Can Regulation De-bias Appraisers?

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Abstract

This paper examines the effect of a regulatory action (the Home Valuation Code of Conduct) that was designed to reduce the incidence of inflated collateral valuations. We identify the impact of the regulation using a difference-in-difference identification strategy. Our baseline results confirm that the regulation reduced inflated valuations in refinance transactions by 16% in the large lender sample, compared to small lenders and a placebo sample. The effect is most significant in low-liquidity and low-distress markets, but not in other markets. We find that the regulation had a significant impact on loan to value ratio and interest rate, and it also led to a significant increase in defaults but a decrease in prepayments.

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1. Introduction

Many factors contributed to the housing and financial crisis of 2007 and 2008, with much research and commentary directed at recommending policy prescriptions designed to mitigate or eliminate future crises. As the crisis deepened, a number of emergency fiscal stimulus programs were enacted in an effort to shore up the financial system. In addition, regulatory agencies began imposing a series of new regulations designed to curtail the perceived excesses and market failures that led to the crisis (e.g., the Dodd-Frank Wall Street Reform and Consumer Protection Act.) The growth in financial regulations and their resulting interconnections throughout the economy has created a need to assess their effectiveness (see Campbell et al., 2011b). Thus, using a novel dataset from the mortgage market, we address this need by examining the effect of a regulatory action, namely, the Home Valuation Code of Conduct (HVCC), that was designed to reduce the incidence of a factor that many believed contributed to the financial crisis: inflated collateral valuations (also known as appraisal bias).

Long before the financial and housing crisis, research confirmed that the leading cause of mortgage default is the condition known as negative equity.[1] Therefore, lenders expend considerable resources during the underwriting process focusing on the collateral that secures the mortgage; one of the central items in this process is the property valuation estimate provided by appraisers that helps underwriters determine the risk associated with a proposed mortgage. However, Ben-David (2011) documents that, with the collusion of appraisers, a significant fraction of highly-leveraged purchase transactions have prices above their true market value. In addition, Griffin and Maturana (2014) provide supporting evidence that over-inflated appraisals could have contributed to the housing crisis.

[1] See, for example, Foster and van Order (1984), Epperson et al. (1985), Campbell and Dietrich (1983), Deng et al. (2000), and Ambrose et al. (2001) for theoretical and empirical validation that collateral value in relation to the mortgage value is the paramount factor determining borrower default.

Our analysis of the regulation designed to curtail appraiser incentives and the ability to inflate valuations relies on combining mortgage data with public sales databases to create a set of matched transaction pairs similar to the repeat sales set-up underlying the well-known Standard & Poor's Case-Shiller Home Price Index. Using the date of the HVCC implementation (May 2009) as the treatment date, we identify mortgage refinance transactions before and after this date. We label these as the first transaction. Since a contract price is unavailable at the time of mortgage refinancing, the lender relies on an appraiser to provide a valuation estimate for this transaction. We then match each transaction to its subsequent sale as revealed in public records, which we label the second transaction. This subsequent sale price serves as a market benchmark allowing us to calculate possible appraisal bias based on the return from the appraised value to the sale price. To gauge the impact of the HVCC, we confine our baseline analysis to cases where the first transaction occurred in the six months before or after the treatment date, a very narrow window. We later expand the sample to larger windows as a falsification test. To perform a clean test, we exclude from the sample all cases associated with the Home Affordable Refinance Program (HARP), transactions that ended in distressed sales, and transactions likely associated with property flipping.

The HVCC established an important exception that exempted "small lenders" from its provisions. Thus, loans originated by small lenders are a natural control group and those originated by large lenders are the treatment group. By utilizing information obtained from the mortgage contract as well as location and time fixed effects, we can compare the returns observed for transactions originated by large lenders with those on comparable transactions by small lenders. The differences in the changes in returns from before and after the HVCC implementation between the two lender groups should reflect the effect of the HVCC in reducing appraisal bias for loans originated by large lenders.

Our method of measuring appraisal bias is similar to that utilized by Agarwal et al. (2015), but differs from the method of Ding and Nakamura (2016), Calem et al. (2015), and Piskorski et al. (2014). For example, Ding and Nakamura (2016) measure appraisal bias using the difference between the appraised values and contract prices for home purchases only, while Piskorski et al. (2014) compare appraised values to an automated valuation model (AVM). Calem et al. (2015) argue that the current mortgage practice of setting the property valuation to the lesser of the contract price and the appraised value provides incentives for substantial information loss. In contrast, our method compares the returns on refinance-purchase transaction pairs in a narrow window before and after the implementation of the HVCC. Thus, we contribute to the new and growing literature that studies the role of current financial regulations due to the crisis with results suggesting that the policy had its intended effect.

Our baseline results, which we verify through a variety of robustness and falsifications tests, support the contention that smaller lenders indeed exploited the exception, since the change in returns following the HVCC's implementation is approximately 1% higher for the transactions originated by small lenders than for those originated by large lenders. This result is the equivalent of roughly \$3,600 for the average appraised property value (e.g., \$366,000) prior to the HVCC—economically very significant for lenders. It also represents a 16% reduction in appraisal bias observed in transactions originated by large lenders. As anticipated, the effect is more pronounced in the cash-out refinance sample, where appraisal bias was most prevalent prior to the crisis and was explicitly targeted by regulators.

Next, we explore the estimated effects associated with heterogeneity in originators, borrowers, and markets. First, we see no change in broker behavior that would help reduce the appraisal bias following the HVCC's implementation, regardless of lender size. On the contrary, there is a significant reduction of appraisal bias in non-broker loans, but only in the large-lender subsample following the HVCC. This result suggests that loans originated by the lenders' own retail branches are responsible for the estimated effects. Second, we show that highly leveraged homeowners do not play a significant role in reducing the appraisal bias in either lender group, yet we do see a reduction in appraisal bias in low-leverage transactions (consistent with evidence in Piskorski et al.

(2014) and Agarwal et al. (2015) of borrowers inflating appraisals in highly leveraged transactions.) Third, we further classify property locations based on the number of sales transactions in the prior 12 months to create a measure of the availability of comparable sales used by appraisers and also by foreclosure rate to measure the market distress. The results indicate that the HVCC had a large and significant impact on reducing appraisal bias only in low-liquidity and low-distress markets.

Given that poor collateral valuation during the mortgage underwriting process could have contributed to the foreclosure crisis, our paper is part of a growing literature that explores the causes and consequences of appraisal bias. However, most prior studies have focused on data prior to the financial crisis. For example, Tzioumis (2017) finds that appraisal bias based on subprime lender loan data in 2005–2006 is unrelated to appraiser work volume or employment prospects. Conklin et al. (2016) find a positive relation between competition in the appraisal industry and appraisal bias using New Century Financial Corporation subprime loan data. Kruger and Maturana (2018), using similar data, document that appraisals exceed automated valuation model valuations 60% of the time and are biased upward by an average of 5%. More recently, Eriksen et al. (2018) find significant differences in the two repeat appraisals when one of these was informed of the contract price and the other was not. Using a similar dataset, Agarwal et al. (2018) examine the underlying mechanisms and market frictions, namely, relational contracts, that could have allowed appraisal bias to persist in equilibrium.

In contrast to studies that focus on appraisal basis in the period prior to the Great Financial Crisis, our paper expands the literature to demonstrate the effects of a post-crisis regulation using an empirical strategy that minimizes the effects of extraneous market forces. We also explore borrower incentives from two different types of refinance transactions and use purchase pairs for a placebo test.

Although two recent studies also studied the effect of the HVCC regulation, our analysis differs in several important dimensions and thus provides new insights. For example, in contrast to Ding and Nakamura (2016) we focus on refinance transactions that have more pronounced appraisal bias while they examine only on purchase transactions. Our paper also differs from Shi and Zhang (2015) in that we implement a clean diff-in-diff identification that exploits the small lender exemption provision in the regulation to isolate both the market trends and different regulatory environments. Finally, our study expands the literature examining the effects of the HVCC regulation by exploring the channels that reduced the appraisal bias.

Our paper proceeds as follows. Section 2 provides details about the single-family appraisal process and the HVCC regulation. Section 3 discusses the empirical identification strategy and data. Section 4 presents the baseline analysis as well as placebo and falsification tests. Section 5 examines possible channels of reduction in appraisal bias across different originators and market segments. Section 6 discusses changes in mortgage characteristics as well as ex post performance following the introduction of the HVCC regulation. Finally, Section 7 summarizes our findings.

2. Background: Appraisals and the Housing Crisis

Lenders engage in mortgage underwriting in an effort to minimize the probability of borrower default and to maximize the lender's potential recovery in the event that the borrower does default. These goals are widely incorporated into the concepts pertaining to the estimation of the borrower's probability of default and the associated loss given default. Central to these concepts is the notion that lenders require an accurate and independent verification of the value of the property that constitutes the collateral for the mortgage.

In response to perceived problems associated with appraisal valuations, the Federal Housing Finance Agency (FHFA), in cooperation with the New York Attorney General's office, issued the HVCC with an effective date of May 1, 2009. The HVCC prohibits Fannie Mae and Freddie Mac from purchasing mortgage loans from mortgage originators that do not follow this code. Following the financial crisis, Fannie Mae and Freddie Mac together purchased and securitized the majority of the single-family mortgage market and the provisions of the HVCC therefore apply to almost all mortgage origination activity. For example, Abernethy and Hollans (2010) note that, although the HVCC regulated activities by Fannie Mae and Freddie Mac, the compliance costs are borne by the mortgage originators, since they face the risk of loan buyback provisions in the event an appraisal used in underwriting does not comply with the terms of the HVCC. The specific practices that the HVCC attempts to eliminate include having lenders hold financial interests in appraisers, lenders engaging in coercive actions against appraisers, providing appraisers with "target valuations," and using second or subsequent appraisals in underwriting.

One of the important features of the HVCC is that it specifically prohibits lender actions that could improperly influence the appraiser. Furthermore, the HVCC requires that the lender establish potentially costly quality control tests for appraisals and report any adverse findings, including noncompliance with the code. Noncompliance with the code or significant appraisal issues can result in the GSEs forcing the lender to buy back the loans at full cost. To address concerns from low-volume originators about the HVCC's implementation, an exception to this provision was created for "small banks" that could find it cost prohibitive to comply with the HVCC's provisions.[2] In addition, responsibility for enforcement of the HVCC (as well as the HVCC provisions subsumed into the Dodd–Frank Wall Street Reform and Consumer Protection Act) rests with the GSEs, which further relaxed the statutory size definition. However, unlike the HVCC, the GSE rules provide no definition of small lenders. Therefore, with limited resources and staff available for enforcement, the GSEs focus on the largest lenders when auditing HVCC compliance. Thus, the exception for "small banks" provides an interesting natural experiment as well as a natural placebo sample. To the extent that implementation of HVCC reduced or eliminated

[2]According to 12 U.S.C. §2908, "small banks" are defined as financial institutions with aggregate assets of not more than $250,000,000.

the practices and problems associated with excessive valuations, then small lenders that are not subject to the same level of scrutiny as large lenders are a natural control group for testing the effectiveness of the new policy. Finally, it is important to note that potential leakage from the control group (that is small lenders observing the HVCC provisions) has the impact of biasing any observed effect toward zero, making our tests conservative.

3. Empirical Identification and Data

Our empirical strategy relies on the small lender exception contained in the HVCC regulation as implemented by the GSEs. This exception effectively creates a natural treatment group (i.e., large lenders as defined by the GSEs) that allows us to test the effect of the HVCC's regulations on a group of appraisals for loans originated by lenders not subject to them. To identify the impact of the change in regulation, we examine the change in property valuation from a mortgage refinancing appraisal and the subsequent arm's length sale transaction, which is presumably not subject to bias. A biased (or inflated) appraisal should be reflected in a lower change in value when measured against the subsequent sale. Thus, we estimate the following diff-in-diff regression to examine the appraisal bias on residential properties before and after the HVCC's implementation:

$$\begin{aligned} AppraisalBias_i &= y_{1,i} - y_{2,i} \\ &= \alpha + \beta_1 \times LargeBanks_i + \beta_2 \times Post_t \\ &\quad + \beta_3 \times (LargeBanks_i \times Post_t) + \theta \times Z_{i,t} + \varepsilon_i, \qquad (1) \end{aligned}$$

where $y_{2,i}$ is the logarithm of the purchase price of the second transaction and $y_{1,i}$ is the logarithm of the valuation of the first transaction observed from an appraisal associated with a mortgage refinance transaction. We multiply $(y_{2,i} - y_{1,i})$, the holding period return, by -1 so that the coefficients on the right-handed variables can be readily interpreted as the inflated value or appraisal bias because inflated properties tend to sell for lower returns. The variable $LargeBanks_i$ is a dummy variable denoting loans originated by a large lender (i.e., one of the 10 largest lenders by volume), $Post_t$ is a dummy variable indicating transaction pairs that occurred after the implementation of the HVCC regulation, and $Z_{i,t}$ is a set of borrower and mortgage control variables as well as time and location fixed effects that capture any systematic differences in property or borrowers. The coefficient on the interaction term $(LargeBanks_i \times Post_t)$ is the diff-in-diff parameter and represents the differential effect of the HVCC regulation on large lenders. If the HVCC regulation was effective in reducing appraisal valuation bias, then we expect β_3 to be negative and significant.

The empirical model in equation (1) is a repeated sales type of specification that compares values on the same property at different points in time. We therefore include a set of time (year–month) and metropolitan statistical area (MSA) fixed effects to control for local variations in markets as well as a variable measuring the time passed between transactions. Sale time fixed effects control for market trends, effectively isolating the general movement in market prices from differences in transaction valuations. A potential concern with our identification strategy is that the observed sales prices could be inflated by the presence of various seller commissions and concessions (Ben-David, 2011). Such practices could bias toward zero the findings of appraisal bias in our diff-in-diff setting, since our measure of appreciation depends on the observed sale price. To explicitly account for this potential bias, we construct a placebo sample of purchase–purchase transaction pairs to test for a differential effect in appraisal bias following implementation of the HVCC. Finding a difference for the interaction term $(LargeBanks_i \times Post_t)$ in the placebo sample would then mitigate concerns that inflated sales prices resulting from seller concessions are biasing our results.

Our empirical estimation of equation (1) requires selecting a relatively narrow time window surrounding the introduction of the HVCC to limit potential confounding effects arising from large changes in market fundamentals. Thus, we combine several unique datasets to assemble a large sample of property transaction pairs within the 12-month window surrounding the HVCC's implementation. First, we collect information on mortgages securitized by a national entity from December 2008 to November 2009 as our baseline sample, six months before and after May 2009, when the HVCC was implemented. These mortgages are conventional conforming loans (not government insured) made to prime borrowers. Conforming mortgages meet the GSE conforming loan limit, which has been $417,000 since 2006 for single-family one-unit properties in most of the United States, with higher limits in high-cost areas. For the purposes of this analysis, prime borrowers are defined as borrowers with relatively high credit scores (620 or higher) compared to subprime borrowers with blemished credit. This dataset contains information about the property as well as loan-level data concerning the mortgage. We select only mortgages originated for a home purchase or to refinance an existing mortgage.

The second dataset consists of information obtained from public records (e.g., record of deeds) on real property transactions that occurred between December 2008 and December 2013. By matching records in the sales transaction database with those in the mortgage origination database, we identify mortgages originated between December 2008 and November 2009 that were ultimately sold by December 2013.

The data consist of two transaction types: (1) a refinancing transaction (either cash-out or rate/term refinancing) followed by a sale transaction and (2) a sale transaction followed by a sale transaction. We identify 79,381 transactions surrounding the six months before and after the HVCC's implementation, 75,835 that had not defaulted by the end of our performance window. Table 1 reports the overall summary statistics for the sample.[3] Except for our regressions on ex post default and prepayment performance, our analysis excludes transactions

[3] We also analyze the second set of purchase–purchase transactions to confirm that transactions originated by small lenders are comparable to those originated by large lenders. The summary statistics for the purchase–purchase transactions are reported in Table A.1 in the Online Appendix.

that defaulted during the observation period, since such transactions typically sell at a discount (e.g., Campbell et al., 2011a; Harding et al., 2012). We note that the average initial appraised value was $367,194 and the subsequent average sale price was $346,909, implying an inverse appreciation of 5.5%. Reflecting the higher underwriting standards associated with conventional conforming loans to prime borrowers, we see that the average note rate was 4.9%, the average borrower FICO score was 763, the average CLTV ratio was 67%, and the average debt-to-income ratio was 31%. The average tenure of the transaction pairs was 29 months, or 2.5 years. We note that 41% of the loans were originated by mortgage brokers (the remainder by retail banks) and 38% of the transactions occurred in the post-HVCC implementation period, with the other 68% in the pre-HVCC period. We also note that 4% of the loans defaulted by 2013.

Panel B of Table 1 compares the descriptive statistics for the mortgages originated by small and large lenders pre- and post-HVCC regulation implementation. The top part reports the statistics for the small-lender subsample of 23,507 observations and the lower part the statistics for the large-lender subsample of 52,328 observations. These two panels show differences between the pre- and post-HVCC implementation periods, as well as between the large- and small-lender subsamples. First, across lender sizes, appreciation in the post-HVCC implementation period is less negative, suggesting an improvement of housing market conditions and a lowering of appraisal bias. The important mortgage characteristics, loan-to-value (LTV) ratio and the broker indicator, are lower in the post-HVCC implementation period, suggesting fewer loans originated through brokers and borrowers putting up more equity. Second, the property values on loans originated by small lenders are lower, possibly attributable to different market compositions. The inverse returns for the large-lender subsample dropped from 6.5% in the pre-HVCC period to 4.1% in the post-HVCC implementation period, a 2.4% reduction, while those for the small-lender subsample dropped from 5.9% to 4.6%, a 1.3% reduction. Thus, the univariate statistics show that the appraised values in the small-lender subsample experience a smaller reduction than large lenders.

Table 2 provides confirmation of the parallel trend assumption underlying our diff-in-diff analysis. The results suggest that refinance transactions by large lenders had a 1.1–1.3% greater appraisal bias in the pre-HVCC period but a 2.4–3.0% lower appraisal bias in the post-HVCC implementation period. The HVCC implementation date seems to be when the trends reversed.

4. Baseline Impact of HVCC

In this section, we report the ordinary least squares (OLS) estimation results for our baseline specification (equation (1)). We focus on the coefficient for the interaction term $LargeBanks \times Post$ that captures the combined effect of lender size in the post-HVCC implementation period.

As noted in Section 2, the actual HVCC implementation agreement created an exception for small banks that could face undue costs or hardship in complying with the code's provisions. We define the large-lender sample as the subset of mortgages originated by the 10 largest lenders (by volume) and whose compliance was checked by GSE staff resources. Our size segmentation strategy is conservative and biases the analysis toward finding no difference between lender size categories, to the extent that the lenders we identify as small also complied with the HVCC regulations.

4.1. Baseline Effect

Panel A of Table 3 reports the baseline estimates (columns (1)-(3), refi-purchase pairs) and placebo estimates (columns (4)-(6), purchase-purchase pairs). All the regressions specifications incorporate borrower and mortgage attributes including credit score, LTV, mortgage product, credit premium, investor dummy, debt-to-income ratio and the tenure from the first transaction to the second. Column (2) introduces sale year and month fixed effects for the second transaction dates. Column (3) includes time and location (MSA) fixed effects along with borrower and mortgage attributes.[4] The coefficient signs and significance

[4] In the interest of space, we report only the coefficients for *LargeBanks*, *Post*, and the interaction term $LargeBanks \times Post$; complete regression results for all the tables are reported

levels are consistent across the three specifications; however, we note that controlling for location and time fixed-effects dampens the impact of appraisal bias.

The interaction term $LargeBanks \times Post$ is negative and statistically significant (at the 1% level), suggesting that the appraisal bias observed in large lenders following the HVCC regulation implementation was 0.99 percentage points lower than for transactions originated by small lenders. In other words, the implementation of the HVCC regulation reduced the observed magnitude of the appraisal valuation bias by approximately 16%, from 6.3% in the pre-HVCC period for loans originated by large lenders relative to loans on similar properties originated by small lenders that were not subject to the HVCC regulation.[5] At the average appraised value of $366,059, this is equivalent to $3,600 in inflated property value used for lending in the absence of the HVCC, an economically significant amount for any lender.

4.2. Placebo Tests

Demiroglu and James (2014) argue that selection bias associated with low appraisals can result in the appearance of appraisal bias. This could be due to fundamental differences in the loans originated by large and small lenders. We address this concern in two ways: first, we re-estimate equation (1) using an alternative sample of 18,772 properties with repeated sales transactions (columns (4)–(6)). These observations come from purchase-money mortgages, where the contract prices are available prior to appraisal and are often used as an important reference by appraisers. Recent Fannie Mae data show that about 30% of appraised values for home purchases are exactly at the contract price and the vast majority are at or above it (Agarwal et al., 2018). If there is a small chance of the appraisals being below the contract price, then buyers usually renegotiate or cancel the offer (Fout and Yao, 2016). Thus, appraisals should have a less binding effect on purchase transactions than on refinancing transactions and should not be affected by the implementation of the HVCC. In

in the Online Appendix.

[5] 0.99 / 6.3 = 15.7%.

this sense, purchase–purchase pairs can be used as an important placebo sample to test the effect of the HVCC. If fundamental differences in the property types underlying loans originated by large and small lenders are the source of the observed differences in returns, then we should also find a similar effect when examining returns based on contract prices, not just appraisal values.

Columns (4) through (6) in Panel A of Table 3 report the baseline estimation results for the alternative purchase–purchase sample. The estimated coefficients reveal striking differences from the refinance–purchase observations (columns (1)–(3)). The estimated coefficients on the interaction of *Post* and *LargeBanks* are not statistically significant, suggesting no change in appraisal bias among large lenders when the first transaction is anchored by a purchase contract. These results stand in stark contrast to the effect found in the refinance–purchase sample, where we argue the implementation of the HVCC regulation reduced the observed magnitude of the appraisal valuation bias by approximately 16% in loans originated by large lenders relative to loans on similar properties originated by small lenders. Thus, the insignificant interaction coefficients suggest that the HVCC, which was designed to address the appraisal bias in refinance transactions, did not affect the valuation of purchase transactions.

Second and more importantly, the concern over sample selection is not applicable in our study because we estimate appraisal bias in a diff-in-diff approach. To see this, let us reiterate the thought experiment motivating our analysis: compare two loans originated the day before and the day after implementation of the HVCC regulation. They are both likely to have the sample selection bias identified by Demiroglu and James (2014). By adopting the diff-in-diff approach, we compare changes in loans originated by large loans around the HVCC implementation date against the similar changes in loans originated by small lenders; the selection bias thus cancels out.

4.3. Different Refinancing Types

Previous literature documents that appraisal bias was much higher in cash-out refinance transactions than in rate/term refinance transactions prior to the crisis, since borrowers in the former type were incentivized to maximize their equity extraction based on appraised value (Agarwal et al., 2015). In other words, inflated appraisals allowed borrowers to maximize the cash received for a given LTV ratio. Thus, in Panel B of Table 3, we explore the HVCC effect in cash-out and rate/term subsamples. In columns (1) through (3), we estimate the model using 27,486 transaction pairs observed from cash-out refinance loans, while, in columns (4) through (6), we use 48,340 rate/term refinance loan transaction pairs. The results in both subsamples confirm our baseline finding that appraisal bias was reduced by a significantly larger amount in loans originated by large lenders. Furthermore, the magnitude of the reduction, 1.17 percentage points, is much more pronounced in the sample of cash-out refinance transaction pairs than the 0.85 percentage points for the rate/term refinance transaction pairs. Thus, the larger effect observed in the cash-out refinance sample confirms that the HVCC regulation was effective in curbing an area of perceived abuse that was explicitly targeted by regulators.

4.4. Falsification Test

As a falsification test for the observed appraisal bias estimate, we construct a counterfactual test where we examine the differences in random six-month windows where regulations did not change. In these regressions, we return to the specification in equation (1), where the dependent variable is the logarithm of appreciation or appraisal bias. In this test, the interaction term ($LargeBanks \times Post$) has no meaning, since we arbitrarily select 12-month windows and test the first six months against the second six months. Figure 1 reports the estimated coefficients and the 99% confidence intervals for the interaction term. As expected, the interaction terms are insignificant in the periods before and after the HVCC window, confirming the validity of the observed negative effect surrounding the HVCC regulation implementation date.

Thus, the falsification test using arbitrary windows provides additional support for our contention that the results reported in earlier testing of the impact of the HVCC's implementation are not spurious.

5. Heterogeneity Analysis

5.1. Broker and Borrower Incentives

In Section 4, we established that the HVCC regulation worked as anticipated, reducing appraisal valuation bias by approximately 16% for mortgages originated by large lenders compared to small lenders. In this section, we examine the effect of the HVCC regulation through the origination channel to understand how the regulation interacted with the mortgage origination process to reduce valuation bias.

We focus on the role that the two primary mortgage origination channels play in creating incentives for valuation bias. First, lenders originate mortgages through retail operations where the lender maintains control over the underwriting process. Second, lenders originate loans delivered by mortgage brokers (referred to as third-party originators) where the lender competes on price to fund the loan. To recognize the role of mortgage brokers in the origination process, we estimate equation (1) for the non-broker and broker subsamples and report the results in columns (1) and (2) in Table 4, respectively. In column (3), we combine the broker and non-broker subsamples and test for the differential impact of brokers by including a set of interaction terms. In columns (1) and (2), the estimated coefficient for the interaction of *LargeBanks* with *Post* is negative and statistically significant, with a magnitude of -1.4% in the non-broker loan sample (column (2)), implying a significant reduction in appraisal bias for loans originated by large banks' retail operations. However, there is no reduction in appraisal bias for loans originated by large banks' broker operations. In addition, the coefficients on *LargeBanks* are insignificant in each sample, suggesting no difference in appraisal bias for loans originated by large banks versus small banks in both broker and retail operations in the pre-

HVCC period. Finally, in column (3), we estimate the model using the full refinance–purchase sample and include the triple interaction of *Broker* with *LargeBanks* and *Post*. We first note that the positive and significant coefficient for the interaction ($LargeBanks \times Post$) again implies that appraisal bias is significantly reduced in the set of large lender loans originated by banks' retail operations. However, the insignificant coefficient for the triple interaction ($LargeBanks \times Post \times Broker$) implies that the HVCC regulation had little effect on broker incentives compared to retail loans. Thus, the results in these three columns suggest that retail loans, not broker loans, contributed to the estimated reduction in appraisal bias among large lenders.

Second, prior literature documents that liquidity-constrained borrowers, defined as those with LTV ratios above 80%, have more incentives to apply pressure on appraisers to inflate values (Piskorski et al., 2014; Agarwal et al., 2015). To test the role of highly incentivized homeowners in the origination process, we estimate equation (1) for subsamples of loans of different leverage. The results are reported in columns (4) through (6) in Table 4. Column (4) reports the results for those with an LTV ratio greater than 80%. Similarly, column (5) reports the results for the subsample of loans with an LTV ratios less than 80%, while column (6) estimates the model using the full sample with an indicator for high-LTV loans interacted with *LargeBanks* and *Post*. In the low-LTV sample, the estimated coefficient for the interaction of *LargeBanks* with *Post* is negative and statistically significant, with a magnitude of 1.3 percentage points, suggesting that low-LTV ratio loans explain most of the estimated effects in the baseline results. The combined results in these columns suggest that it is the less liquidity-constrained homeowners who contribute to the estimated reduction in appraisal bias following the HVCC's implementation.

How did the contraction take place? The HVCC establishes a firewall between interested parties and appraisers so that the former cannot directly pressure the latter to hit a target number. Along with the HVCC regulation, the GSEs also initiated a number of changes to improve appraisal quality. First, they standardized data formats, definitions, and rules in the uniform appraisal form through an industry effort called the Uniform Appraisal Dataset initiative.[6] Second, by working with the appraisal and banking industry, the GSEs created greater consensus on how appraisers should define the subject property neighborhood, identify comparable properties, perform adjustments, and weight the comparable properties. Third, both GSEs and traditional appraisal analytic firms have developed or improved automated appraisal scoring and messaging systems to provide appraisers with real-time feedback and evaluation. Finally, mounting litigation and forced repurchases have pressed the mortgage industry to improve appraisal quality to avoid costly representation and warranty violations. Although the HVCC regulation makes an exception for small lenders, these other changes are industry-wide, affecting all licensed appraisers, appraisal management companies, and mortgage banks. This could explain why there is a material although smaller reduction in appraisal bias for small lenders.

5.2. Market Analysis

Accurate collateral valuation depends largely on the ability to observe comparable transaction prices. Nakamura (2010) notes that the primary reasons for inaccurate appraisals are low transaction volumes, foreclosure sales, and appraiser bias. Of these factors, the transaction volume is critical for appraisers to effectively implement the sales comparison approach to valuation, since a large number of sales transactions are necessary to identify comparable properties (or 'comps'). Reflecting this requirement, Lang and Nakamura (1993) note that the transaction volume provides information that can reduce uncertainty surrounding appraisal valuations.

To estimate the impact of variation in market liquidity, we classify each property's location as either a low-, medium-, or high-liquidity market. We then exclude the medium-liquidity market from the regression sample to focus on the contrast between low- and high-liquidity markets. Table 5 reports the results for this analysis. We define the property neighborhood as the census

[6] More details are available at https://www.fanniemae.com/singlefamily/uniform-appraisal-dataset.

block group and determine the market's liquidity by counting the number of sales transactions in the 12 months prior to the transaction date. We classify neighborhoods with 10 or fewer sales over the previous year as low liquidity, neighborhoods with 11 to 25 sales as having medium liquidity, and areas with more than 25 sale transactions as having high liquidity.

We note that the majority of transactions are located in relatively low-liquidity markets. For example, 61% of the transaction pairs are located in neighborhoods with fewer than 10 property sales in the previous 12 months, while 11% are in areas that had more than 30 sales in the previous 12 months. The impact of differences in neighborhood liquidity becomes apparent when one considers that the typical market data approach to valuation requires between three and six comparable properties. Thus, an appraiser would find it challenging to obtain the requisite number of comparable property transactions to implement the sales comparison approach to valuation in low-liquidity census block groups. Clearly, high-liquidity neighborhoods would provide significantly greater information for appraisers.

Turning to the analysis of whether the HVCC regulation differentially impacted neighborhoods based on market liquidity, we note that the results reported in columns (1) through (3) in Table 5 are consistent with our prior expectations regarding the relationship between price discovery and market liquidity. The negative and significant coefficients for $LargeBanks \times Post$ in the low-liquidity market and $LargeBanks \times Post \times LowLiquidity$ in the combined sample continue to show that the magnitude of the observed valuation bias significantly declined following implementation of the HVCC regulation, but the effect is confined to low-liquidity neighborhoods. The magnitude of the coefficient declines considerably and is insignificant in high-liquidity neighborhoods. Thus, the results suggest that it is the reduction of appraisal bias in low-liquidity markets for large lenders that significantly contributes to the difference between large and small lenders in the baseline results.

Next, we examine the impact of appraisal bias in markets delineated based on foreclosure rates. We also exclude the medium-distress market from the regression sample to focus on the contrast between low- and high-distress markets. This provides a measure of market distress, because a large number of foreclosures exerts downward pressure on market prices resulting from excess supply as well as negative spillover effects (e.g., Campbell et al., 2011a). Columns (4) through (6) in Table 5 report the estimated coefficients. We note that the transactions are relatively evenly distributed across markets. For example, of the 17,402 observations, 7,961 (or 46%) are located in neighborhoods characterized by low distress. The regression results are consistent with prior evidence regarding the relation between appraisal bias and lender size. For example, as in the neighborhood liquidity regressions, we find only a negative and marginally significant coefficient (at the 10% level) on the interaction term ($LargeBanks \times Post$) in the low-distress markets. The coefficient on the interaction term ($LargeBanks \times Post$) is positive but not significant in the high-distress markets. The negative but insignificant coefficient for the triple interaction ($Post \times Large \times LowDistress$) in the combined sample shows no significant difference between low- and high-distress markets in terms of the effect of the HVCC.

6. Effects on Loan Profile and Performance

6.1. Mortgage Characteristics

We have documented a significant reduction of appraisal bias for large lenders who are affected by the regulation. The effect only exists in the HVCC implementation month. We now explore how the change in appraisal bias affects loan quality as well as subsequent performance, since appraisal is only important as an input to the underwriting process. We recast equation (1) with alternative measures reflecting differences in borrower and mortgage attributes as well as loan performance that could be associated with an estimated reduction in appraisal bias.[7] The results of mortgage characteristics are reported in Table 6,

[7]Note that the sample size in this section increases to 79,381 observations, since we now include pairs where the subsequent sale is associated with a foreclosure.

where the column headings indicate the dependent variable in the regression. In column (1), the dependent variable is the borrower's credit (FICO) score and the dependent variable in column (2) is the CLTV ratio. Columns (3) and (4) report the mortgage loan amount and note rate regressions, respectively. Again, the variables of interest are *LargeBanks* (indicating the difference in the pre-HVCC period between loans originated by large lenders versus those originated by small lenders) and the interaction term $LargeBanks \times Post$ (showing the differential impact of the HVCC regulation on loans originated by large lenders), each regression including the full set of control variables (mortgage attributes, borrower attributes, and location fixed effects).

Focusing first on the borrower credit score regressions (column (1)) , we note a marginal difference (significant at the 10% level) in credit quality between the large- and small-lender subsamples in the pre-HVCC period, after controlling for borrower and mortgage attributes. However, the interaction ($LargeBanks \times Post$) is not statistically significant, indicating no difference in borrower credit scores between large and small lenders following the HVCC implementation.

In column (2) (the CLTV ratio regression), we note a positive and statistically significant (at the 5% level) coefficient for the interaction term ($LargeBanks \times Post$), suggesting that LTV ratios increased more for loans originated by large lenders following the HVCC's implementation than for comparable loans originated by smaller lenders. Our baseline results provide evidence that large banks reduced appraisal bias following the HVCC's implementation; therefore, the results reported in column (2) show higher CLTV ratios for large lenders following the regulation's implementation. However, the insignificant coefficient for *Large* implies no meaningful difference between large and small lenders in terms of LTV underwriting standards before the HVCC's implementation.

In column (3), the positive and significant coefficient for *LargeBanks* suggests that borrowers who refinanced via large lenders tend to have more debt than borrowers who worked with small lenders in the pre-HVCC period. The marginally significant (at the 10% level) interaction term implies a slight differential increase in loan amounts for large lenders versus small lenders following the implementation of the HVCC regulation.

Finally, turning to column (4), we examine the pricing effect associated with the pre- and post-HVCC implementation periods. The insignificant coefficient on *LargeBanks* indicates that small lenders do not differentially price loans relative to large lenders. Furthermore, the insignificant interaction term suggests no significant change in mortgage rates between large and small lenders for comparable loans following the implementation of the HVCC regulation.

In Panel B of Table 6, we repeat the analysis for loans originated in distressed markets. Again, distressed markets are defined as MSAs in the top tercile based on default rates. The idea is that less appraisal inflation might not have much financial or real effect when the market is rising and the default rate is very low, but it could have a large effect when the market is distressed. Overall, we note that the estimated coefficients are largely the same sign, magnitude, and statistical significance as for the full sample (Panel A). However, in column (4), the coefficient on $LargeBanks \times Post$ is now negative and significant at the 5% level, suggesting that, in a distressed market, reduced appraisal bias leads to lower interest rates on loans originated by large banks.

6.2. Mortgage Performance

To test the hypothesis that borrower risk shifts during the sample window, in Table 7 we report the estimated coefficients from Cox proportional hazard regressions of the probability of default and prepayment, respectively. The Cox regressions allow us to incorporate time-varying market changes in conditions as well as the base hazard rate and are a standard way to analyze competing risks in mortgage performance. We control for the mark-to-market CLTV ratio and changes in market interest rates from origination to the current quarter as explicit measures of the embedded put and call options. The MSA-level home price index (HPI) data are obtained from CoreLogic. The mark-to-market CLTV ratio is defined as $CLTV_0 \times HPI_t/HPI_0$. The market interest rate is based on Freddie Mac's Primary Mortgage Market Rate Survey. To implement Cox hazard regression, we transform the loan-level data to loan-by-quarter panel data. The sample size thus increases to 770,402 observations in Table 7.

We include three specifications: column (1) has no controls for mortgage attributes at origination; column (2) incorporates controls for the LTV, the borrower's FICO, an adjustable rate mortgage dummy, a 15-year fixed rate mortgage dummy, an investment property dummy, a dummy for loans originated by brokers, the backend debt-to-income ratio; and, finally, in column (3), we add state, origination year, and quarter fixed effects. We use states instead of MSAs as the location measure due to the limited number of defaults in some MSAs (overall default rate only 4% in our sample). The last specification is our preferred one. Turning to default results in columns (1)–(3), we find that the positive and significant coefficients on the mark-to-market CLTV ratio as well as changes in market rate are reasonable and anticipated, confirming that borrowers are more likely to default when there is less equity in the home, as well as when interest rates rise. The positive interaction terms in columns (1)–(3) imply that loans originated by large lenders following the HVCC regulation implementation had significantly higher early default experience, by 0.17 percentage points, than similar loans originated by smaller lenders. The insignificant coefficients for *LargeBanks* suggest no difference in the probabilities of default in the 24 months following origination between loans originated by large and small lenders. In addition, the negative interaction coefficients in columns (4)–(6) imply that loans originated by large lenders had lower prepayment probabilities, by 0.07 percentage points, than similar loans from smaller lenders.

In Panel B of Table 7, we repeat the analysis for loans originated in distressed markets. Again, distressed markets are defined as MSAs in the top tercile, based on default rates. Overall, we note that the estimated coefficients are more significant and of greater magnitude than those in the full sample (Panel A). The coefficient on $LargeBanks \times Post$ in column (3) is now significant at the 1% level, with a magnitude that is more than doubled, suggesting that the HVCC led to a significant higher default rate, by 0.38 parentage points, for loans originated by large lenders, controlling for mortgage characteristics and market conditions. The significant coefficient on $LargeBanks \times Post$ in column (6) also implies that the HVCC led to a significantly lower prepayment probability, by 0.08 percentage points, for loans originated by large lenders.

Why did defaults increase and prepayments decrease following the HVCC? The decrease in prepayments could be due to lower valuations and resulting higher LTV ratios. With the same amount of refinancing incentive, borrowers have less estimated equity based on less inflated appraisals following the HVCC's implementation, which is a significant hurdle for refinancing decisions. The higher default is then an outcome of lower competing prepayment risks. With borrowers less likely to refinance in the event of financial difficulty, they are more likely to miss mortgage payments and even go into foreclosure. Clearly, these are unintended consequences of the HVCC.

7. Conclusion

This paper examines the effect of a regulatory action designed to reduce the incidence of inflated collateral valuations. Our dependent variable is the appraisal bias, measured using the difference between a refinancing valuation and the subsequent sale in public records. We consider transactions from large and small lenders to be our treatment and control groups, respectively, since the HVCC exempts small banks that could find compliance cost prohibitive. Our identification method is a standard diff-in-diff approach that estimates the effect of the HVCC on returns of transactions in the six months before and after the HVCC's implementation and between large and small lenders.

The baseline results confirm that the new regulation effectively reduced inflated valuations in refinancing transactions by large lenders by 16%, equivalent to an additional \$3,600 in the estimated value used for loan underwriting. Our falsification tests, based on randomly assigned treatment dates, confirm that the effects are not caused by other events and are not spurious.

We explore various channels that could account for these results and find evidence that loans originated by non-brokers as well as loans to less liquidity-constrained borrowers, which were associated with lower appraisal bias during the crisis, are primarily responsible for the reduction in appraisal bias following the HVCC's implementation.

At the market level, while loans in high-liquidity markets experience a comparable reduction in appraisal bias for small and large lenders, the magnitude of the reduction is much greater in low-liquidity markets for larger lenders. We also find that the reduction in appraisal bias is significant only in low-distress markets. Taken together, large and small lenders appear to have different strategies or constraints in various markets.

We also explore the possible effects of HVCC regulations on mortgage outcomes. Our results indicate that the HVCC regulation had a limited impact on some mortgage characteristics, including FICO scores, but a significant impact on the CLTV, interest rates, and loan performance. The HVCC led to a significant increase in the default rate but a decrease in prepayments. These results could be explained by a higher CLTV ratio, due to the reduced valuation for our treatment group.

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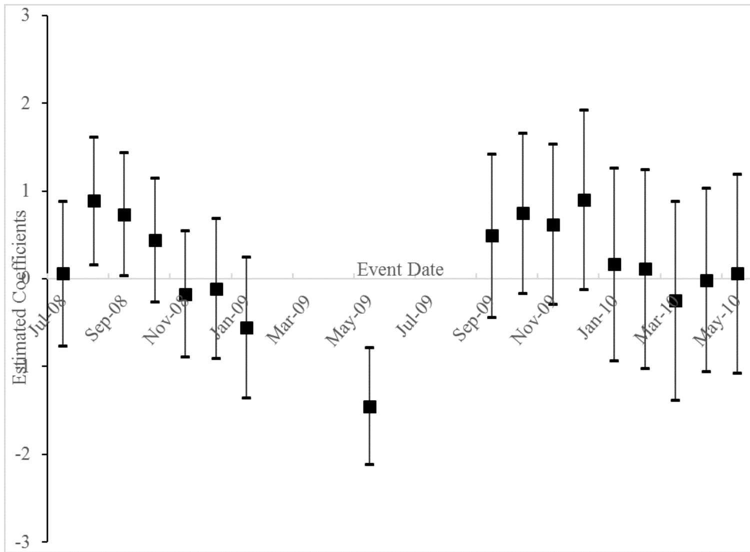
Figure 1: **Falsification Test**



Note: In the figure, we plot the rolling regression estimates for β_2 in equation (1) where Post equals the six month period following the reported date. The rolling regressions cover 12-month periods beginning January 2008 through May 2008 and June 2009 through November 2009 so that none of the estimation windows overlap with the months used in baseline regressions. The mark at May 2009 corresponds to the estimated coefficient for Large $\times$ Post reported in Table 3.

Table 1: **Summary Statistics**

Panel A. Overall Summary

Variable	N	mean	sd	min	p25	p50	p75	max
Initial Property Value	75,835	367,194	184,992	25,690	225,682	325,385	471,698	1,000,000
Sale Price	75,835	346,909	182,052	25,000	210,000	303,699	440,000	1,000,000
Inverse Appreciation (%)	75,835	5.51	11.97	-42.52	-1.60	5.51	13.08	63.46
Note Rate	75,835	4.89	0.37	2.75	4.63	4.88	5.00	7.75
Loan Amount	75,835	12.23	0.50	9.58	11.88	12.25	12.61	13.50
Broker Indicator	75,835	0.41	0.49	0	0	0	1	1
FICO	75,835	763.85	38.35	491.00	743	773	792	888
CLTV	75,835	67.06	15.98	6.00	57	70	80	99
ARM Indicator	75,835	0.04	0.20	0	0	0	0	1
FRM 15 Indicator	75,835	0.19	0.39	0	0	0	0	1
Excess Premium	75,835	-0.02	0.33	-1.76	-0.21	-0.02	0.17	2.59
Investor Indicator	75,835	0.02	0.13	0	0	0	0	1
Debt to Income Ratio	75,835	0.31	0.12	0.01	0.22	0.30	0.40	1
Tenure	75,835	29.06	8.85	13	22	29	36	50
Cum. Sales in Past 6 Months	75,835	14.62	19.91	1	1	11	17	520
Post Indicator	75,835	0.38	0.49	0	0	0	1	1
Default Rate	79,381	0.04	0.21	0	0	0	0	1
Prepay Rate	79,381	0.96	0.21	0	1	1	1	1

Panel B. Large vs Small Banks

	Pre-HVCC		Post-HVCC		Difference	t-stat
	mean	sd	mean	sd		
Small Banks						
Initial Property Value	332,879	174,626	318,449	169,818	-14,430	-6.07
Sale Price	312,318	168,611	304,236	169,009	-8,082	-3.45
Inverse Appreciation (%)	5.85	11.84	4.57	12.01	-1.27	-7.69
Broker Indicator	0.22	0.42	0.18	0.39	-0.04	-7.00
FICO	763.91	38.33	761.20	41.45	-2.71	-4.84
CLTV	67.73	15.93	66.92	17.27	-0.81	-3.47
Cum. Sales in Past 6 Months	12.14	17.44	15.18	18.37	3.04	12.13
No of Pairs	15,722		7,785			
Large Banks						
Initial Property Value	382,795	184,200	387,647	192,049	4,852	1.85
Sale Price	357,543	179,185	372,649	193,576	15,106	5.77
Inverse Appreciation (%)	6.52	11.77	4.11	12.17	-2.41	-14.47
Broker Indicator	0.52	0.50	0.46	0.50	-0.06	-8.89
FICO	765.26	36.79	762.69	39.31	-2.57	-4.81
CLTV	66.98	15.16	66.74	16.68	-0.23	-1.04
Cum. Sales in Past 6 Months	14.04	19.76	17.12	22.00	3.08	10.43
No of Pairs	31,171		21,157			

Note: In Panel *A*, we report the summary statistics of the overall sample that contains all refinance-purchase pairs. Refinance can be cashout or rate-term transactions. All the variables except default and prepay rates are based on non-default transactions while the latter two are based on non-default and default transaction pairs. In Panel *B*, we report the summary statistics of the same sample split by large vs small banks and pre- vs post-HVCC periods. We report the differences of large and small banks along with t-statistics in the last two columns.

Table 2: **Tests of Parallel Trends**

	(1)	(2)
	Appraisal Bias (%)	
Large Banks x Pre-HVCC	1.098***	1.282***
	(10.66)	(4.10)
Large Banks x Post-HVCC	-2.414***	-2.965***
	(-22.72)	(-13.19)
Observations	75835	75835
Adjusted R-squared	0.007	0.023
Sale YM FE	No	Yes

Note: This table reports the simple differences between large and small banks during the pre- and post-HVCC periods separately. It corresponds to the time series of appraisal bias. The right side variables are two dummy variables: large banks interacted with pre- and post-HVCC indicators, respectively. The results reflect that property inverse appreciation is much higher for the large bank sample during the pre-HVCC while they are much higher for the small bank sample during the post-HVCC period. The results confirm that price appreciation trends are different for mortgages originated by large and small banks. t–statistics are in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 3: **Effect of HVCC on Price Appreciation**

Panel A. Baseline and Placebo Estimations

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Var	Appraisal Bias (%)					
Sample	Refi-Purchase Pairs			Purchase-Purchase Pairs		
Large Banks x Post	-1.147***	-1.135***	-0.988***	0.024	-0.143	-0.317
	(-5.72)	(-4.25)	(-5.09)	(0.06)	(-0.29)	(-0.72)
Large Banks	0.660***	0.660*	0.235	-0.179	-0.094	0.099
	(4.79)	(2.05)	(1.95)	(-0.54)	(-0.23)	(0.28)
Post	-1.180***	0.141	-0.080	0.419	1.876***	1.721***
	(-6.83)	(0.46)	(-0.31)	(1.07)	(3.67)	(3.54)
Observations	75835	75835	75835	18772	18772	18766
Adjusted R-squared	0.023	0.036	0.181	0.048	0.065	0.145
Mortgage Attributes	Yes	Yes	Yes	Yes	Yes	Yes
MSA FE	No	No	Yes	No	No	Yes
Sale YM FE	No	Yes	Yes	No	Yes	Yes

Panel B. Estimation by Refinance Type

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Var	Appraisal Bias (%)					
Sample	Cashout Refi-Purchase Pairs			Rate-Term Refi-Purchase Pairs		
Large Banks x Post	-1.037**	-1.063**	-1.168***	-1.163***	-1.128**	-0.851***
	(-3.17)	(-3.30)	(-3.96)	(-4.66)	(-3.22)	(-3.37)
Large Banks	0.416*	0.412	0.132	0.800***	0.807*	0.329*
	(2.09)	(1.37)	(0.72)	(4.73)	(2.15)	(2.02)
Post	-1.476***	-0.123	0.020	-1.062***	0.234	-0.164
	(-5.48)	(-0.32)	(0.06)	(-4.91)	(0.64)	(-0.54)
Observations	27492	27492	27486	48343	48343	48340
Adjusted R-squared	0.028	0.042	0.181	0.018	0.032	0.180
Mortgage Attributes	Yes	Yes	Yes	Yes	Yes	Yes
MSA FE	No	No	Yes	No	No	Yes
Sale YM FE	No	Yes	Yes	No	Yes	Yes

Note: This table reports the baseline results on the effect of HVCC on appraisal bias in different samples. The dependent variable of all the regressions is appraisal bias for refinance-purchase pairs. In Panel *A*, we report regression results based on all refinance-purchase transaction pairs in Columns (1)–(3) and those based on purchase-purchase pairs, as a placebo test, in Columns (4)–(6). In Panel *B*, we report regression results based on cashout and rate-term refinance-purchase transaction pairs separately. All the regressions are OLS regressions based on mortgages originated in December 2008 through November 2009. Besides three main variables reported in the table, we control for LTV, borrower FICO, adjustable rate mortgage dummy, 15-year fixed rate mortgage dummy, investment property dummy, loans originated by broker dummy, backend debt to income ratio, tenure from original mortgage transaction to the subsequent sale, MSA fixed effects and sale year and month fixed effects. Standard errors are clustered around MSA. t–statistics are in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 4: **Mortgage Broker and High-LTV Borrowers**

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Var	Appraisal Bias (%)					
Sample	Refi-Purchase Pairs					
	Broker	Non-Broker	All	High LTV	Low LTV	All
Large Banks x Post	0.190	-1.386***	-1.188**	-0.317	-1.291***	-1.291***
	(0.31)	(-3.73)	(-3.28)	(-0.49)	(-3.68)	(-3.69)
x Broker			0.285			
			(0.45)			
x High LTV						0.772
						(1.06)
Large Banks	-0.585	-0.049	-0.298	-0.963*	0.304	0.279
	(-1.58)	(-0.22)	(-1.45)	(-2.32)	(1.38)	(1.30)
x Broker			0.821***			
			(4.12)			
x High LTV						-0.949*
						(-2.07)
Post	-0.236	-0.384	0.106	-1.295	0.211	0.153
	(-0.32)	(-0.86)	(0.27)	(-1.59)	(0.48)	(0.39)
x Broker			-0.321			
			(-0.57)			
x High LTV						-0.818
						(-1.32)
Observations	11205	16245	27486	4350	23089	27486
Adjusted R-squared	0.198	0.174	0.182	0.191	0.180	0.181
Mortgage Attributes	Yes	Yes	Yes	Yes	Yes	Yes
MSA FE	Yes	Yes	Yes	Yes	Yes	Yes
Sale YM FE	Yes	Yes	Yes	Yes	Yes	Yes

Note: This table reports the results on the different effects of HVCC for loans originated by mortgage brokers as well as those by high-LTV borrowers. The dependent variable of all the regressions is appraisal bias for refinance-purchase pairs. We report regressions based on different subsamples in Columns (1), (2), (4), 54) and those based on entire sample but with interaction terms in Columns (3) and (6). All the regressions are OLS regressions based on cash out refinance mortgages originated in December 2008 through November 2009. Besides the variables reported in the table, we control for LTV, borrower FICO, adjustable rate mortgage dummy, 15-year fixed rate mortgage dummy, investment property dummy, loans originated by broker dummy, backend debt to income ratio, tenure from original mortgage transaction to the subsequent sale, MSA fixed effects and sale year and month fixed effects. Standard errors are clustered around MSA. t–statistics are in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 5: **Effect of HVCC in Different Markets**

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Var	Appraisal Bias (%)					
Sample	Refi-Purchase Pairs					
	Market Liquidity			Market Distress		
	Low	High	All	Low	High	All
Large Banks x Post	-1.309**	-0.159	0.525	-1.328*	0.176	0.164
	(-3.18)	(-0.18)	(0.64)	(-2.01)	(0.34)	(0.32)
x Low Liquidity			-1.867*			
			(-2.02)			
x Low Distress						-1.538
						(-1.80)
Observations	16934	2871	19844	7961	9441	17402
Adjusted R-squared	0.175	0.228	0.178	0.115	0.131	0.199
Mortgage Attributes	Yes	Yes	Yes	Yes	Yes	Yes
MSA FE	Yes	Yes	Yes	Yes	Yes	Yes
Sale YM FE	Yes	Yes	Yes	Yes	Yes	Yes

Note: This table reports the results on the different effects of HVCC for different markets delineated by housing market liquidity as well as distress. Market liquidity is defined on number of sales in the past 6 months at MSA level. Market distress is based on default rate at MSA level. We divide the sample into tercile based on the two criteria: low, medium and high and exclude medium tercile in order contrast low and high tercile. The dependent variable of all the regressions is appraisal bias for refinance-purchase pairs. We report regressions based on different subsamples in Columns (1), (2), (4), (5) and those based on entire sample but with interaction terms in Columns (3) and (6). All the regressions are OLS regressions based on cash out refinance mortgages originated in December 2008 through November 2009. Besides the variables reported in the table, we control for LTV, borrower FICO, adjustable rate mortgage dummy, 15-year fixed rate mortgage dummy, investment property dummy, loans originated by broker dummy, backend debt to income ratio, tenure from original mortgage transaction to the subsequent sale, MSA fixed effects and sale year and month fixed effects. Standard errors are clustered around MSA. t–statistics are in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 6: **Mortgage Characteristics**

Panel A. All

	(1)	(2)	(3)	(4)
Dependent Var	FICO	CLTV	Balance	Note Rate
Sample	Refi-Purchase Pairs (Defaults + Non-Defaults)			
Large Banks x Post	0.589	0.881**	0.015*	-0.004
	(0.80)	(3.11)	(2.16)	(-1.30)
Large Banks	0.859*	-0.175	0.062***	-0.001
	(2.02)	(-1.20)	(11.38)	(-0.21)
Post	-3.579***	0.250	-0.061***	-0.009***
	(-5.43)	(1.00)	(-10.58)	(-4.24)
Observations	79381	79381	79381	79381
Adjusted R-squared	0.101	0.127	0.397	0.765
Mortgage Attributes	Yes	Yes	Yes	Yes
MSA FE	Yes	Yes	Yes	Yes
Sale YM FE	Yes	Yes	Yes	Yes

Panel B. Distressed MSAs

	(1)	(2)	(3)	(4)
Dependent Var	FICO	CLTV	Balance	Note Rate
Sample	Refi-Purchase Pairs (Defaults + Non-Defaults)			
Large Banks x Post	-0.345	1.074*	0.016	-0.013**
	(-0.28)	(2.05)	(1.36)	(-2.95)
Large Banks	1.125	-0.501	0.060***	0.008
	(1.49)	(-1.80)	(6.41)	(1.91)
Post	-2.355	0.522	-0.071***	-0.007
	(-1.90)	(1.25)	(-6.68)	(-1.75)
Observations	26306	26306	26306	26306
Adjusted R-squared	0.097	0.090	0.306	0.756
Mortgage Attributes	Yes	Yes	Yes	Yes
MSA FE	Yes	Yes	Yes	Yes
Sale YM FE	Yes	Yes	Yes	Yes

Note: This table reports the results on the different effects of HVCC on other mortgage characteristics. The dependent variables are the column titles. All the regressions are OLS regressions based on all refinance mortgages originated in December 2008 through November 2009, including both defaults and non-defaults. In Panel *A*, we report regression results based on all MSAs. Results in Panel *B* are based on only MSAs are in the top tercile defined based on default rate. Besides the variables reported in the table, we control for LTV, borrower FICO, adjustable rate mortgage dummy, 15-year fixed rate mortgage dummy, investment property dummy, loans originated by broker dummy, backend debt to income ratio, MSA fixed effects and sale year and month fixed effects except when the variable is the dependent variable. Standard errors are clustered around MSA. t–statistics are in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 7: **Cox Hazard Regressions of Mortgage Performance**

Panel A. All

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Var	Default			Prepayment		
Sample	Refi-Purchase Pairs (Defaults + Non-Defaults)					
Large Banks x Post	0.238**	0.186*	0.174*	-0.064***	-0.071***	-0.066***
	(2.69)	(2.27)	(2.15)	(-3.56)	(-4.12)	(-4.10)
Large Banks	0.049	0.045	-0.021	0.017	0.024*	0.034***
	(0.81)	(0.79)	(-0.37)	(1.52)	(2.18)	(3.35)
Post	0.446***	0.574***	0.198	0.440***	0.711***	0.547***
	(5.73)	(6.48)	(1.55)	(29.51)	(39.44)	(23.34)
mark-to-market CLTV		0.036**	0.024***		-0.009*	-0.011**
		(3.15)	(4.25)		(-2.40)	(-2.87)
Changes in Market Rate		0.263***	0.180*		0.637***	0.532***
		(3.47)	(2.11)		(31.41)	(23.10)
Observations	770402	770402	770402	770402	770402	770402
Adjusted R-squared	0.004	0.040	0.052	0.002	0.003	0.003
Mortgage Attributes	No	Yes	Yes	No	Yes	Yes
State FE	No	No	Yes	No	No	Yes
Origination YQ FE	No	No	Yes	No	No	Yes

Panel B. Distressed MSAs

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Var	Default			Prepayment		
Sample	Refi-Purchase Pairs (Defaults + Non-Defaults)					
Large Banks x Post	0.427***	0.405***	0.384***	-0.090**	-0.099***	-0.083**
	(4.02)	(4.34)	(4.12)	(-2.76)	(-3.37)	(-3.07)
Large Banks	-0.132	-0.119	-0.122	0.044*	0.054**	0.056**
	(-1.57)	(-1.57)	(-1.55)	(2.40)	(2.96)	(2.75)
Post	0.175	0.253*	-0.090	0.493***	0.738***	0.539***
	(1.89)	(2.30)	(-0.50)	(20.59)	(25.42)	(12.42)
mark-to-market CLTV		0.026***	0.016***		-0.011***	-0.015***
		(4.05)	(4.65)		(-3.49)	(-6.54)
Changes in Market Rate		0.225*	0.163		0.617***	0.487***
		(2.36)	(1.40)		(17.51)	(10.84)
Observations	260754	260754	260754	260754	260754	260754
Adjusted R-squared	0.003	0.046	0.051	0.002	0.004	0.005
Mortgage Attributes	No	Yes	Yes	No	Yes	Yes
State FE	No	No	Yes	No	No	Yes
Origination YQ FE	No	No	Yes	No	No	Yes

Note: This table reports the results on the different effects of HVCC on ex post loan performance. The dependent variables are the column titles (default and prepayment). All the regressions are Cox proportional Hazard regressions based on loan x quarter panel data. Loans cover all refinance mortgages originated in December 2008 through November 2009, including both defaults and non-defaults. In Panel *A*, we report regression results based on all MSAs. Results in Panel *B* are based on only MSAs are in the top tercile defined based on default rate. Besides the variables reported in the table, we also control for LTV, borrower FICO, adjustable rate mortgage dummy, 15-year fixed rate mortgage dummy, investment property dummy, loans originated by broker dummy, back-end debt to income ratio, State fixed effects and origination year and quarter fixed effects. State and quarter fixed effects are controlled instead of MSA and month fixed effects because of defaults (4% in the sample) are very thin in some MSA and months. Standard errors are clustered around MSA. t–statistics are in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.