Lending on hold: Regulatory uncertainty and bank lending standards

Stefan Gissler, Jeremy Oldfather, and Doriana Ruffino *

October 2015

Abstract

Does higher regulatory uncertainty constrain credit? This paper focuses on the recent regulation of "qualified mortgages" (QM) and on the effects of the related rule-making process on bank lending. In 2011, the Federal Reserve proposed a set of criteria that would give lenders the presumption of a borrower's ability-to-repay a mortgage–and, thus, legal protection should a borrower sue. But the debt-to-income (DTI) ratio criterion–the most binding in the final rule–was not specified in the proposed rule. The absence of such a bright line created high regulatory uncertainty for banks between the proposed and the final rule. Using public comments submitted by banks in response to the rule proposal, we compute a measure of policy uncertainty at the bank level. We show that more uncertain banks issued fewer loans (and for smaller amounts) after the rule proposal. To control for general economic uncertainty, we instrument our measure by a bank's past legal costs. We confirm that banks that historically were sued more often cut lending more severely during the rule-making process. At a more aggregated level, counties that recorded a large number of mortgage lawsuits also experienced lower house price growth.

*Gissler, Oldfather, and Ruffino are at the Federal Reserve Board. E-Mails: Stefan.Gissler@frb.gov, Jeremy.D.Oldfather@frb.gov, Doriana.Ruffino@frb.gov. This article represents the views of the authors, and should not be interpreted as reflecting the views of the Board of Governors of the Federal Reserve System or other members of its staff.

1 Introduction

Does higher regulatory uncertainty constrain credit? A growing body of literature suggests that uncertainty has real effects for the economy–for example, it may increase firms' cost of capital and decrease investment (Gilchrist, Sim, and Zakrajšek 2014). Investment might be forgone entirely if uncertainty hinders the decision-making process of corporate boards (Garlappi, Giammarino, and Lazrak 2013). In addition to these supply-side effects, high uncertainty dampens consumers' demand for goods and services in a downturn. During the Great Depression, a large drop in consumption was associated with high uncertainty (Romer 1990). High uncertainty may cause consumers to be more cautious, for example when purchasing a car (Eberly 1994).

Government interventions and regulatory policies are leading sources of uncertainty. Fernández-Villaverde, Guerrón-Quintana, Kuester, and Rubio-Ramírez (2015) show how fiscal uncertainty about the timing and form of budgetary adjustments reduces investment, employment, and consumption. Baker, Bloom, and Davis (2013) link the slow recovery from the Great Recession to higher policy uncertainty during the period 2007 to 2009. But while these papers show that expectations over future policy changes do affect economic agents' current decisions—an argument made famous by Lucas (1976) and Kydland and Prescott (1977)—it has proven difficult to disentangle the effects of policy uncertainty from other macroeconomic factors. Furthermore, uncertainty is unobservable, objectively unmeasurable, and may itself induce policy changes so that any inference must deal with the problem of reverse causality.

In this paper we assess how uncertainty about mortgage regulations affected bank lending and house prices. Between 2011 and 2014, the Consumer Financial Protection Bureau (CFPB) proposed and implemented laws setting minimum requirements for mortgage lenders to consider before extending credit to consumers. In January 2013, the CFPB established a set of criteria for "qualified mortgages" (QM). By fulfilling these requirements, a lender proves a borrower's ability to repay a loan and, in return, receives legal protection. This "safe harbor" significantly reduces a creditor's costs and risks of issuing a loan. Among these criteria is a borrower's monthly debt-to-income (DTI) ratio of 43 percent or less. Although the proposed rule of May 2011 listed the DTI ratio among other criteria, it did not specify a precise ratio. This absence of a bright line during the "due process of the law" created high uncertainty about the CFPB's final determination in the 18 months leading up to the final rule. Lenders guessed that the DTI standard eventually would be set between 36–the maximum back-end DTI proposed for qualified residential mortgages (QRM)–and 43–the Federal Housing Administration's (FHA) underwriting standard.

Using differences in regulatory uncertainty across banks, we study how opacity on QM criteria affected bank lending. To measure regulatory uncertainty, we search for "uncertainty words" in the text of over 2,500 public comment letters submitted by large banks and credit unions after each step of the rule development. Our search shows that policy uncertainty varied greatly across lenders. When matched with loan and borrower characteristics by lender, this result allows us to investigate differential changes in housing credit.

Figure 1 summarizes our findings on aggregate changes in credit. It compares the share of loans most likely affected by policy uncertainty–loans with DTI ratios greater than 36 and lower than 44–with the safest loans to be originated–loans with DTI ratios below 21. At the time of uncertainty about the QM definition (between the red vertical lines), the share of 37-43 DTI loans plummeted 6 percent. Meanwhile, the share of loans with DTI ratios below 21 rose by 12 percent. As uncertainty was resolved by the publication of the final rule, the dynamics of the shares reverted.[1] Our main results confirm these findings at the bank level.

Making use of our comment-based measure of uncertainty, we find that if a bank

[1]Interestingly, policy uncertainty appears to have an immediate effect on portfolio composition: the share of 37-43 DTI declines–and the share of loans with DTI ratios below 21 increases–at the time of the rule proposal (the left vertical bar). Anecdotal evidence suggests that the costs of adjusting a banks underwriting model, including, for example, the updating of its information system, are high enough to prompt a bank to act quickly in anticipation of the final rule.

perceives higher uncertainty than other banks, or if it is more adverse to uncertainty than other banks, it is less likely to issue loans with DTI ratios between 37 and 43 prior to publication of the final rule. We also find that more uncertain banks issue fewer loans: a one standard deviation increase in uncertainty reduces a bank's total monthly originations by 1.57 standard deviations. We obtain these results from a large sample of banks, including banks that did not submit a comment on the proposed rule. However, when we restrict the sample to banks that submitted a comment, the results persist. This way, we address the potential concern that banks that submitted a comment might differ from banks that did not.

Another concern is that our uncertainty measure may largely reflect general uncertainty about a bank's future outlook or business environment. We correct this bias through banks' historical legal costs. We reason that the "safe harbor" legal protection granted under the QM rule is more valuable to banks that have historically incurred higher legal costs. To estimate these costs, we collect data from the Public Access to Court Electronic Records (PACER) on court cases opened before the recent housing boom and bust. In particular, we instrument policy uncertainty by the number of lawsuits on the subject "Truth in Lending Act" that were terminated before 2004. Banks (defendants) that historically were sued more often displayed higher uncertainty during the rule-making process between 2011 and 2013 and a larger reduction in lending.

Our estimation strategy allows us to address several identification concerns. First, since the banking sector as a whole might influence the policy making process, we use variation across banks to identify the differential impact of uncertainty on lending. Second, our natural experiment is sufficiently specific to only affect the bank lending channel.[2] By controlling for borrower, lender, and geographical characteristics we can exclude other channels through which policy uncertainty might affect bank lending.

[2] In contrast, higher uncertainty about oil prices might affect the behavior of several agents in the economy. Thus, identifying the transmission channel from higher uncertainty to economic outcomes is more arduous.

Since our results rely on the assumption that banks were uncertain about the future regulatory DTI ratio, we revisit our uncertainty measure to show that it well summarizes banks' sentiment toward the DTI criterion. We uncover hidden topics in bank comments and find that the DTI ratio was the prevalent topic. Further, uncertainty remained high and stable throughout the rule-making process and was resolved at once when the final rule was announced.

We end our analysis by investigating the effect of policy uncertainty on house prices. We show that there exists a correlation between policy uncertainty (instrumented by bank lawsuits) and house prices at the county level. In particular, after the rule proposal, credit was cut more severely in counties that recorded a larger number of mortgage lawsuits. In these counties house prices grew less or declined more than in other counties. Athough more work remains to be done to test and establish the macro-economic effects of policy uncertainty, we provide some evidence that regulatory indecision had (unintended) consequences on both lending and house prices.

Our contribution to past research is threefold. First, we measure the differential effect of policy uncertainty on bank lending—bypassing the issue of reverse causality common to the literature on macroeconomic uncertainty. Second, we provide a detailed study of credit cycles that originated solely from prolonged policy uncertainty. Last, we show that counties that perceived higher policy uncertainty saw a larger decline in lending and house prices.

Section 2 reviews past research relevant to our study. Section 3 provides detailed background information on the QM regulatory framework. Section 4 describes the data. Results on the composition and size of banks' mortgage portfolios are presented in section 5. Section 6 shows that these results are robust to endogeneity and other concerns. Section 7 introduces the geographical analysis and relates policy uncertainty to changes in house prices. Section 8 concludes.

2 Literature review

This paper is related to several strands of past research. First, we add to the literature on economic uncertainty and, in particular, to the growing literature on policy uncertainty.

The literature on uncertainty can be broadly organized into two groups: financial-sector models and models of real economic activity. While development of the former group has been quite limited to date, the latter has received greater attention.

The first papers to include finance models under uncertainty were in the asset pricing literature, particularly optimal portfolio selection. One of the contributions from this literature is to establish that investors generally dislike uncertainty–even beyond their dislike of risk–and that a premium is required for them to hold assets whose returns are uncertain (Maccheroni, Marinacci, and Ruffino 2013, Gollier 2011). Recently, and surely in response to the challenges that banks and financial institutions faced during the financial crisis, the focus of finance-sector models under uncertainty has shifted. Caballero and Krishnamurthy (2008), for example, argue that the complexity and lack of history of some credit products caused excessive uncertainty ahead of the crisis, culminating in a freezing up of credit markets. The market freezing, say Easley and OHara (2010), stemmed from uncertainty about fair asset prices. Because bid and ask prices did not reflect investors' pessimistic beliefs during the crisis, no trading occurred at the quoted prices.

Models of real economic activity under uncertainty, instead, analyze the implications of uncertainty for investment, aggregate output, consumption, and hours worked, among other variables. While most of these models define uncertainty broadly, some narrow its source and analyze specific events. For example, Julio and Yook (2012) document that high political uncertainty causes lower investment in election years, while Pastor and Veronesi (2012) measure movements in stock prices after a policy change is announced. It is in this vein that we develop our paper. Methodologically, our paper is perhaps closest to the work of Baker, Bloom, and Davis (2013), whose measure of uncertainty is also based on text analysis.

The recent financial crisis spurred a great deal of research on the run-up to the crisis and what fueled the credit boom, with an emphasis on sub-prime lending. The lending boom was accompanied by a boom in securitization, which might have led to lower lending standards (Keys, Mukherjee, Seru, and Vig (2010)).[3] Predatory lending (Agarwal, Amromin, Ben-David, Chomsisengphet, and Evanoff (2014)) and borrowers' ability to misreport their income (Garmaise 2015, Jiang, Nelson, and Vytlacil 2014) or to misstate asset values (Ben-David 2011a) also contributed to lowering lending standards.

How lower lending standards affected house prices is also the subject of recent research. Mian and Sufi (2009) find that ZIP codes with a higher share of sub-prime borrowers pre-crisis recorded a faster increase in house prices during the boom and more loan defaults during the bust.[4] Of course, borrowers lack of sophistication also contributed to overpaying for properties (Ben-David 2011b) and, overall, to inflated house prices (Chinco and Mayer 2014).

Finally, several papers investigate the effects of lower lending standards on the real economy, beyond house prices. Chodorow-Reich (2014) shows that, following Lehman Brothers' bankruptcy, firms connected to distressed lenders cut employment. Greenstone, Mas, and Nguyen (2014) find a similar effect on small businesses. Post-crisis declines in credit supply also affected investment, especially in non-tradable sectors (Di Maggio and Kermani 2014).

3 Regulatory framework

Enacted in 1968, the Truth in Lending Act (TILA) established requirements on the disclosure of terms and costs in consumer credit transactions. In 2010, TILA was substantially amended with the introduction of the Dodd-Frank Wall Street Reform

[3]Further evidence on the role of securitization in the expansion of subprime credit is provided by Nadauld and Sherlund (2013).

[4]The effects of credit supply on house prices are also studied by (Adelino, Schoar, and Severino 2012) and Favara and Imbs (2015), among others.

and Consumer Protection Act (commonly referred to as Dodd-Frank).[5] This section explains the changes initiated by Dodd-Frank and the introduction of the notion of qualified mortgages (QM).

Title XIV of Dodd-Frank established that lenders may only issue a mortgage if they can ensure that borrowers will have the "ability to repay" (ATR) it. Qualified mortgages under this title were to be fully defined by the Board of Governors of the Federal Reserve System and would provide the lender with varying degrees of legal protection should the borrower decide to litigate under the ATR standards.

In May 2011, the Board of Governors of the Federal Reserve System proposed two alternative definitions for a "general qualified mortgage". The definitions included various ATR standards, as well as loan-level characteristics, and ensured that the lender would receive legal protection in the form of either a conclusive presumption (ie., "safe harbor") or a rebuttable presumption.[6] Only the rebuttable presumption alternative included a borrowers debt-to-income ratio as a guideline for qualified mortgages. However, even this definition lacked a concrete limit. After the rule proposal, the mortgage community was given the opportunity to comment on it three times: May 11-July 22, 2011, June 5-July 9, 2012, and August 10-October 9, 2012.

In January 2013, the CFPB issued the final rule and resolved the statutory uncertainty around ATR standards and the legal protection provided by a qualified mortgage. The rule required lenders to consider a list of eight factors in assessing a borrower's ATR, including a monthly DTI ratio less than or equal to 43. Lenders issuing a qualified mortgage would secure "safe harbor" legal protection.

Anecdotal evidence suggests that lenders were surprised by the final rule on two

[5] TILA is implemented through Regulation Z, which was issued by the Board of Governors of the Federal Reserve System and was subsequently amended by the Consumer Financial Protection Bureau (CFPB).

[6] A lender may be sued for breaching TILA regardless of the type of presumption. However, a "safe harbor" would have provided a lender with a clear path for disposing of spurious complaints pre-trial, whereas the precedence of a rebuttable presumption suggested that a case would not be resolved until the plaintiff was given the opportunity to present evidence in the trial stage. Consequently, a rebuttable presumption was preceived as the more costly alternative and, absent a bright line on DTI, more difficult to defend successfully.

fronts.[7] First, the rule included a clear DTI cutoff. Prior to the second comment period, the CFPB had solicited opinions on the inclusion of a DTI cutoff. In response, lenders expressed concerns that a DTI ratio too low would constrain credit excessively. Instead, most lenders favored combining a DTI ratio requirement with other (less stringent) conditions. Second, the rule fixed the DTI ratio limit at 43. This limit was the upper bound of lenders' expectations. Indeed, an early proposal setting guidelines for qualified residential mortgages (QRM) had indicated a DTI ratio limit of 36. The Federal Housing Administration's (FHA) underwriting standard was, instead, set at 43. As lenders' uncertainty about the DTI ratio was spread over the range 37-43, we focus on this range for the analysis that follows.

4 Data

This section details the data and introduces the uncertainty measure.

4.1 Mortgage data

Our analysis utilizes monthly residential mortgage data from the Residential Mortgage Servicing Database (RMS). We focus on 30-year fixed rate mortgages originated between 2010Q1 and 2014Q4 and study loan characteristics (closing date, mortgage rate, loan type, origination amount, original term, prepayment penalties, and recourse), collateral characteristics (loan-to-value ratio, appraisal amount, property type, property state and ZIP Code), and borrower characteristics (debt-to-income ratio, credit score, occupancy type, documentation, and loan purpose). While RMS provides comprehensive coverage of newly originated loans, it does not include lender characteristics. To address this concern, we merge RMS data with regulatory and confidential data through the Home Mortgage Disclosure Act (HMDA). HMDA

[7] "The measure has been among the most hotly contested post-financial crisis US rules [...] and fears over the rules have contributed to currently tighter mortgage standards." From *The Financial Times*: US home loan rules to be unveiled, January 10, 2013.

records mortgage applications, whether they were denied, approved, and originated, as well as lender identifiers for depository institutions. To merge the two datasets, we match loans by closing date, origination amount, loan purpose, and the Zip Code Crosswalks for Census geographies from the Department of Housing and Urban Development (HUD).[8] We successfully match 1.86 million loans or 38 percent of the loans in RMS.

4.2 Uncertainty measure

We measure policy uncertainty by analyzing the text of over 2500 public comments submitted by banks and credit unions during the "due process of the law" – between 2011 and 2013.[9] We search the comments for "uncertainty" and "negative" words from the sentiment dictionaries by Loughran and McDonald (2011).[10] Our measure of a lender's uncertainty is the share of uncertainty and negative words over the total number of words in that lender's comment. Banks that did not submit a comment are given uncertainty equal to zero. This specification, however, may bias our estimates. Since it was mostly large banks that submitted comments, we also present results for the restricted sample of banks that did submit a comment. In addition, the share of uncertain words summarizes banks' sentiment toward all the proposed criteria for qualified mortgages, not solely the debt-to-income criterion. To prove that the debt-to-income criterion is the source of uncertainty, we conduct further textual analysis using natural language processing (NPL). Details on our application of NPL to the present context and on our results are provided in Subsection 6.2.

[8]The Zip Code Crosswalks allow us to match loan-level ZIP Codes in RMS to loan-level Counties in HMDA.

[9]In particular, comments on the proposed rule were submitted over the periods May 11-July 22, 2011, June 5-July 9, 2012 and August 10-October 9, 2012.

[10]We choose to count negative words because the mere count of uncertainty words would conceal the repeated use of phrases from the rule proposal and, therefore, it could amplify any uncertainty introduced by the regulators in the proposal.

5 Results

This section studies the effects of policy uncertainty on banks' lending practices. First, we show how uncertainty changed the composition of banks' mortgage portfolios (the intensive margin–Subsection 5.1). Then, we show that total lending shrunk due to higher policy uncertainty (the extensive margin–Subsection 5.2)

5.1 On the composition of banks' mortgage portfolios

Between the times the proposed and the final rule were published, the share of 37-43 DTI loans declined by a third. Such decline was more than offset by the sharp rise in the share of loans with DTI ratios below 21 (Figure 1). But how well did these aggregate shares summarize the effects of policy uncertainty for individual banks? We find that banks did not perceive policy uncertainty equally. In particular, banks that perceived uncertainty more negatively changed their portfolio composition more drastically. We specify the following bank-level model:

$$y_{i,t} = \beta * (proposal_t * uncertainty_i) + \gamma_{i,t} x_{i,t} + \epsilon_{i,t} \tag{1}$$

where $y_{i,t}$ is the ratio of loans featuring a DTI ratio of 37 to 43 over the total number of loans or over the number of loans featuring a DTI ratio of 20 or less by bank i during month t. $proposal_t$ is a dummy that takes value 1 between May 2011 and December 2012 and 0 otherwise. $uncertainty_i$ is the share of uncertain and negative words over the total number of words in bank i's comment and 0 if a bank has not submitted a comment, and $x_{i,t}$ includes bank-specific and time-specific fixed effects. Monthly fixed effects control for market-wide unobserved heterogeneity and bank-specific fixed effects control for heterogeneity across lenders.

Table 2 shows the results. The first column suggests that at least some of the changes in portfolio composition seen in Figure 1 are due to policy uncertainty. More uncertain banks decrease their ratio of 37-43 DTI loans over safer loans with a DTI ratio below 21.[11] In particular, if a bank's uncertainty during the time of the policy proposal is one standard deviation higher than the mean uncertainty value, the bank's share of 37-43 DTI ratio loans relative to loans with a DTI ratio below 21 decreases by 31 percent (column 1). However, uncertainty does not appear to lower the likelihood of a bank originating a 37 to 43 DTI-ratio loan more than any other loan: the point estimate in column 2 is negative but insignificant at conventional statistical levels. This result could be explained by a decrease in the total number of originations, not only loans with a 37-43 DTI ratio (section 5.2).

These results confirm the compositional portfolio effect of Figure 1. The decrease in the share of 37-43 DTI ratio loans was mainly offset by an increase in the share of < 21 DTI ratio loans. This effect persists when we focus on the sub-sample of banks that submitted a comment following the proposed rule (columns 3 and 4). A bank perceiving uncertainty that is one standard deviation higher than the mean uncertainty value, decreases by 20 percent its share of loans with DTI ratio of 37-43 relative to loans with DTI ratio below 21 (column 3). Even within the restricted group, the decrease in the share of 37-43 DTI ratio loans relative to the overall portfolio is statistically insignificant (column 4).

Did uncertainty, however, only change the composition of banks' mortgage portfolios? Or did it, perhaps, also change their size? We answer these questions in the next section.

5.2 On the size of banks' mortgage portfolios

In this section, we consider the size of banks' mortgage portfolios. We measure the size of a bank's mortgage portfolio in two ways: by the logarithm of the total (dollar) loan amount and by loan issuances (that is, the total number of originations). We

[11] Here, we deem a loan "safe" if its issuance would impart a creditor low costs or risks.

estimate the following model:

$$y_{i,t} = \beta * (proposal_t * uncertainty_i) + \gamma x_{i,t} + \epsilon_{i,t} \tag{2}$$

where $y_{i,t}$ is either measure listed above, computed monthly between May 2011 and December 2012 for bank i. On the right-hand-side, the variable of interest remains the interaction term between a bank's uncertainty and the time dummy over the proposed rule period. We estimate the model by DTI classes and control for both bank and time fixed effects, $x_{i,t}$.

Tables 3 and 4 present the results. Column 4 reports the point estimate for 37-43 DTI ratio loans–the DTI class most likely affected by uncertainty about the DTI threshold. It shows that if a bank's uncertainty during the time of the policy proposal is one standard deviation higher than the mean uncertainty value, the bank's monthly loan amount decreases by 0.52 standard deviations (column 4, table 3) and the number of originations decreases by 1.57 standard deviations (column 4, table 4).[12] That is, the size of the bank's portfolio of newly originated loans shrinks as uncertainty rises. This effect is significant for all DTI classes (in both tables) and its economic significance persists when we restrict the sample to banks that submitted a comment (table 5). Indeed, we find that a one standard deviation increase in uncertainty caused a bank to reduce its total number of monthly originations by 0.15 standard deviations.[13] The bank-level results of tables 3, 4, and 5 are even more important when compared with aggregate lending dynamics. Figure 2 shows origination amounts by DTI ratio classes before and after the proposed rule (marked by the left vertical bar) and after the announcement of the final rule (marked by the

[12] A one standard deviation increase in uncertainty would cause a bank to reduce its total monthly loan amount by 0.31, 0.43, 0.47, and 0.36 standard deviations for DTI ratio classes < 21 (column 1), 21-28 (column 2), 29-36 (column 3), and 44-50 (column 5), respectively. Also, a one standard deviation increase in uncertainty would cause a bank to reduce its total monthly loan issuances by 1.07, 1.64, 1.79, and 0.61 standard deviations for DTI ratio classes < 21 (column 1), 21-28 (column 2), 29-36 (column 3), and 44-50 (column 5), respectively.

[13] Within the restricted sample, a one standard deviation increase in uncertainty would cause a bank to reduce its total monthly loan issuances by 0.19, 0.21, 0.21, and 0.18 standard deviations for DTI ratio classes < 21 (column 1), 21-28 (column 2), 29-36 (column 3), and 44-50 (column 5), respectively.

right vertical bar). Although origination amounts of high DTI ratio loans (> 50) remained stable between the proposed and the final rule, origination amounts in all other classes increased more or less conspicuously. In light of this evidence the differential effect of uncertainty on bank lending appears even more important: as documented in table 3, higher uncertainty about the rule proposal unambiguously decreased total origination amounts. Jointly, these results suggest that policy uncertainty slowed the post-crisis recovery and curbed credit supply.

In the next section we further our analysis, with an eye to endogeneity concerns that our uncertainty measure might bring about.

6 Robustness

Our main results so far are that banks that perceive higher policy uncertainty (or that are most adverse to it) change the composition of their mortgage portfolio and reduce its size. Next, we offer a number of robustness tests to validate these results and rule out alternative explanatory channels. First, we correct for any endogeneity that our uncertainty measure might generate (subsection 6.1). Second, we challenge the assumption that our uncertainty measure represents a bank's attitude toward the DTI criterion–and not its attitude toward all criteria proposed in the rule (subsection 6.2).

6.1 On the issue of endogeneity

Our measure of uncertainty about the DTI ratio presents an advantage: by varying across banks, it allows us to effectively control for macroeconomic uncertainty. We cannot, however, rule out that this source of uncertainty be correlated with general uncertainty by the bank (which might also reduce lending). To cope with this possible endogeneity, we introduce an identification strategy that makes use of new data on mortgage lawsuits against banks for mortgage-related activities.

Although intuitive that a bank's uncertainty about future underwriting standards ought to be positively correlated to the bank's general uncertainty about its future outlook, the direction in which such correlation might bias our results is unclear. On the one hand, banks might shy away from weaker creditors fearing that tighter regulations might prevent them from eventually selling the risky loans. On the other hand, banks might rush to originate riskier, higher yielding loans and make the last "easy" profits in anticipation of future tighter regulations. We aim to correct this bias through an instrumental variable that identifies only the changes in (DTI ratio-related) uncertainty that are uncorrelated to general bank uncertainty during the period 2010-2014.

Our choice of instrument is motivated by a key aspect of the rule proposal: when issuing a qualified mortgage, the bank secures "safe harbor" legal protection should the borrower decide to litigate under the ATR standard. Such legal protection might be more valuable to banks that have needed to defend themselves against mortgage fraud suits and, possibly, that have been slammed with fees. Such legal protection might also be embraced by banks predominantly located in areas where borrowers are more prone to take legal actions, or where the courts have been historically more lenient toward borrowers. Our conjecture is that uncertainty amplifies declines in credit by banks that have faced high legal costs for their mortgage activities.

We estimate banks' legal costs by collecting lawsuits against banks on the subject to the "Truth in Lending Act", starting in 2000. We obtain over 9,000 circuit court cases from Public Access to Court Electronic Records (PACER), provided by the Federal Judiciary. For each case we save the filing date, the termination date, the banks name (defendant) and ZIP Code, the plaintiffs ZIP Code, and the demand and disposition of the case. If the plaintiff is not self-representing, then we save the ZIP Code of her attorney. The sample include 70 banks, evenly distributed across district courts.

To satisfy the exclusion restriction, the lawsuits brought against a bank cannot be correlated with the bank's general uncertainty over the period of interest

(2010-2014). Although the majority of our sample is made of cases either filed or terminated during the recent financial crisis or in its aftermath, we cannot employ them for our analysis. If we did, our measure of bank legal costs would only mirror the risky behavior of some of the banks during the economic boom and, thus, their more negative attitude toward uncertainty during and post crisis. Instead, we focus on cases terminated by 2004 (prior to the inception of the sub-prime lending boom).

Our measure of bank legal costs is given by the number of cases where a bank appeared as the defendant and that were terminated by 2004. Table 6 reports the correlation coefficients between a bank's legal costs measure and its lending growth between 2004 and 2006, computed two ways: by the (percentage) change in total (dollar) loan amount and by the (percentage) change in total number of loan originations. We find that our measure is uncorrelated with lending growth, even at the height of the housing boom. This provides some confidence that we are not simply measuring bank risk.

To implement our identification strategy we estimate the following model:

$$proposal_t * uncertainty_i = \delta proposal_t * cases_i + \gamma x_{it} + \epsilon_{i,t}. \tag{3}$$

$proposal_t$ is a dummy that takes value 1 between May 2011 and December 2012 and 0 otherwise, $uncertainty_i$ is the share of uncertainty and negative words over the total number of words in bank i's comment, and $cases_i$ is the number of cases where a bank appeared as the defendant, and that were terminated by 2004. We only need to instrument the interaction term of the baseline model (subsection 5.2), as time and bank fixed effects control for unobservable time-varying and bank-varying heterogeneity.[14] Table 7 reports estimates for different samples, each given by a different DTI class. We find that banks that were sued more often before the housing boom exhibit higher uncertainty after the rule proposal. Each additional lawsuit be-

[14]The first-stage regression would deliver the same results if we used the uncertainty measure on the right-hand-side, without conditioning on the proposal period. We choose to present this regression to be consistent with our previous regressions.

fore the housing boom increases by 0.3 percent the number of uncertain or negative words in a comment, on average (that is, an increase of about one standard deviation). When we restrict the sample to banks that submitted a comment, the point estimates are still highly significant and larger: an additional lawsuit terminated before 2004 increases by 1.8 percent the number of uncertain or negative words in a comment, on average (that is, an increase of 1.2 standard deviations).

Using fitted values of the uncertainty measure, we estimate the following (second-stage) regression:

$$y_{i,t} = \beta * (proposal_t * uncertainty_i)^{IV} + \gamma x_{i,t} + \epsilon_{i,t} \tag{4}$$

where $y_{i,t}$ is either the total (dollar) loan amount or the total number of loan originations by bank i in month t, both computed monthly between May 2011 and December 2012. $proposal_t$ is a dummy that takes value 1 between May 2011 and December 2012 and 0 otherwise. The interaction term $(proposal_t * uncertainty_i)^{IV}$ is given by the fitted values from the first stage regression summarized in Table 7. $x_{i,t}$ includes bank-specific and time-specific fixed effects. The results are reported in tables 8, 9, and 10 (restricted sample), by DTI classes.

The two-stage least squared (2SLS) estimates are larger than the corresponding ordinary least squared (OLS) point estimates (tables 3 and 4). The difference is particularly large for DTI class 44-50. This difference might indicate that, even if uncertainty about mortgage requirements reduced a banks propensity to originate high DTI ratio loans, general uncertainty by the bank did not especially discourage such loans. This is only partly surprising if we recall that the DTI ratio is only an imperfect measure of a borrower's risk. While a borrower's loan-to-value ratio or credit score reliably predict loan defaults, the DTI ratio cannot. It is plausible that, even at times of great general uncertainty, banks would be willing to extend credit to high-wealth, low-DTI individuals.

Banks that submitted a comment, however, behaved differently. The 2SLS estimates of table 10 are consistently lower than the corresponding OLS estimates (table

5). These results suggest that banks that were so uncertain about future mortgage regulations that they submitted a public comment about it, curbed credit both in response to regulatory uncertainty and general uncertainty across all DTI classes.

In sum, within the full sample our proposed uncertainty measure provides a conservative estimate of the effects of regulatory uncertainty on bank lending (OLS estimates are upward biased). It remains to be determined, however, if such measure represents a bank's attitude toward the DTI criterion–and not its attitude toward other criteria proposed in the rule.

6.2 On the source of uncertainty in public comments

This subsection challenges our assumption that uncertainty in banks' comments pertains to the DTI ratio. We show that comments covered a limited number of topics and that the DTI ratio was predominant among them. We also show that uncertainty remained stable during the 18 months between the rule proposal and the final rule. This fact provides support to our treatment of uncertainty as a constant over the period of interest.

As mentioned in Section 4.2, our proposed uncertainty measure does not only reflect banks' sentiment toward the debt-to-income criterion but also their sentiment toward all other proposed criteria for qualified mortgages (for example, monthly payments on simultaneous loans or mortgage-related obligations such as property taxes). To investigate the topics in banks' comments we borrow from the natural language processing (NLP) literature. In short, NPL uncovers words or sentences that frequently appear in a given context.[15] We find over 8,000 unique words and selectively examine the most pertinent to QM standards. We report selected words in table 11, along with the number of times each word appears and the total number of documents in which it appears. The words "dti", "tdti", "debt-to-income", "residual", and "income" are used very frequently in comments. There also appear,

[15]We refer the reader to the appendix for detailed information about NPL and its application to the present context.

however, words unrelated to the DTI ratio but crucial to the new regulation. For example, “fees” or “small” might refer to the issues of maximum fees and small creditors. The next step is to establish whether banks uncertainty pertains to the DTI ratio, to fees or to any other topic listed in table 11.

We tackle this next step by adapting the Latent Semantic Analysis models of Deerwester, Dumais, Landauer, Furnas, and Harshman (1990) and Landauer, Foltz, and Laham (1998). We study how often the words in table 11 are used together with words from the uncertainty dictionary employed in the construction of our uncertainty measure. Table 12 summarizes the results. It ranks words from table 11 by their correlation with the uncertainty dictionary. Correlations have a straightforward interpretation: high correlation values indicate that a word appears next to uncertainty words frequently (in the same paragraph or document). In the body of comments, all and banks-only, words related to the legal protection that could be secured through QM were highly correlated with uncertainty. Whether such protection would be in the form of rebuttable presumption or safe harbor was of great concern to banks. This result also speaks to the relevance of choosing historical legal costs to instrument for uncertainty (section 6.1). Immediately following words about banks’ legal protection, are all words about the DTI ratio (rank 4 through 11). Banks rarely use other words, including “fees”, in conjunction with uncertainty words.

The last step consists of verifying the accuracy of our assumption that uncertainty between the rule proposal and the final rule well proxies uncertainty perceived during any of the three comment periods. If this were not the case, then our measure of bank uncertainty (which we hold constant over time) would be inappropriate. While we cannot provide definitive proof of our assumption, we can measure the aggregate evolution of uncertainty over time (that is, all banks at once) depicted in figure 3. If the variance of our uncertainty measure did change a little over time, median uncertainty did not decrease closer to the announcement of the final rule. While we cannot rule out that bank-specific uncertainty also remained constant, figure 3 provides at least some support to our assumption.

In the next section, we further our analysis at a more aggregate geographical level. We analyze how house prices moved in counties more susceptible to policy uncertainty about QM.

7 On the effects of policy uncertainty on house prices

Past research suggests that banks' capacity to extend credit can be linked to housing demand. We take this evidence as our prior and consider the impact of policy uncertainty on housing demand, through the bank credit channel.

The recent housing boom and bust have spurred a vast literature on the effects of credit supply on housing. Pre-crisis, the volume of mortgages by banks, as well as other non-banks financial institutions, increased exponentially. Lending to sub-prime borrowers increased at an especially fast rate and overall lending standards worsened (Agarwal, Amromin, Ben-David, Chomsisengphet, and Evanoff 2014). ZIP codes with a higher share of sub-prime borrowers pre-crisis recorded a higher share of delinquencies during the crisis (Mian and Sufi 2009). Such changes in lending practices, in turn, were related to changes in house prices–see Di Maggio and Kermani (2014), among others.

Here, our aim is twofold. First, to document that after the rule proposal credit was cut more severely in counties that recorded a larger number of mortgage lawsuits before 2004–our instrument for county-level policy uncertainty. Second, to quantify the effect of policy uncertainty on house prices in the counties under observation.

To connect policy uncertainty, bank lending, and house prices, we aggregate the data in our RMS-HMDA merged sample by county. We compute monthly (dollar) loan amounts in any given county, normalized by county population from the 2010 Census. Similarly, we match banks' ZIP codes from mortgage lawsuits to corresponding counties and normalize the number of cases terminated prior to 2004 by county population from the 2000 Census.

We estimate two regressions and summarize the results in table 13. First, we estimate the correlation between the monthly CoreLogic home price index (HPI) at the county level and the logarithm of the per capita total (dollar) loan amount originated in county c in month t (column 1). The goal of establishing a causal link between house prices and lending is beyond our scope. We can confirm, however, that a positive correlation between the two variables exists (in line with the findings of several papers, including a few mentioned above). In columns 2 and 3 we provide the results of the following regression:

$$y_{c,t} = \beta * (proposal_t * cases_c) + \gamma x_{c,t} + \epsilon_{c,t} \tag{5}$$

where the dependent variable, $y_{c,t}$, is the logarithm of the per capita total (dollar) loan amount originated in county c in month t (column 2) or the monthly CoreLogic home price index at the county level (columns 3). The interaction term $proposal_t * cases_c$ is the county-level equivalent of the interaction term in table 7. That is, $proposal_t$ is a dummy that takes value 1 between May 2011 and December 2012 and 0 otherwise, and $cases_{c,t}$ is logarithm of the per capita number of cases terminated by 2004 in county c per capita. $x_{c,t}$ includes county-specific and time-specific fixed effects.

We find that counties with higher records of cases pre-crisis, cut credit supply more severely during the rule-making period (column 2). A one percent increase in the number of cases pre-crisis (per capita, in a given county) is associated with a decline in monthly lending by almost three percent. These findings suggest that the negative effect of policy uncertainty on bank lending (sections 5 and 6) was significant enough to bring aggregate consequences at the county level.

In column 3, we relate county-level cases (per capita) to house prices. A one percent increase in the number of cases pre-crisis (per capita, in a given county) is associated with a decline in house prices by almost one percent in any given month during the rule-making process.

If these results do not establish a causal relationship, they are nonetheless indicative of one macro-economic effect of policy uncertainty. Although more work remains to be done to test and establish the macro-economic effects of policy uncertainty, we provide some evidence that regulatory indecision had (unintended) consequences on both lending and house prices.

8 Conclusion

It took regulators 18 months, between 2011 and 2013, to provide a definition of "qualified mortgage". During that period, credit standards tightened and it became increasingly difficult for borrowers to get credit. US President Barack Obama echoed this reality and warned that "overlapping regulations keep responsible young families from buying their first home".[16] We provide evidence for this claim.

Merging detailed mortgage data with a bank-specific measure of uncertainty, we show that banks cut lending in response to prolonged uncertainty about future regulatory lending standards. We also add to the understanding of how policy uncertainty can translate to aggregate outcomes including higher volatility, lower employment, and lower investment (Baker, Bloom, and Davis 2013). In particular, we provide suggestive evidence that policy uncertainty which reduced lending ultimately affected house prices–recent research confirms that changes in lending standards can affect the real economy in various ways (Chodorow-Reich 2014, Greenstone, Mas, and Nguyen 2014). Further, our estimates of the effects of policy uncertainty on lending and housing may be quite conservative. Indeed, since our uncertainty measure is based on comments submitted mostly by large banks, we fail to account for uncertainty perceived by small and medium-size banks which did not submit a comment.

Our findings have at least one important implication for policy makers. Sec-

[16]Remarks by US President Barack Obama in the State of the Union Address, February 12, 2013.

tors where the adoption of new standards set by regulatory reforms is especially costly, will anticipate the implementation of such reforms. In the banking sector, high costs of adjusting underwriting models impacted lending decisions immediately following the rule proposal. Then, long delays to finalize rules may unintentionally but severely distort economic activity.

References

Adelino, M., A. Schoar, and F. Severino (2012): "Credit supply and house prices: evidence from mortgage market segmentation," *NBER Working Paper*.

Agarwal, S., G. Amromin, I. Ben-David, S. Chomsisengphet, and D. D. Evanoff (2014): "Predatory lending and the subprime crisis," *Journal of Financial Economics*, 113(1), 29–52.

Baker, S. R., N. Bloom, and S. J. Davis (2013): "Measuring economic policy uncertainty," *Working Paper*, (13-02).

Ben-David, I. (2011a): "Financial constraints and inflated home prices during the real estate boom," *American Economic Journal: Applied Economics*, pp. 55–87.

——— (2011b): "High leverage and willingness to pay: Evidence from the residential housing market," *Working Paper*.

Bird, S., E. Klein, and E. Loper (2009): *Natural Language Processing with Python: Analyzing Text with the Natural Language Toolkit*. O'Reilly, Beijing.

Caballero, R., and A. Krishnamurthy (2008): "Knightian uncertainty and its implications for the TARP," *Financial Times Economists' Forum*.

Chinco, A., and C. Mayer (2014): "Misinformed speculators and mispricing in the housing market," *NBER Working Paper*.

Chodorow-Reich, G. (2014): "The employment effects of credit market disruptions: Firm-level evidence from the 2008–9 financial crisis," *The Quarterly Journal of Economics*, 129(1), 1–59.

Deerwester, S. C., S. T. Dumais, T. K. Landauer, G. W. Furnas, and R. A. Harshman (1990): "Indexing by latent semantic analysis," *JAsIs*, 41(6), 391–407.

Di Maggio, M., and A. Kermani (2014): "Credit-induced boom and bust," *Working Paper*, (14-23).

Easley, D., and M. OHara (2010): "Liquidity and valuation in an uncertain world," *The Journal of Financial Economics*, 97(1), 1–11.

Eberly, J. C. (1994): "Adjustment of consumers' durables stocks: Evidence from automobile purchases," *Journal of Political Economy*, pp. 403–436.

Favara, G., and J. Imbs (2015): "Credit supply and the price of housing," *The American Economic Review*, 105(3), 958–992.

Fernández-Villaverde, J., P. A. Guerrón-Quintana, K. Kuester, and J. Rubio-Ramírez (2015): "Fiscal volatility shocks and economic activity," *American Economic Review, forthcoming.*

Garlappi, L., R. Giammarino, and A. Lazrak (2013): "Ambiguity in corporate finance: Real investment dynamics," *Working Paper.*

Garmaise, M. J. (2015): "Borrower misreporting and loan performance," *The Journal of Finance*, 70(1), 449–484.

Gilchrist, S., J. W. Sim, and E. Zakrajšek (2014): "Uncertainty, financial frictions, and investment dynamics," *NBER Working Paper.*

Gollier, C. (2011): "Portfolio choices and asset prices: The comparative statics of ambiguity aversion," *The Review of Financial Studies*, 78(4), 1329–1344.

Greenstone, M., A. Mas, and H.-L. Nguyen (2014): "Do credit market shocks affect the real economy? Quasi-experimental evidence from the Great Recession and normaleconomic times," *NBER Working Paper*.

Jiang, W., A. A. Nelson, and E. Vytlacil (2014): "Liar's loan? Effects of origination channel and information falsification on mortgage delinquency," *Review of Economics and Statistics*, 96(1), 1–18.

Julio, B., and Y. Yook (2012): "Political uncertainty and corporate investment cycles," *The Journal of Finance*, 67(1), 45–83.

Keys, B. J., T. Mukherjee, A. Seru, and V. Vig (2010): "Did securitization lead to lax screening? Evidence from subprime loans," *The Quarterly Journal of Economics*, 125(1), 307–362.

Kydland, F. E., and E. C. Prescott (1977): "Rules rather than discretion: The inconsistency of optimal plans," *The Journal of Political Economy*, pp. 473–491.

Landauer, T. K., P. W. Foltz, and D. Laham (1998): "An introduction to latent semantic analysis," *Discourse processes*, 25(2–3), 259–284.

Lucas, R. E. (1976): "Econometric policy evaluation: A critique," in *Carnegie-Rochester conference series on public policy*, vol. 1, pp. 19–46. Elsevier.

Maccheroni, F., M. Marinacci, and D. Ruffino (2013): "Alpha as ambiguity: Robust mean-variance portfolio analysis," *Econometrica*, 81(3), 1075–1113.

Mian, A., and A. Sufi (2009): "The consequences of mortgage credit expansion: Evidence from the US mortgage default crisis," *The Quarterly Journal of Economics*, 124(4), 1449–1496.

Nadauld, T. D., and S. M. Sherlund (2013): "The impact of securitization on the expansion of subprime credit," *Journal of Financial Economics*, 107(2), 454–476.

Pastor, L., and P. Veronesi (2012): "Uncertainty about government policy and stock prices," *The Journal of Finance*, 67(4), 1219–1264.

Ramos, J. (2003): "Using tf-idf to determine word relevance in document queries," in *Proceedings of the first instructional conference on machine learning*.

Romer, C. D. (1990): "The great crash and the onset of the Great Depression," *The Quarterly Journal of Economics*, 105(3), 597–624.

Turney, P. D., P. Pantel, et al. (2010): "From frequency to meaning: Vector space models of semantics," *Journal of artificial intelligence research*, 37(1), 141–188.

Table 1

Summary statistics. This table provides summary statistics for the loan-level and bank-level variables used in our analysis. Values are computed on the RMS-HMDA merged sample. Origination amount is the original loan amount in thousands of dollars. DTI is the back-end debt-to-income ratio. Loan issuances is the total number of loan originations by a bank. Loan amount is the sum of origination amounts by a bank, in millions of dollars. Uncertainty is bank's uncertainty, defined as the share of uncertainty and negative words over the total number of words in that bank's comment. Equity is a bank's equity as reported in the Reports of Condition and Income (Call Report) data, in millions of dollars. N is the number of observations.

	(1) Mean	(2) STDEV	(3) Median	(4) N
Loan-level variables				
Origination amount ($K)	319.7	331.5	232	301,801
DTI	32.31	13.89	31	301,801
Bank-level variables				
Loan issuances	17753	59421.9	3	17
Loan amount ($M)	5.675	18.487	0.001	17
Equity ($M)	20.983	51.397	0.182	14
Uncertainty	0.0313	0.0152	0.0240	16

Table 2

Composition of mortgage portfolio. This table provides the results of the regression: $y_{i,t} = \beta * (proposal_t * uncertainty_i) + \gamma x_{i,t} + \epsilon_{i,t}$. $proposal_t$ is a dummy that takes value 1 between May 2011 and December 2012 and 0 otherwise. $uncertainty_i$ is the share of uncertainty and negative words over the total number of words in bank i's comment. $x_{i,t}$ includes bank-specific and time-specific fixed effects. The dependent variable is the log of the ratio of the number of loans with a DTI between 37 and 43 over the number of loans with a DTI below 21 (columns 1 and 3) or the log of the ratio of loans featuring a DTI ratio of 37 to 43 over the total number of loans (columns 2 and 4). The first two columns report estimates for the full bank sample while the last two columns report estimates for the sub-sample of banks that submitted a comment.

	(1) $\frac{37-43}{<21}$	(2) $\frac{37-43}{N}$	(3) $\frac{37-43}{<21}$	(4) $\frac{37-43}{N}$
proposal*uncertainty	-6.783***	-2.027	-14.03**	-5.546
	(-3.11)	(-1.36)	(-2.03)	(-1.23)
time FE	Yes	Yes	Yes	Yes
bank FE	Yes	Yes	Yes	Yes
N	4129	8360	225	261
R^2	0.568	0.638	0.457	0.567

Table 3

Loan amount. This table reports the results of the regression: $loan\ amount_{i,t} = \beta * (proposal_t * uncertainty_i) + \gamma x_{i,t} + \epsilon_{i,t}$. $loan\ amount_{i,t}$ is the logarithm of the total (dollar) loan amount originated by bank i in month t, by DTI classes. $proposal_t$ is a dummy that takes value 1 between May 2011 and December 2012 and 0 otherwise. $uncertainty_i$ is the share of uncertainty and negative words over the total number of words in bank i's comment. $x_{i,t}$ includes bank-specific and time-specific fixed effects. The results are reported by DTI class as follows: < 21 (column 1), 21-28 (column 2), 29-36 (column 3), 37-43 (column 4), and 44-50 (column 5).

	(1) < 21	(2) 21-28	(3) 29-36	(4) 37-43	(5) 44-50
proposal*uncertainty	-11.95**	-15.57***	-16.19***	-17.76***	-12.34**
	(-2.09)	(-2.90)	(-3.38)	(-3.42)	(-2.53)
time FE	Yes	Yes	Yes	Yes	Yes
bank FE	Yes	Yes	Yes	Yes	Yes
N	7165	9051	9297	8360	6136
R^2	0.823	0.807	0.802	0.793	0.806

Table 4

Loan issuances. This table reports the results of the regression: $loan\ issuances_{i,t} = \beta * (proposal_t * uncertainty_i) + \gamma x_{i,t} + \epsilon_{i,t}$. $loan\ issuances_{i,t}$ is the total number of loan originations by bank i in month t, by DTI classes. $proposal_t$ is a dummy that takes value 1 between May 2011 and December 2012 and 0 otherwise. $uncertainty_i$ is the share of uncertainty and negative words over the total number of words in bank i's comment. $x_{i,t}$ includes bank-specific and time-specific fixed effects. The results are reported by DTI class as follows: < 21 (column 1), 21-28 (column 2), 29-36 (column 3), 37-43 (column 4), and 44-50 (column 5).

	(1) < 21	(2) 21-28	(3) 29-36	(4) 37-43	(5) 44-50
proposal*uncertainty	-5375.9**	-6480.3**	-6420.0***	-4256.0***	-2481.4***
	(-2.29)	(-2.49)	(-2.58)	(-2.62)	(-2.86)
time FE	Yes	Yes	Yes	Yes	Yes
bank FE	Yes	Yes	Yes	Yes	Yes
N	7165	9051	9297	8360	6136
R^2	0.658	0.525	0.489	0.539	0.253

Table 5

Loan issuances: Restricted sample. This table reports the results of the regression: $loan\ issuances_{i,t} = \beta * (proposal_t * uncertainty_i) + \gamma x_{i,t} + \epsilon_{i,t}$. $loan\ issuances_{i,t}$ is the total number of loan originations by bank i in month t, by DTI classes. $proposal_t$ is a dummy that takes value 1 between May 2011 and December 2012 and 0 otherwise. $uncertainty_i$ is the share of uncertainty and negative words over the total number of words in bank i's comment. $x_{i,t}$ includes bank-specific and time-specific fixed effects. The results are reported by DTI class as follows: < 21 (column 1), 21-28 (column 2), 29-36 (column 3), 37-43 (column 4), and 44-50 (column 5). These estimates are generated from the sub-sample of banks that submitted a comment.

	(1) < 21	(2) 21-28	(3) 29-36	(4) 37-43	(5) 44-50
proposal*uncertainty	-9048.8**	-10727.0**	-10297.0**	-5399.6**	-3137.4**
	(-2.09)	(-2.32)	(-2.32)	(-2.01)	(-2.02)
time FE	Yes	Yes	Yes	Yes	Yes
bank FE	Yes	Yes	Yes	Yes	Yes
N	248	261	258	261	238
R^2	0.403	0.379	0.396	0.400	0.444

Table 6

Correlation matrix: Legal cases and lending growth. This table shows the correlation coefficients between the number of cases where a bank appeared as the defendant, and that were terminated by 2004, and the banks lending growth between 2004 and 2006, measured two ways: by the (percentage) change in total (dollar) loan amount and by the (percentage) change in total number of loan originations.

	cases	growth in l. amount	growth in l. issuances
cases	1		
growth in l. amount	0.000264	1	
growth in l. issuances	-0.000143	0.873***	1

Table 7

Instrumental Variable: First stage regression. This table reports the results of the regression: $proposal_t * uncertainty_i = \delta * proposal_t * cases_i + \gamma x_{it}$. $proposal_t$ is a dummy that takes value 1 between May 2011 and December 2012 and 0 otherwise. $uncertainty_i$ is the share of uncertainty and negative words over the total number of words in bank i's comment. $cases_i$ is the number of cases where a bank appeared as the defendant, and that were terminated by 2004. $x_{i,t}$ includes bank-specific and time-specific fixed effects. The results are reported by DTI class as follows: < 21 (column 1), 21-28 (column 2), 29-36 (column 3), 37-43 (column 4), and 44-50 (column 5).

	(1) < 21	(2) 21-28	(3) 29-36	(4) 37-43	(5) 44-50
Full sample					
proposal*cases	0.00320***	0.00331***	0.00328***	0.00353***	0.00335***
	(6.24)	(6.45)	(6.25)	(6.12)	(6.23)
time FE	Yes	Yes	Yes	Yes	Yes
bank FE	Yes	Yes	Yes	Yes	Yes
N	7165	9051	9297	8360	6136
R^2	0.096	0.090	0.088	0.094	0.102
Restricted sample					
proposal*cases	0.0188***	0.0188***	0.0183***	0.0178***	0.0188***
	(27.68)	(25.81)	(22.99)	(22.51)	(24.82)
time FE	Yes	Yes	Yes	Yes	Yes
bank FE	Yes	Yes	Yes	Yes	Yes
N	248	261	258	261	238
R^2	0.972	0.971	0.964	0.956	0.971

Table 8

Instrumental variable: Loan amount (second stage regression). This table provides the results of the regression: $loan\ amount_{it} = \beta * (proposal_t * uncertainty_i)^{IV} + \gamma x_{it} + \epsilon_{it}$. $loan\ amount_{it}$ is logarithm of the total (dollar) loan amount originated by bank i in month t, by DTI classes. $proposal_t$ is a dummy that takes value 1 between May 2011 and December 2012 and 0 otherwise. $uncertainty_i$ is the share of uncertainty and negative words over the total number of words in bank i's comment. The interaction term $(proposal_t * uncertainty_i)^{IV}$ is given by the fitted values from the first stage regression summarized in Table 7. $x_{i,t}$ includes bank-specific and time-specific fixed effects. The results are reported by DTI class as follows: < 21 (column 1), 21-28 (column 2), 29-36 (column 3), 37-43 (column 4), and 44-50 (column 5).

	(1) < 21	(2) 21-28	(3) 29-36	(4) 37-43	(5) 44-50
proposal*uncertainty	-12.33	-43.45***	-36.43***	-33.48***	-21.43**
	(-1.22)	(-4.05)	(-3.91)	(-3.59)	(-2.46)
time FE	Yes	Yes	Yes	Yes	Yes
bank FE	Yes	Yes	Yes	Yes	Yes
N	7165	9051	9297	8360	6136
R^2	0.084	0.071	0.065	0.062	0.042

Table 9

Instrumental variable: Loan issuances (second stage regression). This table provides the results of the regression: $loan\ issuances_{it} = \beta * (proposal_t * uncertainty_i)^{IV} + \gamma x_{it} + \epsilon_{it}$. $loan\ issuances_{it}$ is the total number of loan originations by bank i in month t, by DTI classes. $proposal_t$ is a dummy that takes value 1 between May 2011 and December 2012 and 0 otherwise. $uncertainty_i$ is the share of uncertainty and negative words over the total number of words in bank i's comment. The interaction term $(proposal_t * uncertainty_i)^{IV}$ is given by the fitted values from the first stage regression summarized in Table 7. $x_{i,t}$ includes bank-specific and time-specific fixed effects. The results are reported by DTI class as follows: < 21 (column 1), 21-28 (column 2), 29-36 (column 3), 37-43 (column 4), and 44-50 (column 5).

	(1) < 21	(2) 21-28	(3) 29-36	(4) 37-43	(5) 44-50
proposal*uncertainty	-11980.7***	-14150.6***	-13732.2***	-10490.7***	-10244.0***
	(-2.95)	(-3.15)	(-3.30)	(-3.53)	(-4.27)
time FE	Yes	Yes	Yes	Yes	Yes
bank FE	Yes	Yes	Yes	Yes	Yes
N	7165	9051	9297	8360	6136
R^2	0.016	0.008	0.006	-0.012	-0.012

Table 10

Instrumental variable: Loan issuances (second stage regression, restricted sample). This table provides the results of the regression: $loan\ issuances_{it} = \beta * (proposal_t * uncertainty_i)^{IV} + \gamma x_{it} + \epsilon_{it}$. $loan\ issuances_{it}$ is the total number of loan originations by bank i in month t, by DTI classes. $proposal_t$ is a dummy that takes value 1 between May 2011 and December 2012 and 0 otherwise. $uncertainty_i$ is the share of uncertainty and negative words over the total number of words in bank i's comment. The interaction term $(proposal_t * uncertainty_i)^{IV}$ is given by the fitted values from the first stage regression summarized in Table 7. $x_{i,t}$ includes bank-specific and time-specific fixed effects. The results are reported by DTI class as follows: < 21 (column 1), 21-28 (column 2), 29-36 (column 3), 37-43 (column 4), and 44-50 (column 5). These estimates are generated from the sub-sample of banks that submitted a comment.

	(1) < 21	(2) 21-28	(3) 29-36	(4) 37-43	(5) 44-50
proposal*uncertainty	-5733.1*	-8893.3**	-8613.0**	-7027.8***	-2514.2**
	(-1.78)	(-2.46)	(-2.36)	(-2.68)	(-2.16)
time FE	Yes	Yes	Yes	Yes	Yes
bank FE	Yes	Yes	Yes	Yes	Yes
N	248	261	258	261	238
R^2	0.283	0.258	0.273	0.259	0.280

Table 11

Proposal terms summary. This table reports the prevalence of our selected proposal terms for all submitted comments and those specifically submitted by the banks in our analysis. *Count* is the total number of occurances of the term and *Documents* is the total number of documents in which the term is found.

	Banks		All Comments	
Term	Count	Documents	Count	Documents
affiliate	9	3	322	74
balloon	24	6	465	110
burden	24	10	624	193
creditor	251	10	2446	180
debt	61	8	956	170
debt-to-income	8	4	211	91
dti	45	5	1308	104
fee	220	17	3299	296
income	106	16	2568	275
ltv	6	2	142	40
mortgage-related	6	2	127	59
obligation	57	12	858	171
point	174	13	2194	262
presumption	190	10	1584	161
proof	14	5	180	55
ratio	26	8	919	165
rebuttable	80	9	881	143
residual	8	5	485	94
rural	21	8	342	108
simultaneous	2	1	148	57
small	36	14	1188	244
tdti	51	3	135	17

Table 12

Proposal terms ranked by similarity to uncertainty. This table ranks our selected proposal terms by the correlation similarity measure, $\bar{\rho}_i$, over the split between the full corpus of comments and those submitted by banks in our analysis.

	Banks		All Comments	
	$Term_i$	$\bar{\rho}_i$	$Term_i$	$\bar{\rho}_i$
1	proof	0.2437	proof	0.2263
2	presumption	0.2264	obligation	0.1872
3	rebuttable	0.2182	burden	0.1498
4	residual	0.1759	presumption	0.1388
5	burden	0.1664	rebuttable	0.1196
6	tdti	0.1594	simultaneous	0.0984
7	debt-to-income	0.1467	income	0.0935
8	income	0.1460	creditor	0.0896
9	obligation	0.1112	point	0.0844
10	simultaneous	0.0968	tdti	0.0825
11	ratio	0.0724	fee	0.0744
12	dti	0.0477	debt-to-income	0.0649
13	creditor	0.0465	mortgage-related	0.0452
14	point	0.0444	residual	0.0377
15	ltv	0.0443	debt	0.0238
16	fee	0.0365	affiliate	0.0124
17	mortgage-related	0.0251	ratio	0.0026
18	affiliate	0.0219	ltv	-0.0067
19	debt	0.0161	dti	-0.0096
20	balloon	-0.0081	small	-0.0140
21	rural	-0.0565	balloon	-0.0267
22	small	-0.0578	rural	-0.0298

Table 13

House prices. This table provides the results of two regressions. The point estimate in column 1 measures the correlation between the monthly CoreLogic home price index (HPI) at the county level and the logarithm of the per capita total (dollar) loan amount originated in county c in month t. In columns 2 and 3 we provide the results of the regression : $y_{c,t} = \beta * (proposal_t * cases_c) + \gamma x_{c,t} + \epsilon_{c,t}$. The dependent variable, $y_{c,t}$, is the logarithm of the per capita total (dollar) loan amount originated in county c in month t (column 2) and the monthly CoreLogic home price index at the county level (columns 3). $proposal_t$ is a dummy that takes value 1 between May 2011 and December 2012 and 0 otherwise. $cases_{c,t}$ is logarithm of the per capita number of cases terminated by 2004 in county c per capita. $x_{c,t}$ includes county-specific and time-specific fixed effects.

	(1) HPI	(2) loan amount	(3) HPI
loan amount	0.245***		
	(5.41)		
proposal*cases		-0.878***	-0.0285***
		(-5.77)	(-2.66)
time FE	Yes	Yes	Yes
county FE	Yes	Yes	Yes
N	59057	6703	6925
R^2	0.911	0.952	0.746

Figure 1

Loan issuances for selected DTI ratios. This graph shows the ratio of loans issued in month t and featuring a DTI ratio of 21 or less over the total number of loans issued in t. It also depicts the ratio of loans issued in month t and featuring a DTI ratio of 37 to 43 over the total number of loans issued in t.

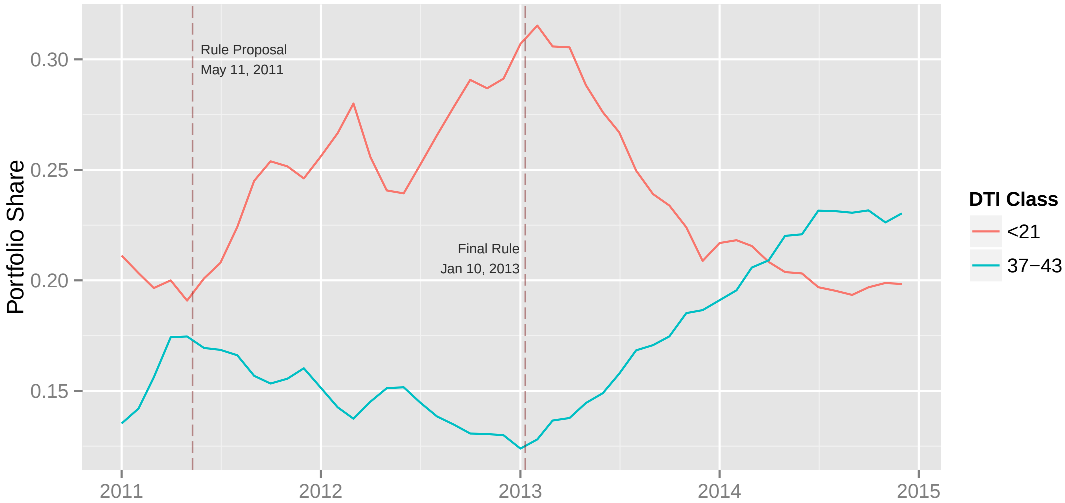


Figure 2

Origination amounts by DTI ratio. This graph shows monthly origination amounts disaggregated by DTI classes.

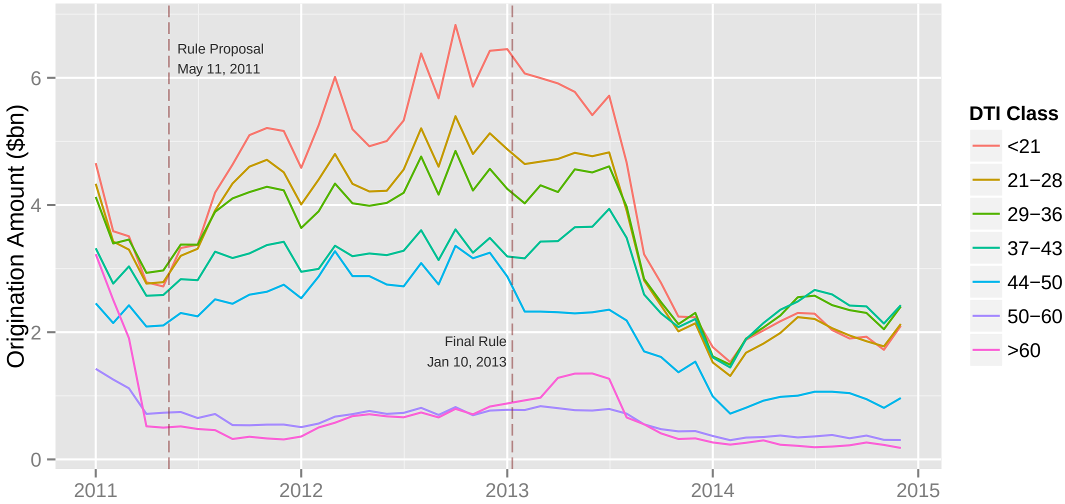
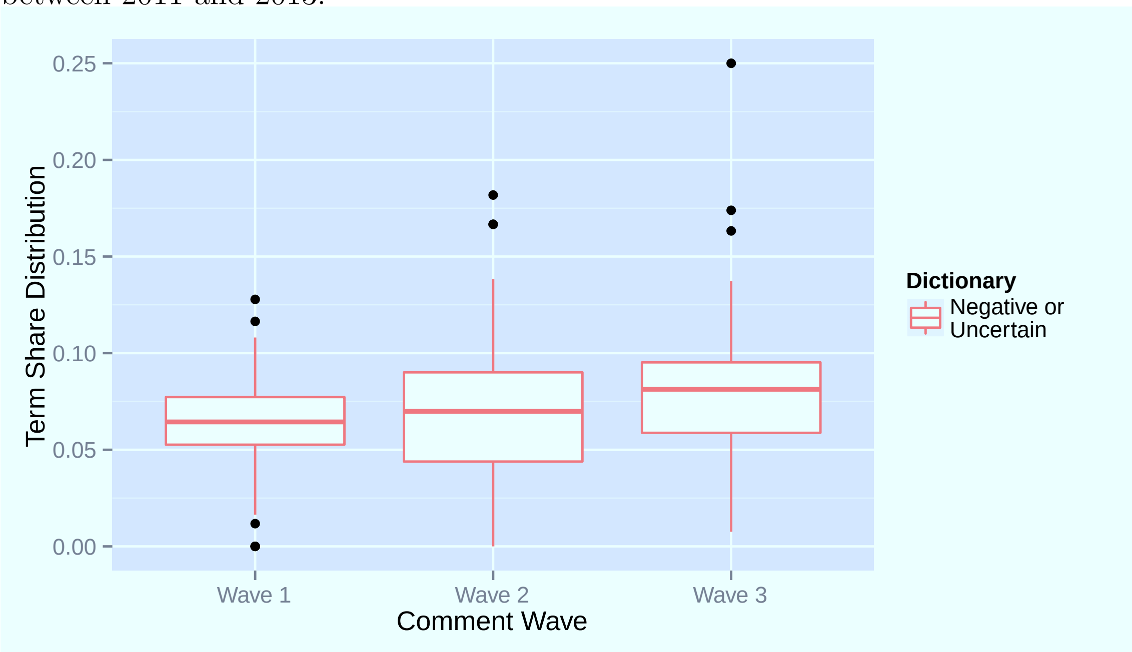


Figure 3

Distribution of uncertainty by comment wave. This graph shows the variation in the share of uncertain and negative words in the public comments submitted between 2011 and 2013.



Appendix: Modeling topics in comments

Our corpus—*a collection of documents*—for this exercise is the set of public comments from which we extracted our measure of a lender's uncertainty in Section 4.2. After tokenizing the corpus to allow for hyphenated terms, we remove stopwords—a set of the most prevalent english words whose occurrence in a document is uninformative—as provided by Python's NLTK module (Bird, Klein, and Loper 2009) and then lemmatize this set of terms so that only the dictionary forms of words appear in our corpus vocabulary. We also filter the vocabulary to include only terms that occur five or more times within the corpus. Our resulting corpus is composed of a dense set of 8108 unique terms. Table 11 summarizes a subset of the corpus vocabulary that would be the most useful for describing the proposal criteria.

Latent Semantic Similarity

Vector space models (VSMs) (Turney, Pantel, et al. 2010) extract semantic cues from a corpus and are useful for modeling the similarity between terms and contexts (for example, documents, paragraphs, or sentences). More concretely, latent semantic analysis (LSA) (Deerwester, Dumais, Landauer, Furnas, and Harshman 1990, Landauer, Foltz, and Laham 1998) is a singular value decomposition on a *term-document* matrix $X^{(|V|\times|D|)}$, where $|V|$ is the number of terms in the vocabulary V, and $|D|$ is the number of documents in corpus D. The decomposition $X = TSD^\top$ further allows for the selection of the k most important and reliable features of the term-document matrix and the approximation $X \approx \hat{X}_k = T_k S_k D_k^\top$. The choice of k in other applications is made with the goal of dimensionality reduction. In LSA, k is a smoothing parameter over the sparse term-document matrix, X.

This smoothed term-document representation leads to a *term-term* similarity matrix $M_t = \hat{X}\hat{X}^\top = TS^2T^\top$ and a *document-document* similarity matrix $M_d = \hat{X}^\top\hat{X} = DS^2D^\top$ whose elements $M_{i,j}$ are the dot products between columns i and j of the *term representation* matrix $\hat{X}^\top$ and the *document representation* matrix

$\hat{X}$ respectively. For high dimensional learning tasks, this reformulation provides a tractable solution at the cost of being susceptible to variations in scale and location. Since our task is relatively small, we instead elect to measure similarity directly from $\hat{X}^\top$ as the cross-correlation matrix ρ. The correlation coefficient $\rho_{i,j}$ is more straightforward to interpret and is equivalent to a dot product that is centered and normalized to account for magnitude.

With this measure in mind, we would like to rank, by their similarity to our uncertainty dictionary, the terms that pertain solely to the debt-to-income criterion against terms that would likely correspond to other proposed criteria. We form X using standard TF-IDF scaling (Ramos 2003) to adjust for the disparity of term prevalence evident in table 11 and compute ρ from $\hat{X}_{40}$. For each criterion term row ρ_i, we define the mean similarity over the 769 columns that correspond to the uncertainty terms found in our corpus as $\bar{\rho}_i = E(\rho_{i,j}|i)$.

Table 12 reports $\bar{\rho}_i$ for each term with respect to the entire comment corpus as well as the subset of comments submitted by the banks in our analysis. Within the context of banks' comments, the majority of proposal terms are more highly correlated with the uncertainty vocabulary. The exceptions are *small, creditor, point, fee,* and *debt.* All other terms are more closely related to uncertainty with regard to banks' feedback. The terms ranking highest for banks are those used to describe the rebuttable presumption in general and followed closely by terms that would occur in a discussion of the debt-to-income criterion. Phrases like *debt burden, residual income, debt obligation,* and *total debt-to-income (TDTI) ratio* are used synonymously within the public comments. *Burden* may also rank highly because the phrase *burden of proof* is likely to co-occur in a discussion about presumed innocence.