>(0.128)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>nonfinancial change</td>
<td>0.167</td>
<td>0.167</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.165)</td>
<td>(0.128)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>financial level</td>
<td>-0.0689**</td>
<td>0.683**</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.0175)</td>
<td>(0.0954)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>financial change</td>
<td>0.114</td>
<td>0.442</td>
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<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>0.244</td>
<td>0.475</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Constant</td>
<td>0.119</td>
<td>0.346</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>0.619</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Observations: 57

---

Standard errors in parentheses

+ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$
Table 3.7: U.S. revenue or expenditure (dependent variable) against debt, output deviation, and expenditure deviation across sectors

<table>
<thead>
<tr>
<th></th>
<th>Revenue</th>
<th>Expenditure</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
</tr>
<tr>
<td>debt</td>
<td>-0.0196**</td>
<td>-0.0174*</td>
</tr>
<tr>
<td></td>
<td>(0.00715)</td>
<td>(0.00742)</td>
</tr>
<tr>
<td>output deviation</td>
<td>26.50**</td>
<td>25.95**</td>
</tr>
<tr>
<td></td>
<td>(5.752)</td>
<td>(6.037)</td>
</tr>
<tr>
<td>expenditure deviation</td>
<td>-15.58*</td>
<td>-16.60*</td>
</tr>
<tr>
<td></td>
<td>(7.012)</td>
<td>(8.431)</td>
</tr>
<tr>
<td>household level</td>
<td>-0.0289**</td>
<td>0.0868**</td>
</tr>
<tr>
<td></td>
<td>(0.00820)</td>
<td>(0.0197)</td>
</tr>
<tr>
<td>nonfinancial level</td>
<td>-0.0343*</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.0135)</td>
<td></td>
</tr>
<tr>
<td>financial level</td>
<td></td>
<td>-0.0167**</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.00616)</td>
</tr>
<tr>
<td>constant</td>
<td>20.77**</td>
<td>21.45**</td>
</tr>
<tr>
<td></td>
<td>(0.652)</td>
<td>(1.123)</td>
</tr>
<tr>
<td>Observations</td>
<td>67</td>
<td>67</td>
</tr>
<tr>
<td>Adjusted $R^2$</td>
<td>0.406</td>
<td>0.369</td>
</tr>
</tbody>
</table>

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

4, 6). All of the results are significant except for the changes in nonfinancial corporate debt. The positive reaction of the primary surplus for changes in debt may be indicative of a government’s desire to increase fiscal space in anticipation of having to bail out over-leveraged sectors, although of course the interpretation here should be cautious, particularly since high levels of debt do not correspond with higher primary surplus.

Table 3.7 investigates the reaction of revenues and expenditures to levels of debt per sector. In each sector, as levels of debt rise, government revenues fall and expenditures rise. This result is somewhat surprising. For instance, one could imagine that households borrow in order to spend, which would in turn raise revenues raised from sales taxes. This result indicates that some other mechanism must be at play, since in fact increased levels of household borrowing correspond to decreased revenues. One potential mechanism could be a decrease in GDP. This would tend to increase the level of borrowing per unit output, even holding the stock of debt constant. This would also potentially explain a decrease in
Table 3.8: U.S. revenue or expenditure (dependent variable) against debt, output deviation, and expenditure deviation across sector debt changes

<table>
<thead>
<tr>
<th></th>
<th>Revenue</th>
<th>Expenditure</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
</tr>
<tr>
<td>debt</td>
<td>-0.0214**</td>
<td>-0.0239**</td>
</tr>
<tr>
<td></td>
<td>(0.00774)</td>
<td>(0.00784)</td>
</tr>
<tr>
<td>output deviation</td>
<td>20.05**</td>
<td>16.98**</td>
</tr>
<tr>
<td></td>
<td>(5.022)</td>
<td>(5.100)</td>
</tr>
<tr>
<td>expenditure deviation</td>
<td>-0.634</td>
<td>0.0397</td>
</tr>
<tr>
<td></td>
<td>(5.240)</td>
<td>(5.219)</td>
</tr>
<tr>
<td>household change</td>
<td>0.0611</td>
<td>0.0397</td>
</tr>
<tr>
<td></td>
<td>(0.0794)</td>
<td>(0.136)</td>
</tr>
<tr>
<td>nonfinancial change</td>
<td>0.113+</td>
<td>0.0263</td>
</tr>
<tr>
<td></td>
<td>(0.0612)</td>
<td>(0.136)</td>
</tr>
<tr>
<td>financial change</td>
<td>0.209**</td>
<td>-0.429**</td>
</tr>
<tr>
<td></td>
<td>(0.0372)</td>
<td>(0.0847)</td>
</tr>
<tr>
<td>constant</td>
<td>18.67**</td>
<td>18.70**</td>
</tr>
<tr>
<td></td>
<td>(0.289)</td>
<td>(0.274)</td>
</tr>
</tbody>
</table>

Observations 67 67 67 67 67 67
Adjusted $R^2$ 0.313 0.338 0.482 0.210 0.123 0.308

*Standard errors in parentheses
+ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$

revenues (even as a fraction of GDP) if the decline in GDP occurred simultaneously with decreases in consumption.

More insight can be gained from the breakdown into the reaction of government expenditure and revenue to changes in debt levels in Table 3.8. The results indicate that as households increase debt, revenues do increase (slightly and not statistically significantly), while expenditures decrease to a much larger extent (and statistically significantly). This is consistent with the story that governments may be building a fiscal buffer in order to potentially bail out leveraged sectors in the future. However, it is also possible that the growth in debt could be picking up a boost in economic activity that is not captured in the detrended output series, and that the more relevant consideration for the U.S. government is that it is building a fiscal buffer during a good economic time rather than building up a bailout fund in a time of increasing leverage.

Table 3.9, which looks at leverage more historically, is consistent with the findings on
sector-level debt data. This regression runs from 1897-2008, using Schularick and Taylor’s data on leverage, defined as bank loans / assets. The reaction of the primary surplus to levels of leverage is slightly negative but insignificant; although revenues tend to be higher as levels of leverage are higher, the higher level of expenditure tends to exceed revenues. The primary surplus does tend to be higher as leverage increases (column 4), which appears to be driven both by higher revenues and lower expenditures, although neither component is statistically significantly affected by the change in leverage.

Overall, the results indicate that historically, the U.S. government has responded to changes in private-sector debt. In particular, over the past 60 years, increases in household and financial sector debt have corresponded to increases in the primary surplus, driven both by increases in revenue and decreases in expenditure. This also holds true looking over the past century, using historical measures of leverage from Schularick and Taylor (2012).

The rationale for this is that governments may perceive high debt as a harbinger of potential disaster. For instance, during the recent financial crisis, deleveraging has occurred
amongst the private sector – in particular financial institutions – but often at the cost of increased levels of public debt. Moreover, as discussed in Lo and Rogoff (2015), spillovers from sector-level debt may further slow economic growth; hence, looking at debt from the economy as a whole may be more appropriate than simply taking stock of government debt in assessing the dangers of debt overhang.

3.5 Directions

3.5.1 Lessons from Estimation of Simple Fiscal Reaction Functions

The results of this paper must be interpreted with caution. The “output deviation” term, although standard in the literature, is clearly imperfect; it is therefore possible that the measured effect of debt on primary surplus is impacted by real economic conditions, particularly of debt levels covary with economic conditions not picked up in the output deviation term. For instance, perhaps financial institutions tend to increase their leverage during good economic times, and this coincides with times when governments increase their primary surplus to facilitate lower debt levels and save for bad times. Hence, if the regression does not properly control for economic conditions, the results are extremely difficult to interpret. To check for this going forward, more robustness tests on the “output deviation” variable should be performed, perhaps including other measures of economic activity (such as unemployment) to determine whether the output deviation term is properly capturing the state of the economy.

Moreover, it is unclear that this regression should measure a statistically significant reaction function. Government expenditures may be subject to political pressures that are difficult to capture over such a long period in a quantitative model. What the government perceives to be its “threshold” level of debt may also vary over time, and while partially determined by economic prospects, may also be subject to forecasts on demographic change and the government’s risk aversion against rare disasters. Taken together, while the notion of a reaction function is intuitive – governments may want to work down debts when they
are highly indebted – measuring this reaction quantitatively poses challenges, particularly over a historical period spanning over a century.

3.5.2 Understanding Government Perceptions of Risk and Rare Disasters

The estimates in this paper are fairly straightforward but miss a lot of depth in terms of government considerations in reality. The optimal amount of “fiscal space” will be informed by the perceived probability of a disaster. More specifically, the type of disaster matters substantially: the possibility of wars would increase the desire to save, but the possibility of an inflationary event may have less of an impact on the desired fiscal buffer.

The risks perceived by the government are difficult to measure. Wachter (2013) provides some notion of the perceived disaster risk worldwide (Figure 5). The International Crisis Behavior database has a similar metric of disaster risk. The measures include several different types of crises, including inflation crises and flu epidemics, which may be of varying importance to our exercise at hand. Further work should evaluate which are the relevant disasters for consideration and how to integrate the expectation of rare disasters into the fiscal reaction framework.

3.5.3 Cost of Borrowing

The cost of borrowing matters significantly for expenditure decisions yet is not included in this regression. One reason is that, although the ex-post cost of borrowing is observable, the aversion to potential higher borrowing costs may be the more relevant consideration, and these are unobservable. (A more fully fledged model should account for the endogenous feedback between the costs of borrowing and historical fiscal behavior). Another is that the cost of debt is simply outside the scope of our dataset: while we have estimates on the long-term interest rate, the data on the maturity and structure of debt is harder to parse together. Still, the government reaction function should account for the cost of borrowing, and further work remains to be done here.
3.5.4 Financial Repression

The primary surplus captures the active expenditure decisions of the government, but this is not the only channel through which governments may deal with high debt. As documented in Reinhart and Rogoff (2011) and Reinhart and Sbrancia (2011), governments have historically undertaken financial repression to help decrease debt loads, and these incidents are more common than often remembered. Reinhart and Sbrancia measure financial repression as periods when interest rates paid by the government on its debt are essentially capped relative to the market rate, perhaps through unanticipated inflation, capital flow regulations, or explicit or implicit caps on interest rates. While their work may be generous in using the term “financial repression”, which implies malevolent intentions by the government, the general point stands that debt levels can be addressed not only through reducing expenditures relative to revenues, but also through inflation and partial default.

3.6 Conclusion

There are a few important implications of this work. First, my findings point toward one mechanism by which debt may slow growth. To the extent that government expenditure can help stimulate the economy, a pullback of expenditure in times of high debt may contribute to slow growth. As some scholars have emphasized, this may feed into a vicious cycle between debt and growth. Second, the results indicate that the U.S. government has recently entered a period of fiscal imprudence, with the response of the primary surplus to debt much lower particularly after the crisis. While deviations from fiscal prudence are not unprecedented, particularly in times of economic recovery, history hints that high debt levels are unsustainable, and the government may have to build up its fiscal space upon return to normal times. This will likely take the form of government expenditure reductions. Third, overall levels of debt matter, and the government has historically compensated for growing household and financial institution debt by increasing its own fiscal space. The results
generally are suggestive of fiscal prudence on the part of the U.S. government, although the causes and consequences of the recent changes to the government fiscal reaction function may warrant further investigation.
References


Consumer Financial Protection Bureau (2015a). Consumer voices on credit reports and scores.


REINHART, C. and ROGOFF, K. (). Debt and growth revisited.


Appendix A

Appendix to Chapter 1

A.1 Further detail about the mortgage market

In this section, I give further details about the mortgage market that support the use of the regression discontinuity design in this paper.

**Locking Rates.** Although many lenders offer that borrowers can pay a small fee to “lock” a rate for some time (typically 30, 45, or 60 days) – essentially, to ensure the rate does not change between mortgage application and mortgage closing – the formal agreement in the contracts is that if the borrower’s credit score falls between the lock and the mortgage closing, then she must pay some additional points to keep the “locked” rate. The rate may

<table>
<thead>
<tr>
<th>Year</th>
<th>Conforming</th>
<th>FHA</th>
</tr>
</thead>
<tbody>
<tr>
<td>2008</td>
<td>1910642</td>
<td>1099531</td>
</tr>
<tr>
<td>2009</td>
<td>1473077</td>
<td>1509258</td>
</tr>
<tr>
<td>2010</td>
<td>1231015</td>
<td>1259203</td>
</tr>
<tr>
<td>2011</td>
<td>1222996</td>
<td>878942</td>
</tr>
<tr>
<td>2012</td>
<td>1289119</td>
<td>669041</td>
</tr>
<tr>
<td>2013</td>
<td>1300823</td>
<td>498998</td>
</tr>
<tr>
<td>2014</td>
<td>1076761</td>
<td>308979</td>
</tr>
</tbody>
</table>

Table A.1: Conforming and FHA mortgage counts by year. Purchase mortgages only. Data source covers approximately 70% of the mortgage market. Source: McDash LLC
Table A.2: Summary statistics about Equifax Risk Score, general population. Data is pulled for all of 2007 and the first half of 2008, so both time-series and cross-sectional data are included. The population is 5% of all individuals with a credit history in the United States. The mean credit score shown here is lower than in Table 1.3, reflecting the fact that purchase mortgages after the crisis disproportionately went to higher-credit individuals than historical norm. Unsurprisingly, credit scores for individuals without a mortgage are substantially lower than those with a mortgage. Source: McDash LLC and NY Fed CCP/Equifax.

<table>
<thead>
<tr>
<th></th>
<th>mean</th>
<th>sd</th>
<th>p1</th>
<th>p10</th>
<th>p25</th>
<th>p50</th>
<th>p75</th>
<th>p90</th>
<th>p95</th>
<th>p99</th>
</tr>
</thead>
<tbody>
<tr>
<td>No mortgage</td>
<td>673.32</td>
<td>111.17</td>
<td>400.00</td>
<td>522.00</td>
<td>588.00</td>
<td>685.00</td>
<td>775.00</td>
<td>808.00</td>
<td>820.00</td>
<td>826.00</td>
</tr>
<tr>
<td>Has mortgage</td>
<td>722.22</td>
<td>96.31</td>
<td>423.00</td>
<td>582.00</td>
<td>671.00</td>
<td>751.00</td>
<td>797.00</td>
<td>820.00</td>
<td>825.00</td>
<td>830.00</td>
</tr>
<tr>
<td>Total population</td>
<td>689.39</td>
<td>108.96</td>
<td>406.00</td>
<td>534.00</td>
<td>609.00</td>
<td>712.00</td>
<td>784.00</td>
<td>815.00</td>
<td>822.00</td>
<td>828.00</td>
</tr>
</tbody>
</table>

also change if the appraisal comes in differently from expected or if the borrower chooses to pay a different amount of down payment.¹

A.2 Back of the envelope: Mortgage Payments

Note the standard annuity formula which applies to fixed rate mortgages is:

\[ A = P \frac{i(1+i)^n}{(1+i)^n - 1} \]

where \( A \) is the periodic payment amount, \( P \) is the principal amount on the loan net of down-payment, \( i \) is the periodic interest rate, and \( n \) is the total number of payments.

For a 30-year fixed rate mortgage, \( n = 360 \) months. Our standard back-of-the-envelope calculation assumes an origination amount of $200k and a mortgage rate of 5%, so \( i = 5/12 \).²

For our baseline, the above formula gives an annual payment of $1073.64.

To think about what happens when the mortgage payment stays fixed and we lower the interest rate to 4% (=0.33 % monthly), we solve for \( P_2 \) such that:

\[ \bar{A} = 1073.64 = P_2 \frac{0.0033 \times (1.0033)^{360}}{(1.0033)^{360} - 1} \]

¹See [http://www.consumerfinance.gov/askcfpb/143/whats-a-lock-in-or-a-rate-lock.html](http://www.consumerfinance.gov/askcfpb/143/whats-a-lock-in-or-a-rate-lock.html)

²This is the standard in the mortgage industry, so think of \( i \) as an annual percentage rate (APR) rather than an annual interest rate
Table A.3: Amortization details for a $200k 30-year fixed rate mortgage at 5% versus 4%.

<table>
<thead>
<tr>
<th>Month</th>
<th>Payment</th>
<th>Principal</th>
<th>Interest</th>
<th>Balance</th>
<th>Payment</th>
<th>Principal</th>
<th>Interest</th>
<th>Balance</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>1073.64</td>
<td>240.31</td>
<td>833.33</td>
<td>199759.69</td>
<td>954.83</td>
<td>288.16</td>
<td>666.67</td>
<td>199711.84</td>
</tr>
<tr>
<td>60</td>
<td>1073.64</td>
<td>307.12</td>
<td>766.52</td>
<td>183964.59</td>
<td>954.83</td>
<td>350.68</td>
<td>604.15</td>
<td>180895.03</td>
</tr>
<tr>
<td>180</td>
<td>1073.64</td>
<td>505.84</td>
<td>567.80</td>
<td>135767.82</td>
<td>954.83</td>
<td>522.80</td>
<td>432.03</td>
<td>100955.11</td>
</tr>
<tr>
<td>360</td>
<td>1073.64</td>
<td>1069.19</td>
<td>4.45</td>
<td>186511.57</td>
<td>954.83</td>
<td>951.66</td>
<td>3.17</td>
<td>143739.01</td>
</tr>
</tbody>
</table>

which gives us $P_2 = 225,976$.

A.2.1 Further intuition

It may come as a surprise to some readers that reducing the interest rate from 5% to 4% – or 20 percent – only decreases the mortgage payment by approximately 10%, from 1073 to 954 (see Table). This section gives further intuition.

Part of the monthly payment goes toward paying off the principal of the loan, while the other part goes toward interest. At the beginning of a 30-year FRM, the vast majority of the payment goes toward interest payment, with very little principal paid down. The interest due for any given payment is simply the debt owed at the beginning of the period multiplied by the interest rate. So for a $200k loan, the first interest payment is $5/12 \times 1/100 \times 200,000 = 833.33$. The total payment is fixed at $1073.64$, so the amount that goes toward paying back the principal is simply $240.31$.

A.3 Points and rates

This section gives further detail on the point-rate tradeoff for mortgages.

Figure A.1 show an example of the mortgage ratesheet points and rates for two FICO scores, FICO 680 and FICO 750, across two different (arbitrarily chosen) days.

First, it is obvious that the points offered per rate is higher for FICO 750 than it is for FICO 680. Or, put another way, on September 9, 2009, if both FICO borrowers wanted a yield spread premium of 100 (no points), then the FICO 750 borrower would have obtained
Table A.4: Hypothetical monthly payments or alternate origination amount, as interest rates change

<table>
<thead>
<tr>
<th>mortgage rate</th>
<th>monthly rate</th>
<th>holding orig. amount constant monthly payment</th>
<th>holding mortgage payment constant orig. amount</th>
</tr>
</thead>
<tbody>
<tr>
<td>3</td>
<td>0.25%</td>
<td>843</td>
<td>303,555</td>
</tr>
<tr>
<td>3.25</td>
<td>0.27%</td>
<td>870</td>
<td>313,349</td>
</tr>
<tr>
<td>3.5</td>
<td>0.29%</td>
<td>898</td>
<td>323,312</td>
</tr>
<tr>
<td>3.75</td>
<td>0.31%</td>
<td>926</td>
<td>333,443</td>
</tr>
<tr>
<td>4</td>
<td>0.33%</td>
<td>955</td>
<td>343,739</td>
</tr>
<tr>
<td>4.25</td>
<td>0.35%</td>
<td>984</td>
<td>354,197</td>
</tr>
<tr>
<td>4.5</td>
<td>0.38%</td>
<td>1,013</td>
<td>364,813</td>
</tr>
<tr>
<td>4.75</td>
<td>0.40%</td>
<td>1,043</td>
<td>375,586</td>
</tr>
<tr>
<td>5</td>
<td>0.42%</td>
<td>1,074</td>
<td>386,512</td>
</tr>
<tr>
<td>5.25</td>
<td>0.44%</td>
<td>1,104</td>
<td>397,587</td>
</tr>
<tr>
<td>5.5</td>
<td>0.46%</td>
<td>1,136</td>
<td>408,808</td>
</tr>
<tr>
<td>5.75</td>
<td>0.48%</td>
<td>1,167</td>
<td>420,172</td>
</tr>
<tr>
<td>6</td>
<td>0.50%</td>
<td>1,199</td>
<td>431,676</td>
</tr>
</tbody>
</table>

a mortgage at approximately 4.75%, whereas the FICO 680 borrower would have obtained a mortgage at approximately 5.25%. Alternatively, if the higher FICO borrower were willing to borrow at the higher rate of 5.25%, she would have obtained about 1.8 points at closing. For a $200,000 loan, this is worth an upfront payment of $3600 in exchange for a mortgage payment that is $70 per month higher.

Solving for the implicit discount factor, we know that

\[
PV = A \frac{1 - \frac{1}{(1+r)^n}}{r} 
\]

Recalling the average loan origination amount of $200,000, this is approximately $3600. (With an LTV of 80%, the appraisal amount would be $250,000 and borrowers would need to put down approximately $50k to begin with). The monthly payment on the 4.75% loan is 1043 (total cost of $375,586), and for the 5.25% loan is 1104 (total cost of $397,587).
Figure A.1: Points and rates examples. Source: Optimal Blue.
A.4 Bubb-Kaufman Replication

I replicate Bubb-Kaufman using first-liens, single-family mortgages originated between January 1, 2003 and December 31, 2007. As with Bubb-Kaufman, I keep only those mortgages that show up in the sample within 6 months of origination. Unlike Bubb-Kaufman, I use only purchase originations and no-cashout refis.3

3%labelfig:bk_t5

The graphs below show the default rates by FICO score, as defined by being 60+ days delinquent at any point in the 36 months after origination.

As pointed out by Bubb-Kaufman, the securitization rate seems relatively consistent across FICO. As in their paper, the below-620 are actually more likely to become securitized, although the change in the probability is economically small.

Now that I’ve established I can replicate the Bubb-Kaufman results, I argue that higher FICO scores were not prone to differential lender screening at threshold cutoffs.

3Because the Bubb-Kaufman sample includes other types of loans such as home improvement, second mortgage, unknown, and other loans, their observation count is much higher than mine, approximately twice. Still, within my select sample, the trends delineated in that research still hold – and I show that these trends do not hold for higher FICO scores, which are of interest to my current work.
Figure A.3: Securitization comparison of my sample and Bubb-Kaufman (JME) sample. Source: McDash LLC

Figure A.4: Default rates by FICO score for high FICO scores, 2003-2007. Source: McDash LLC
A.5 FHA vs Conventional Loans

A.5.1 Focus on Conventional Mortgages

There are two major types of mortgages: “conventional” (Fannie and Freddie) and Federal Housing Administration (FHA) loans. In this study, I solely measure the margins of adjustment with respect to conventional loans. This is justified by a number of reasons. First, with regard to the RD strategy, only conventional mortgages are subject to the pricing breakpoints across FICO scores, and given the smoothness of FHA mortgage acquisition (discussed further in Section 1.5.2), we can safely abstract from FHA switching and still maintain valid estimates. Second, FHA loans are generally more expensive, and conventional wisdom suggests that

Conventional loans require a down payment of at least 20% or private mortgage insurance (PMI) if the LTV is higher than 80%. To work around this limit, some borrowers take out “piggyback” loans, or a conventional first loan with up to 80% LTV and a second loan

Figure A.5: Count of loans by FICO score, 2003-2007. Source: McDash LLC
(in place of PMI), often under a higher rate as it cannot be securitized via Fannie/Freddie.

FHA loans are often thought to be targeted at lower-income borrowers, with 580 FICO allowing eligibility for maximum financing. The standards tend to be looser but the fees higher. FHA loans only require 3.5% down payment, and this can be paid using gifted funds (whereas conventional loans often have standards in terms of personal income versus gifts), making the down payment more affordable for low-income individuals.

The higher cost of FHA loans comes from two targeted mortgage insurance premiums. First, the upfront mortgage insurance premium (UFMIP) charges the borrowers a premium of 1.75%\(^4\), which can be paid upfront at closing or rolled into the mortgage. In order to compare across loans, I roll these costs into the rates. Because the FHA UFMIP is a percent of the mortgage size, the FHA rate for lenders who are otherwise identical, including identical LTVs, but with different absolute mortgage sizes will have different implied FHA rates.

Second, FHA loans come with a annual MIP (typically paid monthly with the mortgage payments) that differ depending on the borrower LTV, loan size, and loan length.

FHA loans also are more lax with the debt-to-income ratio, with conventional mortgages requiring borrowers to have DTI of 45% or less, while FHA allows borrowers to spend up to 56% of their income on monthly obligations like credit card payments...

The number of loans originated by FHA relative to conventional mortgages has increased substantially. During the subprime boom from 2003 to 2007, less than 10% of the purchase loans originated each year were backed by the FHA. By the end of 2009, that number ballooned to about 40% of all purchase originations. As the FHA increased its mortgage premia, that number has fallen to approximately 25%.

Is this increase in demand for FHA loans due to the easy credit standards or due to cheaper mortgage rates? Industry experts argue that conventional loans are generally less expensive for borrowers in almost all cases\(^5\).

\(^4\)This has changed over time, which has slightly changed the relative attractiveness of FHA mortgages over time.

An additional level of complexity is that FHA loans and conforming loans have varying loan limits to qualify for the best rates. FHA standard loans are for amounts up to $271050 and FHA jumbo loans are for amounts up to $625500 although the maximums vary by county. On conventional loans, the conforming standard loan limit is for amounts up to $417000; the conforming jumbo loans are up to $625500 with maximum amounts varying by county. Mortgages exceeding this amount are not eligible for purchase by Fannie or Freddie.

**Conventional PMI.** One realistic simplifying assumption that allows me to run a robustness test is that PMI premia hardly change. Hence, any week-to-week variation in the number of mortgages obtained can be attributed to changes in base rates rather than changes in the relative attractiveness of an under-80 LTV loan and an over-80 LTV loan.

### A.6 Additional methodology details

In this section, we provide the methodological details underlying our calculations. For most readers, the level of detail included in the main body of the paper should suffice; the level of detail in this appendix is more appropriate for replication of our exact steps.

We first take the rate sheets provided by Optimal Blue and restrict the data to the Los Angeles MSA, a 750 FICO, 80% LTV, 30-year fixed-rate, $300,000 loan amount, conforming mortgage with a 30-day lock period on an owner-occupied property. A similar exercise is performed in the SQL backup database provided to us for data pre-September 2009.

For lenders with multiple rate sheets in one day, we take the mean of points offered for any given rate. Because some rates are quoted in non-round numbers (e.g. 4.99 instead of 5), we round note rates within 2 basis points to the closest “round” rate. We also omit

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6A simple archive.org search on Genworth’s rate sheets indicate that many mortgage insurance premia are in effect for several months: for instance, as of March 21, 2012, the mortgage insurance premium ratesheet for August 1, 2011 was still in effect, and on April 20, 2015, the mortgage ratesheet for November 18, 2013 was still in effect. Individuals in the industry recognize that default risk changes, but note that the mortgage insurance premia are fixed for the life of the loan. These companies assume that default risk for a longer-term view (5-10 years) doesn’t change that quickly, hence the mortgage insurance premia also change slowly.

7This may be due to lenders attempting to market their mortgages; sorting by rate would list these mortgages first even if they are essentially identical rates.
dominated offers, meaning we omit any rate/point combinations where the rate is higher but points lower than another combination on the same rate sheet.

For each lender, we extrapolate rates to the desired points (101 in our base case) by linearly interpolating between the two surrounding rate/point combinations. For example, if a lender offers 100.8 points for a 5.5 rate and 101.2 for a 5.625 rate, the “Rate101” would be right between the two rates, 5.5625. We drop observations where we have to extrapolate Rate101 beyond the range of points of any rate listed on the rate sheet. Then, for each lender, we extrapolate the $p_{YSP}^{Rate101_t}$ by taking the Rate101 for the previous business day for that lender and extrapolating the points that correspond to that rate, again using a linear extrapolation of the two closest rate/point combinations. If the lender is not in the sample in the previous business day, this lender-day combination does not factor into our results.

At this point, we take the median of all relevant variables across lenders for any given day. In order to calculate $\phi$, we take the Rate101 for any given day, subtract the g-fee, and interpolate the 45-day-to-notification $p_{TBA}$ to this rate. We then subtract the LLPA (including the “adverse market delivery charge”, or AMDC) and the relevant YSP (101 in our baseline).

To calculate $\pi$, we take the Rate101 for any given day, subtract the $gfee$ and 25 basis points, and interpolate the 45-day-to-notification $p_{TBA}$ to this rate. We then subtract the LLPA (incl. AMDC), and the relevant YSP, and add the 25 basis points multiplied by the MIAC multiple.

### A.7 Passthrough in rate-yield space

In Table A.5, we report results from passthrough regressions similar to the ones in column (2) of Table 2.2 in the main text. However, instead of analyzing changes in YSP/price space, we now run regressions of changes in the mortgage rate on changes in MBS yields. For mortgage rates, we use either our Rate101 (available daily) or the Freddie Mac Primary Mortgage Market Survey rate (available weekly). For MBS yields, in line with what researchers studying this market would typically do, we rely on the “current coupon” MBS yield (from J.P. Morgan). An increase in MBS prices corresponds to a decrease in MBS yields.

The first three columns of the table use Rate101. In column (1), we see that the estimated
passthrough coefficients at daily frequency are almost identical to those in Table 2.2, although the $R^2$ is lower, suggesting more noise in rate/yield measures than in YSP/prices. The asymmetry discussed in the main text is also present for rates: an MBS yield increase is on average completely passed through to rates, while a yield decrease passes through by only 80 percent.

In column (2), we take weekly averages of both rates and yields. The estimated coefficients stay almost identical, while the $R^2$ increases somewhat. In column (3), we do the same at the monthly frequency.\(^8\) Perhaps surprisingly, passthrough appears to get weaker when taking monthly averages. This is likely due to the fact that, as emphasized in our main analysis, lower frequency shifts in the price of intermediation (due to changes in demand, or cost shifters) will be reflected in these longer-horizon passthrough estimates (while at the daily frequency these are more likely to remain unchanged). Furthermore, as discussed in Section 2.7.1, rate/yield changes also reflect changes in the valuation multiplier.

In the remaining columns of the table, we repeat the weekly and monthly regressions using the Freddie Mac rate instead, over the same sample period for which we have Rate101

\(^8\)For both weekly and monthly averages, we only retain MBS yields for days on which we also have Rate101 (as noted in the main text, there are 49 missing). Furthermore, we only retain months for which we have at least 18 daily observations.
(columns 4 and 6) and also over a longer period starting in 1992 (columns 5 and 7).\footnote{Since the Freddie Mac rate reflects loan offers from Monday to Wednesday within a week (according to \url{http://www.freddiemac.com/pmms/pmms_faqs.html}), we also only use MBS yields for Monday to Wednesday.} We also control for changes in reported origination fees/points (though not doing so leaves the other coefficients almost unchanged). Column (4) shows that at weekly frequency, the estimated passthrough is significantly weaker than with Rate101, suggesting that Rate101 may be a “cleaner” measure since it holds borrower/loan characteristics exactly constant. In contrast, “noise” in the Freddie Mac rate could be correlated with changes in MBS yields, thereby somewhat attenuating the coefficients. At monthly frequency, as shown in column (6), the Freddie Mac results move closer to those based on Rate101. Looking at the longer sample does not lead to materially different coefficients at weekly frequency (column 5) though it does increase estimated passthrough at monthly frequency (column 7).

In sum, the finding of asymmetric passthrough of changes in the MBS market value of a loan to the primary market is robust to looking at rates instead of YSPs, to using different rate series, and to different horizons over which changes are computed. Passthrough does not increase when looking at longer horizons, because of changes in the factors driving the price of intermediation, and changes in valuation multipliers.

\section{A.8 Historical $\phi$}

In Figure A.6, we present a historical time series of $\phi$. Since we do not have the Optimal Blue data before October 2008, we rely on the 30-year conventional fixed rate from the Freddie Mac Primary Mortgage Market Survey series (as in the previous section), subtract g-fees, and interpolate between MBS coupons to derive our series for $\phi$.\footnote{A similar figure is presented as Chart 2 in Fuster \textit{et al.} (2013). There is a difference in levels between the chart in Fuster \textit{et al.} (2013) and our $\phi$ because here we subtract 101 from $p_{TBA}$ while there it was only 100. There are also small differences in assumed g-fees between the two calculations, but these only have minor effects on the evolution of the series.}

In Figure A.6, we present a historical time series of $\phi$. Since we do not have the Optimal Blue data before October 2008, we rely on the 30-year conventional fixed rate from the Freddie Mac Primary Mortgage Market Survey series (as in the previous section), subtract g-fees, and interpolate between MBS coupons to derive our series for $\phi$.\footnote{Since the Freddie Mac rate reflects loan offers from Monday to Wednesday within a week (according to \url{http://www.freddiemac.com/pmms/pmms_faqs.html}), we also only use MBS yields for Monday to Wednesday.}
Figure A.6: Historical $\phi$, rolling 4-week average. In contrast to the baseline $\phi$, which is calculated using Optimal Blue data, historical $\phi$ is calculated using the 30-year fixed mortgage rate from the Freddie Mac Primary Mortgage Market Survey.

A.9 Variation in expected lifespan of new loans

It is difficult to obtain a good measure of the expected time a new loan will remain open, but we can use two proxies obtained from the J.P. Morgan MBS model (consisting of a prepayment model and an interest rate model). One is the “Weighted Average Life” (WAL), which is the expected average time until the mortgage principal is repaid (either by scheduled amortization or by unscheduled prepayments). This is calculated under a single assumed mortgage rate path, which is a shortcoming because the desired measure would take into account that rates vary in the future, which in turn affects prepayments. A measure that does take this into account is the “Option-Adjusted Duration” (OAD), which is the weighted average time until mortgage cash flows are received (both coupon payments and principal payments). This is again not a perfect measure for us, since we are not interested in the coupon payments for our purpose, but changes in OAD should be a good proxy for changes in expected lifespan of a new loan.

We obtain time series of WAL and OAD corresponding to Rate101 based on coupon-level
Figure A.7: Expected life span of new mortgages and the price of intermediation. See text in Section 2.6.2 for discussion.

measures from J.P. Morgan. These are plotted in Figure A.7, against $\phi$. The chart suggests two things: first, the spikes in the price of intermediation do not seem to be associated with spikes in the expected lifespan of new loans; if anything, the opposite relationship holds. Second, there is no upward trend in WAL or OAD since early 2010, while $\phi$ has drifted upward over that time.

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To do so, we take the note rate that J.P. Morgan assumes for each MBS coupon, and directly interpolate between these rates and corresponding WALs/OADs to where our Rate101 would be.