Did investors price regional housing bubbles? A Tale of Two Markets

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Abstract

The recent experience of a massive cycle in mortgage defaults was associated with a matching fluctuation in housing prices. Both events were very unequally distributed across local housing markets. This paper tests the hypothesis that spatial variation in the jumbo/conforming spread indicates investor perception of spatial differences in credit risk at any given time. The jumbo/conforming spread reflects spatial variation in credit risk perceptions in the jumbo market because conforming mortgage rates vary over time but not spatially. If investors in the jumbo market priced spatial differences in credit risk then spatial variation in the jumbo/conforming spread should predict spatial variation in the future change in house prices. The empirical tests, performed here for the first time, show the results are both economically and statistically significant. Specifically, a one standard deviation increase in the jumbo/conforming spread is associated with 0.87%- 1.27% lower housing price appreciation at the state level and 0.52%-1.37% lower appreciation at the MSA level. Overall, it appears that investors in the jumbo market were aware of spatial differences in the size of housing market bubbles and priced credit risk differences across housing markets, especially in large MSAs. Furthermore, failure of conforming rates to reflect these expectations likely accentuated the size of the largest local bubbles.

Keywords

jumbo/conforming spread, housing price index, Government-Sponsored Enterprises(GSEs)

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1 Introduction

Well before the financial crisis, Case and Shiller (2003) noted that, in selected local housing markets, the increases in housing prices appeared unsustainable and well above long run replacement cost. Nevertheless, prices continued to rise in spite of such warnings from economists. While homebuyers can be forgiven for not reading Case and Shiller, capital markets should have been aware of the unsustainable nature of housing price increases in the "sand" states. The hypothesis tested here is whether spatial differences in housing price fluctuations were priced in mortgage markets where interest rates were free to reflect such geographic differences in expected housing price change. This is the first ever test of the ability of the jumbo/conforming spread to predict spatial variation in future house price appreciation.

As shown in Figures 1 and 2, local housing price indexes (HPIs) diverge from one another and hence from the national average. The differential nature of housing price movements across urban markets is illustrated in Figure 2. In Austin, Denver, Nashville and Baton Rogue, the housing crisis was little more than a pause in a general increase in housing prices. However, for Phoenix, Riverside, Las Vegas and Fort Lauderdale, the rise in house prices was spectacular and the subsequent fall was equally abrupt. In these cities, prices are still noticeably below their previous peak during the boom. These differences were identified by Case and Shiller rather early but they should have been apparent to all informed investors by 2005.

The immediate question is "how could markets get it so wrong?" There are many explanations for individual homeowner and investor myopia. Prior to the financial crisis, the traditional mortgage supply process was largely converted to the "originate and distribute" model and subsequently mortgage lending criteria were relaxed and securitization rose. There is a substantial literature documenting the relation between mortgage lending criteria and securitization(Brunnermeier (2009)). Mian and Sufi (2009) demonstrate that the expansion of mortgage credit in zipcodes where subprime lending was concentrated led to three times higher default rates than zipcodes where prime lending was dominant in the same metropolitan area. While the long run effect of interest rates on housing prices may be negligible, many authors cite the expansion of mortgage credit as a short run factor promoting, or at least facilitating, the housing bubbles shown in Figure 2. Faulty underwriting and problematic subprime mortgage products certainly led to elevated foreclosure losses. However, these mortgage products and underwriting standards were available in cities on both sides of the house price diagrams in Figure 2. Clearly in addition to uniform national risks associated with lending practices, large differences in local risk were evident in the movements of house prices.

The task of this research is not to test whether differences in risk among alternative loan products were priced in markets, although that interesting question has not been fully resolved. Instead the question is whether geographic differences in house price risks based on local housing market conditions were recognized by investors and priced when and where market based pricing was possible. Was the substantial difference in the ex post evolution of housing prices in Figure 2 associated with ex ante differences in mortgage pricing?

Fortunately, the jumbo/conforming spread allows direct testing of this hypothesis.

Hurst et al. (2016) have recently chronicled the fact that, in spite of their desire to do so, GSEs do not price the higher credit risk in regions with declining economic conditions, meaning they do not consider differences in geographic risk. They estimate that this uniform pricing policy implies a transfer of $47 billion from better performing regions to depressed regions through general equilibrium effects on local house prices. This transfer arises due to relatively permanent institutional effects. Pricing decisions in the conforming market are dominated by two government-sponsored enterprises (GSEs), the Federal National Mortgage Association (Fannie Mae) and the Federal Home Loan Mortgage Corporation (Freddie Mac) along with FHA. The GSEs and FHA are prohibited from explicitly pricing spatial differences in credit risk across cities or states due to opposition by Congress, realtors and a number of organized housing groups. Given that the GSEs dominate the conforming portion of the market and have the advantage of an implicit government guarantee, geographic variation in conventional mortgage pricing is minimal. Differential pricing of mortgage credit to reflect spatial variation in perceived lending risk is thus left to the jumbo market where rates are not determined by constraints imposed on the GSEs and FHA. This leads to a natural test that the spatial variation in the jumbo/conforming spread should reflect the difference between market and administrated prices.

The jumbo/conforming spread is the difference in interest rates between jumbo mortgages and conforming ones and is a direct measurement of GSE effects on mortgage market rates.[1] Passmore et al. (2005) measure the variation over time in the jumbo/conforming spread and attribute the differential to mortgage demand, origination costs and securitization fees. This topic has been studied extensively in the literature (Hendershott and Shilling (1989), Cotterman and Pearce (1996), Torregrosa (2001), Ambrose et al. (2001), Ambrose et al. (2004), Blinder et al. (2006) and Sherlund (2008)). The aforementioned studies have estimated the jumbo/conforming mortgage rate differential using loan originations for certain states or the national average for a number of time periods in order to indirectly measure GSEs' subsidy to mortgage market from their funding liquidity perspective. The estimated spread ranges between 8 and 60 basis points depending on the sample period and study areas. McKenzie (2002) argues for its convergence over time. Using the Monthly Interest Rate Survey, the national jumbo/conforming mortgage interest rate spread is estimated to be 11-23 bps during the entire sample period between 2004 and 2014, consistent with existing literature.[2] The

[1] The conforming status can not be determined from MIRS due to its data limitation. FICO score and documentation completeness are not observable here, but following the naming convention in previous literature, the jumbo/non-jumbo spread is called jumbo/conforming spread in this paper.

[2] The nationwide spread is estimated using the following equation which is discussed in the text below:

$$I_{ist} = \alpha_0 + \alpha_1 J_i + \alpha_2 X_{ist} + \alpha_3 D_t + \alpha_4 D_s + \epsilon_{ist}$$

where I_{ist} is the contract rate (effective rate) for each loan origination (i) in state (s) year (t), X_{ist} is the loan characteristic including loan amount (in log, inverse and quadratic forms in 3 different specifications), purpose, interaction of ltv with jumbo status, whether a loan was issued in the last three months of a year and whether a loan was issued in a cbsa. D_s is state fixed effects and D_t is year fixed effect. The coefficient α_1 captures the average nationwide jumbo/conforming spread.

objective of this paper is not to measure national spreads but to explore the spatial variation in pricing at any given time and to determine if this variation can be used to predict future changes in housing prices which are a primary determinant of credit risk.

This paper departs from previous literature in its level of disaggregation and focuses on spatial differences in the spread at the state and MSA level using micro level loan origination data. The magnitude of the spread at the national level is consistent with previous studies but this research focuses at the local level testing if the jumbo/conforming spread varies geographically with housing price dynamics. This is the first paper to focus on the spatial variation in the spread and the first to test the hypothesis that spatial variation can be used to predict geographic differences in the rate of future house price appreciation. It is also the first paper to directly test if investors were pricing the differences in expected price movements anticipated by Case and Shiller (2003). To the extent that investors in the jumbo market anticipated the differential size of housing price bubbles, the results would suggest that the policy of forcing the GSEs to ignore these differences allows bubbles to form in some local markets without facing the market discipline forced on investors by higher interest rates. It also contributes to the "cap" credit risk literature (Passmore and Sherlund (2016)) from a different angle. Instead of discussing the post-crisis role of the GSEs, this paper addresses the effects of the GSEs on promoting bubbles in local markets. The findings of this paper suggest that the current policy forcing the GSEs to ignore local differences in credit risks promotes the local housing bubbles demonstrated in Figure 2.

The rest of this paper proceeds as follows. Section 2 describes data sources and estimates the jumbo/conforming spread using alternative specifications. The impact of mortgage rate differentials on housing price dynamics is evaluated in Section 3. Robustness checks are conducted in Section 4. The last section concludes.

2 Data and Estimates of the Jumbo/Conforming Spread

2.1 Data

The jumbo/conforming spread at the state and MSA levels is estimated using the Monthly Interest Rate Survey from Federal Housing Finance Agency (FHFA) between July 2004 and December 2014. This nationally representative survey is conducted monthly for a sample of mortgage lenders on all single-family, fully amortized, purchase money, non-farm loans that they close during the last five business days of the month. It contains information regarding contract interest rate, effective rate, loan amount, house prices, loan types, loan terms and geographic details including zipcode, cbsa and state.[3] As shown in Table 1, the entire sample contains 1.2M observations with 9.6% jumbo loans. California is the biggest jumbo origination state with a 35.88% share through the sample period. Other states, such as Florida, Maryland, New Jersey, New York and Virginia, also play an important role in the

[3]The major weakness of MIRS data is it lacks information regarding borrower creditworthiness and whether the loan has mortgage insurance.

jumbo loan market though jumbo market is geographically concentrated due to relatively high housing cost in those areas.

Only 30 year fixed-rate mortgages are considered because securitization of adjustable rate mortgages has been less prevalent and 30 years is the most common loan term, thus no need to adjust for changes in the slope of the yield curve over time. This is a common approach following Cotterman and Pearce (1996) among others. Results shown in Table 2 further support this statement: Adjustable rate mortgages constitute only 19.81% of the entire sample.[4] Origination volumes in both markets drastically shrank during financial turmoil and recovered in recent years. To avoid loan type misclassification, the procedures in McKenzie (2002) are used to exclude mortgages with an interest rate more than 50 basis points less than the Freddie Mac monthly average for 30-year fixed-rate mortgages.[5] The final sample only includes 30-year fixed-rate loans to make term-structure comparable among all mortgages.[6]

Final sample descriptive statistics are provided in Table 3. The effective interest rate, defined as annual contract rate plus an amortized amount of any fees charged at closing over 10 years, has a mean of 5.822% slightly higher than mean contract rate 5.171%. The national average loan size is approximately $200000 with a standard deviation of $140000. This implies substantial variation in housing prices across geographical regions. Loan to value ratio (LTV) is concentrated at 80% with mean of 78.51% because it requires additional insurance for LTV above 80%. The majority of loans issued (63.8%) are within MSAs and only 6.44% loans are jumbo ones. Most mortgages, specifically 84.6%, are originated for existing housing structures rather than new ones.

2.2 Jumbo/Conforming Spread Estimation

Comparison of the nationwide average contract and effective rate differential between jumbo and conforming loans (Table 4 and Table 5) suggests a differential does exist but the magnitude of the average differential is generally not economically significant. Conforming loans have a lower contract rate compared to jumbo ones before 2012 but the pattern is reversed afterwards. The magnitude is only 1-3 basis points before the financial crisis and rises dramatically to 15-20 basis points during 2008-2009. The pattern is reversed recently, since 2013, which may indicate the expansion of privately labeled security markets and the housing market recovery. Differences between jumbo and conforming loan national mean effective rates in Table 5 are more mixed and sometimes the signs are even opposite compared to differences in the contract rates. The difference arises from fees charged at closing. In addition, the nationwide spread may be obscured by variation at smaller geographic regions like states and MSAs. Moreover, the unconditional rate spread differential may arise due to many reasons such as loan and borrower characteristics. This underscores the importance of controlling

[4] 248793/(248793+1007266)=19.81%

[5] Freddie Mac monthly average for 30-year fixed-rate mortgages: `http://www.freddiemac.com/pmms/pmms_archives.html`

[6] 30-year fixed-rate loans comprise 91.6% of the entire sample and the conclusions are not sensitive to this restriction.

for other factors affecting jumbo/conforming differential besides the GSEs status, such as the prepayment, credit risks as well as origination costs for the two types of mortgages.

The average national differential in jumbo/conforming loan pricing is not the object of this research. The focus of this paper is on the spatial variation in differential pricing across smaller geographical units where there may be substantial differences in credit risk related to expected housing price movements. Equation 1 is used empirically to estimate the spread in loan pricing for jumbo and conforming mortgages in each geographic unit (state or MSA) and year. Specifically, the estimation is performed by state and year (51*11) and by MSA and year (433*11) combinations :

$$I_i = \delta_1 + \delta_2 J_i + \delta_3 \mathbf{X_i} + \epsilon_i \tag{1}$$

I_i is the contract rate at each loan origination.[7] $\mathbf{X_i}$ includes loan size, LTV, its interaction with the jumbo dummy, loan purpose, a non-MSA dummy and a dummy to indicate whether a loan is originated during the last three months of a year. Loan size is included in log, inverse and quadratic format in three different specifications to account for economies of scale in loan origination cost. LTV is a measure of credit risks of the borrowers at endorsement. The LTV variable is constructed as the true loan to value ratio minus 80% if positive and zero otherwise. Non-metropolitan is a dummy to identify loans originated in a metropolitan area because of possible differences in the origination and servicing costs in urban areas compared to rural counterparts. [8] Estimating the jumbo/conforming spread in each regression allows for unobserved state and time heterogeneities including foreclosure laws (Mian et al. (2015)) and demographic characteristics (Nothaft and Perry (2002)). Accordingly, the estimated coefficient (δ_2) of the jumbo dummy variable (J_i) in each equation identifies the jumbo/conforming spread for each specific region and year as shown in Table A.3. [9]

As shown in Table A.3 as well as Figure 3 and 4, the annual state (MSA) specific spreads vary significantly. The spread peaked during the financial crisis extended to 2009 and fell gradually following the recovery of entire economy. Jumbo/conforming spread loans even became negative in 2014 and the differential can be as high as 20-40 bps. The convergence of jumbo/conforming spread captures the structural changes in the secondary market as well as transitory factors like default and prepayment probability as documented in Cotterman and Pearce (1996). The enhanced liquidity of jumbo-backed securities facilitated by the housing market recovery may have been a factor in narrowing the loan rate differential. In addition, transitory factors like financial market condition would differentially affect the two markets. The lowering rates in jumbo loans are likely to reflect the lower perceived probability in default and prepayment with the burgeoning economy.

[7]Regression results using effective rate are in Online Appendix

[8]The non-metropolitan dummy is dropped when estimating the spread at MSA level.

[9]See Online Appendix for MSA jumbo/conforming spread.

3 Testing Investor Expectations

As is evident from Figure 2, housing prices exhibit distinct local patterns that imply substantial differences in credit risk for otherwise similar mortgages. A quick glance down any column of Table A.3 or at Figures 3 and 4 indicates that, in any given year, there is substantial variation in the jumbo/conforming spread across locations. It is also apparent that the spread varies over time. This confirms the hypothesis that, given the spatial stability of conforming rates because the uniform guarantee fee removes credit risks to investors and compared to the credit risks in the jumbo market, geographic differences in risk perceptions are reflected in the jumbo/conforming spread. This is unsurprising but it is formally demonstrated for the first time in this paper.

The far more ambitious hypothesis being tested here concerns whether investors priced the credit risks associated with differential house price appreciation. If private investors foresaw the underlying risk differentials related to differential house price appreciation and priced them accurately, differences in subsequent rates of house price appreciation across space should be revealed in the jumbo/conforming spread. This gives rise to a simple test of investor expectations. The jumbo/conforming spread across locations should vary inversely with changes in expected future house price across locations because credit risk varies inversely with house price appreciation. Increasing house value is directly reflected in collateral value and reduces the potential credit risks and vice versa.

Hypothesis 1: *Geographic variations in jumbo/conforming spread predict housing price movements in real estate market.*

As noted above, other papers have argued that investors failed to perceive credit risks accurately. This paper deals with a different dimension of that risk, spatial variation. The question here is whether the large geographic differences in actual housing price movements were priced by investors in jumbo mortgages, compared to the GSEs' uniform spatial price scheme. Without GSE's securitization, jumbo mortgages are either held on originators' balance sheet or sold to private investors through MBSs, thus jumbo investors need to bear the credit risk themselves and should price risks as they perceive it. In other words, the spatial variation in jumbo/conforming spread is primarily driven by jumbo market to incorporate regional risks in real estate market fluctuations.

Further, this paper tests the pricing mechanisms used by mortgage originators. It intends to investigate whether the Wall Street uses aggregate market fundamental information such as median household income, unemployment rate and population or more detailed micro level data to price mortgage market risks. It turns out this spatial differential in mortgage risk pricing, the jumbo/conforming spread, relies more on micro unobservables than aggregate fundamentals.

Hypothesis 2: *Mortgage investors price spatial differentials in the jumbo/conforming spread based on more detailed micro rather than readily available aggregate information.*

3.1 Methodology

This paper uses a panel structure to study the ability of spatial variation in the jumbo/conforming spread to predict spatial differentials in housing price changes. The results shed light on the drastic changes in house prices during the study period between 2004 and 2014. This period covers the initial boom till 2007, later collapse in 2008 and final recovery. It's an ideal time span to investigate whether the abnormal house price fluctuation can be accounted for by housing fundamentals or other risk factors. In addition, this paper further tests the pricing mechanism for the jumbo/ conforming spread. It intends to answer the question whether spatial variation in credit risks reflected in house price appreciation are priced appropriately by jumbo investors in the mortgage interest rate, contrary to uniform pricing policy implemented by GSEs.

A parsimonious model from default literature (Campbell and Cocco (2015)) indicates a negative relationship between default rate and the change in housing price. In addition, mortgage pricing equation implies a positive relationship between interest rate and default risks. Specifically,

$$d_{it} = D(\Delta p_{it}, \phi_i, \gamma_t) \tag{2}$$

$$r_{it} = R(d_{it}, \mu_i, \omega_t) \tag{3}$$

where d_{it} is the default rate, p_{it} is the housing price, r_{it} is the interest rate, ϕ_i and μ_i are region specific shocks and γ_t and ω_t are time specific shocks.

Combining the default equation 2 where $D_{\Delta p} < 0$ and mortgage pricing equation 3 where $R_d > 0$, the following equation is used to guide empirical analysis below:

$$\Delta p_{it} = F(r_{it}, \eta_i, \theta_t, \varepsilon_{it}) \tag{4}$$

where $F_r < 0$ indicating future housing prices incorporate mortgage pricing information that both reflects and reveals potential credit risks.

Housing price variation is measured using repeat sales house price indices obtained from the FHFA developmental annual index for single-family housing at state and MSA level separately between 2004 and 2014. HPIs developed by FHFA provide a broad measure of the movement of single-family house prices and serve as a timely, accurate indicator of house price trends at various geographic levels. The HPI developed by FHFA shares a similar trend with other established indices, notably the one constructed by S&P Corelogic. The wide geographic coverage of FHFA HPI provides an advantage over others. Housing market fundamentals on both demand side such as household income, unemployment rate as well as population and supply side like geography and typology are key determinants of real estate dynamics as illustrated in Peek and Wilcox (1991) and Saiz (2010). State level median household income, unemployment rate and population are obtained from American Community Survey 1-year estimate. Jumbo-conforming spread at state and MSA level is estimated in Section 2.2.

The summary statistics for aforementioned variables are presented in Table 6. Jumbo/conforming spread has more variation at MSA level compared to state level. Local differentials are prominent at smaller geographic regions. The standard deviation of jumbo/conforming spread at the MSA level is 8.3 bps higher than state level. House price has similar pattern: more spatial variation at MSA level in contrast with state level. MSAs experienced more extreme fluctuations in housing prices, with the highest depreciation of 43.9% in Stockton, CA MSA in 2008.

From the data described above, there are 3 key variables in the analysis: (1) HPI, refers to annual housing price index; (2) F, a vector of housing market fundamentals, includes median household income, population and unemployment rate; (3) Spread, refers to the annual jumbo/conforming spread estimated in Section 2.2.

The empirical strategy involves estimating a model of house price change:

$$\Delta log(HPI_{i,t}) = \gamma_1 + \gamma_2 F_{i,t-1} + \gamma_3 Spread_{i,t-1} + \epsilon_{i,t} \tag{5}$$

The dependent variable ($\Delta log(HPI_{i,t})$) is the change in the logarithm of a repeat sale housing price index. Housing market fundamentals incorporate information on both the demand and supply side to capture underlying housing market variations. Geography and typography affect housing supply elasticity thus housing supply overall as mentioned in Saiz (2010). Though with some variation across states, supply elasticity and housing market regulations neither change over time nor differ much across the U.S. The location (State/CBSA) fixed effects could capture supply shifters and are differenced out after first differencing by model construction. In this paper only demand shifters (F_{it}) are included such as income, unemployment rate and population which are deemed as important determinants of housing market dynamics.

Hypothesis 1, tested using Equation 5, predicts that the estimated value of the parameter γ_3 is negative. Jumbo/conforming spread is expected to reflect real estate market dynamics through mortgage pricing based on credit risks. As jumbo/conforming spread widens, it implies accumulatively rising risks in local housing market and investors would expect a downturn in future housing price, thus a negative coefficient. Equation 5 also attempts to determine whether investors base their pricing policy on any housing market fundamentals. If housing market fundamentals incorporate information about future house price fluctuations, the coefficients (γ_2) would be statistically significant. To mitigate endogeneity issues, lagged fundamentals and jumbo/conforming spread are used. In addition, jumbo mortgages is only a small fraction of the entire mortgage market thus this paper doesn't try to build a causal relationship between jumbo/conforming spread and future housing price. Instead, it tries to argue jumbo/conforming spread reflects spatial variation in credit risks based on investors' expectation of future housing market behavior.

To test hypothesis 2, the jumbo/conforming spread is regressed on housing market fundamentals to investigate if mortgage investors price regional credit risks based on market fundamentals included in the analysis:

$$Spread_{i,t} = \theta_1 + \theta_2 F_{i,t} + \varphi_{i,t} \tag{6}$$

3.2 Empirical Results

Table 7 reports the results for hypothesis 1 if the jumbo/conforming spread vary inversely with the actual future change in house prices at state and MSA level respectively. The jumbo/conforming interest rate spread is a proxy for credit risks because investors would price mortgages based on their expectation of the housing market. The restricted sample is constructed by including only states/MSAs with spread series in all years to have a balanced panel.

Column 1 and 3 in Table 7a are from OLS with standard errors clustered at each state to account for serial correlation across years. The results imply that lagged spread is negatively associated with housing price appreciation after controlling for state heterogeneities and time specific shocks. In Column 2 and 4, lagged housing fundaments are added to test if investors form their expectations using market fundamentals. Median household income and unemployment rate are statistically significant. However, income bears the sign of wrong direction and is too economically too small to affect the housing dynamics. It also indicates market fundamentals during the study period only account for a small portion of the market abnormality. Instead, other underlying mechanisms, such as the credit supply expansion, exotic securitization products etc,. were underway. Surprisingly, the jumbo-conforming spread plays an important role in predicting subsequent housing price index during the sample period, 100 bps rise in the spread change predicts 3.47% fall in following HPI in full sample and 5.34% fall for the restricted sample (Table 7a) or one standard deviation increase in the spread (25.08 and 23.72 bps) predicts 0.87%-1.27% fall in the future housing price. This results suggest mortgage market investors price geographic credit risks in response to future expectation in the housing market.

The results for MSAs in Table 7b are more pronounced in the restricted sample column 4 as those are the metropolitan areas where jumbo loans are more prevalent. It indicates a 100 bps rise in the spread is associated with 4.86% fall in the housing price subsequently or one standard deviation increase in the spread (28.11 bps) predicts 1.37% drop in the following housing price index. Though striking, it quite intuitive since large MSAs are usually the places have higher housing prices and with jumbo loan concentration. Investors in large MSAs are more experienced in pricing risks and foresee potential upcoming risks.

Table 8 supports hypothesis 2 that none of the aggregate housing market fundamentals are statistically significant. It implies mortgage investors do not price regional risks based on general market fundamentals available to the public, at least not on median household income, unemployment rate and population. Instead, wall street investors have their own model to predict mortgage market credit risks, probably more detailed micro level data on borrower and loan characteristics.

A high fraction of conforming loans are securitized by GSEs thus contains less default risks compared to jumbo ones. The interest rate charged for conforming loans usually reflects government guarantee fees and administration costs without too much spatial variation. In sharp contrast, the spatial variation in jumbo mortgage rate changes contains information regarding investors' expectation of future housing price change in the form of risk premium charged by lenders. These results are consistent with Mian and Sufi (2009) who find that mortgages sold to non-GSE investors for securitization experienced a disproportionate increase in default rates. This phenomena happened because institutional investors for private-labeled MBSs foresaw potential risks in those mortgages and required higher return at origination. Alternatively, those investors are aware of moral hazard in originators to sell bad mortgages to unaffiliated investors for non-GSE securitization.

Was the spatial variation in severity of the financial crisis really a complete surprise to the wall street? It appears that private market investors had information sources that allowed them to engage in successful spatial risk pricing. Without any safe nets, private labeled MBSs investors meticulously measure the potential risks in jumbo mortgage pools, such as default and prepayment risks. In fairness, it should be noted that, on more than one occasion, the GSEs have asked fro limited ability to price spatial differences in credit risks. However, they have been obstructed by opponents in Congress, unions, realtors and investors who want to maintain housing affordability in areas where house prices are rising rapidly by not pricing the risk associated with the bubble. The good intentions that might motivate pooling all conforming loans might have potential unintended consequences. Constrained by the need to offer uniform rates, the existence of GSEs by securitizing conforming mortgages fail to price local credit risks and encourage future bubbles.

4 Robustness Check

The results are also robust to different sample screening criteria and estimation specification with details presented in Appendix. This section will address the issues one by one.

To circumvent loan type misclassification and interest rate outlier, contract rate more than 100bps below the monthly average from Freddie Mac are excluded from the sample. The results are similar to the preferred specification, a one standard deviation in jumbo/conforming spread is associated with 1.30% and 1.48% fall in housing prices at state and MSA level respectively in the preferred specification column 4 under restricted sample. (Table A.4)

Housing price growth rate is path dependent, so lagged housing price appreciation rate is added in the main regression Equation 5 to address its autoregressive behavior. Once lagged dependent variable is added, the empirical specification used becomes:

$$\Delta log(HPI_{i,t}) = \gamma_1 + \gamma_2 \Delta log(HPI_{i,t-1}) + \gamma_3 F_{i,t-1} + \gamma_4 Spread_{i,t-1} + \epsilon_{i,t} \tag{7}$$

However, OLS and FE estimates are biased because OLS is subject to omitted variables problems and FE violates zero mean independence assumption. A System GMM approach is used to account for endogenous lagged housing price appreciation rate assuming the lagged income, unemployment rate and population are exogenous. The results imply a one standard deviation in jumbo/conforming spread is associated with a fall of 1.3%-1.54% at state level and 0.52%-1.37% at MSA level (see Table A.5 and Table A.6) in subsequent housing price appreciation. [10]

[10] One concern is the jumbo/conforming spread is correlated with lagged housing price. Then the results shown in Table A.5 and A.6 simply reflect the serial correlation behavior of housing market dynamics. To address this issue, Table A.7 illustrates jumbo/conforming spread is not correlated with lagged housing prices.

Some may even argue conforming and jumbo market may incorporate local risks by charging different closing fees and coupon rate. To test this alternative hypothesis, the jumbo/conforming spread is re-estimated using effective interest rate at state and MSA level respectively. The results remain unchanged as shown in Table A.8, one standard deviation change in jumbo/conforming spread is associated with housing prices drop by about 0.85%-1.34% at state level and 0.44%-1.3% at MSA level.

5 Conclusion

This paper departs from the extensive literature on the aggregate jumbo/conforming spread estimation. Instead it constructs a panel data set measuring the spatial variation in the jumbo/conforming spread at smaller geographic regions such as states and MSAs between July 2004 and Dec 2014. The estimated mortgage interest rate spreads provide an instrument to determine if private investors succeeded in pricing spatial variation in credit risks associated with localized housing price bubbles. The resulting test is the first time that jumbo/conforming spreads have been used to forecast future house price changes.

The results of this test of the relation between the spatial variations in the spread and subsequent house price appreciation rate are important for two reasons. First, they help to answer questions of whether investors in the jumbo market knew about the substantial spatial variation in the severity of housing price bubbles given that these differences had been forecast by Case and Shiller (2003) among others. Second, the test confirms the hypothesis that the conforming market failed to price differences in house price expectations in a manner that encouraged rather than attenuated the more extreme local bubbles. Finally, the hypothesis that the basis for pricing of differential credit risk by jumbo investors was related to specific indicators of local housing price fundamentals is examined for the first time.

The local spreads exhibit huge spatial variation over the sample period indicating heterogeneities in regional housing market risks. The results clearly demonstrate that spatial differentials in the jumbo/conforming spread predict differences in future housing price appreciation rates during the boom and bust period. It provides evidence that investors accurately perceived the spatial risk differentials across geographic regions. Moreover, the pricing differential is driven by the jumbo market because the conforming loan interest rate set by GSEs, as a policy choice, doesn't price spatial risk differentials. The empirical results at state and MSA level imply a one standard deviation increase in the jumbo/conforming spread is associated with 1.27%-1.37% decrease in subsequent housing prices. Private market investors foresee future risks and thus price loans accordingly, whereas GSEs doesn't closely follow the invisible market force. Given that housing price variation is a local phenomenon, failure to price spatial differences in credit risk can amplify price variation and likely contribute significantly to the boom and bust in the housing markets that exhibited the most extreme cycles. Attempts to relate the spread to standard fundamental indicators that might be used to assess spatial differences in housing market conditions failed. This suggests that investors used other information or more complex ways of combining that information to price spatial risk differentials. Overall it appears that investors not only knew about these risk differentials but that in pricing them they provided additional information about the future path of housing prices not incorporated in simple models of local housing market conditions.

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Table 1: Mortgage Issuance Distribution across States (2004.07-2014.12)

	Conforming		**Jumbo**	
State	Freq	Percent	Freq	Percent
AK	2,451	0.216	17	0.0141
AL	10,360	0.912	246	0.204
AR	5,631	0.496	59	0.0489
AZ	30,701	2.704	1,812	1.502
CA	96,180	8.471	43,275	35.88
CO	27,451	2.418	2,250	1.866
CT	9,330	0.822	1,634	1.355
DC	3,416	0.301	1,653	1.371
DE	10,297	0.907	360	0.298
FL	109,073	9.606	8,054	6.678
GA	53,860	4.743	2,746	2.277
HI	3,850	0.339	287	0.238
IA	13,566	1.195	106	0.0879
ID	6,517	0.574	221	0.183
IL	40,263	3.546	2,811	2.331
IN	14,119	1.243	167	0.138
KS	13,590	1.197	333	0.276
KY	8,260	0.727	114	0.0945
LA	9,405	0.828	220	0.182
MA	15,985	1.408	2,834	2.350
MD	39,945	3.518	7,804	6.471
ME	4,974	0.438	130	0.108
MI	18,684	1.646	554	0.459
MN	36,451	3.210	1,556	1.290
MO	17,701	1.559	355	0.294
MS	3,606	0.318	24	0.0199
MT	3,994	0.352	111	0.0920
NC	50,116	4.414	2,036	1.688
ND	4,099	0.361	13	0.0108
NE	9,016	0.794	53	0.0439
NH	4,361	0.384	209	0.173
NJ	39,778	3.503	7,045	5.841
NM	9,204	0.811	252	0.209
NV	12,321	1.085	1,217	1.009
NY	38,203	3.365	7,565	6.273
OH	33,975	2.992	557	0.462
OK	8,208	0.723	99	0.0821
OR	15,360	1.353	956	0.793
PA	57,021	5.022	1,836	1.522
RI	2,077	0.183	187	0.155
SC	27,297	2.404	1,071	0.888
SD	3,963	0.349	22	0.0182
TN	28,436	2.504	849	0.704
TX	67,504	5.945	2,726	2.260
UT	6,904	0.608	454	0.376
VA	51,090	4.500	9,315	7.724
VT	2,208	0.194	70	0.0580
WA	33,252	2.929	3,936	3.264
WI	15,034	1.324	298	0.247
WV	4,252	0.374	54	0.0448
WY	2,116	0.186	51	0.0423
Total	1135455		120604	

Percent represents the column percentage among all issuances across states

Table 2: Mortgage Issuance Distribution, 2004.07-2014.12

Year	Conforming Freq (Percent)	Jumbo Freq (Percent)	Fixed-rate Freq (Percent)	Adjustable-rate Freq (Percent)	Adjustable-rate Jumbo Freq (Percent)	Fixed-rate Jumbo Freq (Percent)
2004	124,096	14,999	79,219	59,876	11,616	3,383
	(10.93)	(12.44)	(7.865)	(24.07)	(19.63)	(5.507)
2005	211,475	27,918	158,028	81,365	19,524	8,394
	(18.62)	(23.15)	(15.69)	(32.70)	(33.00)	(13.66)
2006	195,826	17,883	162,200	51,509	10,883	7,000
	(17.25)	(14.83)	(16.10)	(20.70)	(18.39)	(11.39)
2007	153,434	11,683	147,370	17,747	5,433	6,250
	(13.51)	(9.687)	(14.63)	(7.133)	(9.182)	(10.17)
2008	104,650	4,336	102,821	6,165	1,294	3,042
	(9.217)	(3.595)	(10.21)	(2.478)	(2.187)	(4.952)
2009	77,047	5,052	79,756	2,343	491	4,561
	(6.786)	(4.189)	(7.918)	(0.942)	(0.830)	(7.424)
2010	57,142	5,031	58,951	3,222	519	4,512
	(5.033)	(4.172)	(5.853)	(1.295)	(0.877)	(7.345)
2011	47,424	5,005	46,294	6,135	1,271	3,734
	(4.177)	(4.150)	(4.596)	(2.466)	(2.148)	(6.078)
2012	53,234	7,230	53,389	7,075	2,085	5,145
	(4.688)	(5.995)	(5.300)	(2.844)	(3.524)	(8.375)
2013	62,171	10,631	66,307	6,495	2,600	8,031
	(5.475)	(8.815)	(6.583)	(2.611)	(4.394)	(13.07)
2014	48,956	10,836	52,931	6,861	3,455	7,381
	(4.312)	(8.985)	(5.255)	(2.758)	(5.839)	(12.01)
Total	1135455	120604	1007266	248793	59171	61433

Note: column 1+ column 2= column 3+column 4=total loan origination in the survey in each year; column 6 and 7 add up to column 2; the number in parenthesis represents the annual percentage originations for each type of mortgage (in the corresponding column) among all its originations.

Table 3: Summary Descriptive Statistics

VARIABLES	N	mean	sd	min	max
contract rate	850,667	5.718	1.044	2.875	15.30
effective rate	850,667	5.810	1.035	2.064	11.63
loan size	850,667	216,031	138,220	10,000	1.036e+06
ln(loan size)	850,667	12.10	0.620	9.210	13.85
LTV (raw)	850,667	78.53	15.61	2.500	100
Jumbo status	850,667	0.0644	0.245	0	1
nonMSA	850,667	0.361	0.480	0	1
PURPOSE	850,667	0.845	0.362	0	1

Table 4: Non-jumbo & Jumbo Loan Base Rate

Year	Non-jumbo	Jumbo	Difference	p-value
2004	6.07	6.10	-0.03	0.00
2005	6.07	6.08	-0.01	0.16
2006	6.67	6.70	-0.03	0.00
2007	6.52	6.53	-0.01	0.05
2008	6.18	6.38	-0.20	0.00
2009	5.10	5.25	-0.15	0.00
2010	4.88	4.94	-0.06	0.00
2011	4.75	4.74	0.02	0.02
2012	3.87	3.90	-0.03	0.00
2013	4.10	4.01	0.09	0.00
2014	4.41	4.16	0.25	0.00

Table 5: Non-jumbo & Jumbo Loan Effective Rate

Year	Non-jumbo	Jumbo	Difference	p-value
2004	6.16	6.16	0.00	0.69
2005	6.14	6.13	0.01	0.06
2006	6.75	6.75	-0.01	0.35
2007	6.61	6.59	0.02	0.01
2008	6.28	6.44	-0.16	0.00
2009	5.23	5.33	-0.10	0.00
2010	5.03	5.04	-0.01	0.19
2011	4.91	4.84	0.07	0.00
2012	4.02	3.99	0.03	0.00
2013	4.25	4.11	0.15	0.00
2014	4.59	4.26	0.32	0.00

Table 6: Variable Summary Statistics

(a) Panel A: State level

	(1)	(2)	(3)	(4)	(5)
VARIABLES	N	mean	sd	min	max
Spread	507	0.226	0.295	-0.432	1.732
Median income	507	50,586	8,557	31,504	73,971
Total population	507	6.388e+06	6.909e+06	492,534	3.880e+07
Unemployment rate in labor force	507	4.957	1.336	2.100	9.400
HPI	507	498.7	168.7	258.6	1,223
Δ log(HPI)	507	0.0163	0.0689	-0.262	0.261

(b) Panel B: CBSA level

	(1)	(2)	(3)	(4)	(5)
VARIABLES	N	mean	sd	min	max
Spread	1,918	0.210	0.378	-0.988	1.984
Median income	1,918	50,641	7,868	31,642	73,971
Total population	1,918	1.172e+07	1.082e+07	495,226	3.880e+07
Unemployment rate in labor force	1,918	5.053	1.313	2.100	9.400
HPI	1,918	502.8	220.4	103.0	1,531
Δ log(HPI)	1,918	0.0287	0.0879	-0.439	0.289

Table 7: Housing Price Prediction

(a) Panel A: State-level

	$\Delta log(HPI)$, Full Sample		$\Delta log(HPI)$, Restricted Sample	
Variables	(1)	(2)	(3)	(4)
Lag Spread	-0.0284*	-0.0347**	-0.0434*	-0.0534**
	(0.0166)	(0.0156)	(0.0242)	(0.0233)
Lag Income		-1.06e-05**		-1.15e-05**
		(4.72e-06)		(5.49e-06)
Lag Population		4.01e-09		1.15e-09
		(7.08e-09)		(8.21e-09)
Lag Unemployment Rate		-0.0185***		-0.0196***
		(0.00568)		(0.00628)
Constant	0.114***	0.667***	0.127***	0.763**
	(0.0107)	(0.242)	(0.0137)	(0.289)
Observations	429	429	320	320
R-squared	0.676	0.722	0.697	0.744
# of States	51	51	32	32
State FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES

(b) Panel B: MSA-level

	$\Delta log(HPI)$, Full Sample		$\Delta log(HPI)$, Restricted Sample	
Variables	(1)	(2)	(3)	(4)
Lag Spread	-0.0128*	-0.0155**	-0.0421***	-0.0486***
	(0.00748)	(0.00743)	(0.0145)	(0.0138)
Lag Income		-1.71e-05***		-1.88e-05***
		(3.63e-06)		(6.21e-06)
Lag Population		7.53e-09		1.26e-08**
		(4.84e-09)		(4.93e-09)
Lag Unemployment Rate		-0.0140***		-0.0205**
		(0.00530)		(0.00851)
Constant	0.141***	0.915***	0.158***	0.975***
	(0.00639)	(0.176)	(0.0116)	(0.318)
Observations	1,260	1,260	570	570
R-squared	0.624	0.667	0.667	0.714
# of MSAs	243	243	57	57
MSA FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES

Table 8: Spread Pricing Mechanism

(a) Panel A: State-level

	Spread, Full Sample		Spread, Restricted Sample	
	(1)	(2)	(3)	(4)
Income	-8.37e-06***	3.89e-06	-6.67e-06***	-3.70e-06
	(1.34e-06)	(9.59e-06)	(1.41e-06)	(6.44e-06)
Population	-1.60e-09	-8.08e-09	-1.94e-09	-1.76e-08
	(1.32e-09)	(1.39e-08)	(1.71e-09)	(1.30e-08)
Unemployment Rate	-0.0120	0.0134	0.0149	0.0351*
	(0.0165)	(0.0192)	(0.0145)	(0.0183)
Constant	0.642***	0.0104	0.419***	0.287
	(0.105)	(0.443)	(0.114)	(0.376)
Observations	507	507	352	352
R-squared	0.498	0.534	0.595	0.627
State FE	NO	YES	NO	YES
Year FE	YES	YES	YES	YES
# of States	51	51	32	32

(b) Panel B: MSA-level

	Spread, Full Sample		Spread, Restricted Sample	
	(1)	(2)	(3)	(4)
Income	-6.39e-06***	-6.83e-07	-5.70e-06***	-5.07e-06
	(1.18e-06)	(5.33e-06)	(1.70e-06)	(5.46e-06)
Population	-1.35e-10	-2.67e-08**	-1.76e-09**	-1.95e-08
	(8.24e-10)	(1.30e-08)	(8.13e-10)	(1.30e-08)
Unemployment Rate	-0.00755	-0.00558	-0.000336	0.0223
	(0.0117)	(0.0177)	(0.0152)	(0.0213)
Constant	0.528***	0.552*	0.490***	0.599
	(0.0900)	(0.325)	(0.133)	(0.368)
Observations	1,918	1,918	627	627
R-squared	0.298	0.362	0.485	0.509
MSA FE	NO	YES	NO	YES
Year FE	YES	YES	YES	YES
# of MSAs	376	376	57	57

Figure 1: National HPI between 1991q1 and 2016q3

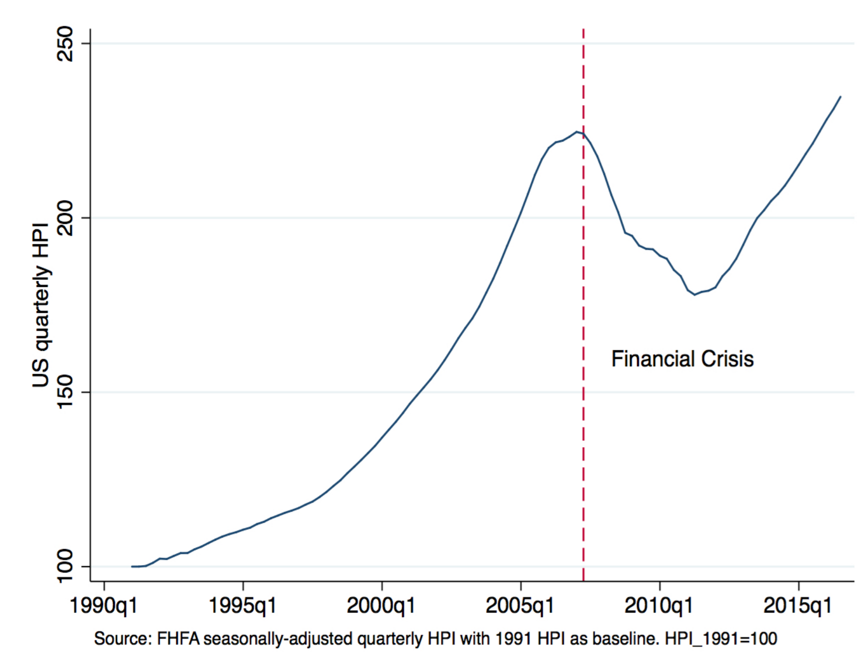

Figure 2: Major MSAs HPI between 1991q1 and 2016q3

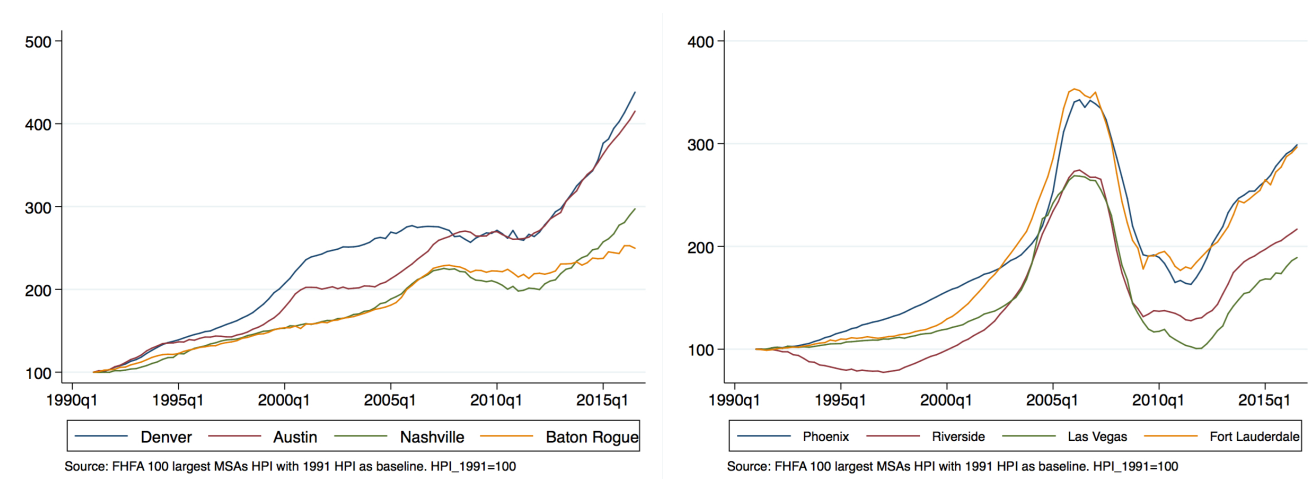

Figure 3: Jumbo/conforming spread in 6 major jumbo issuance states

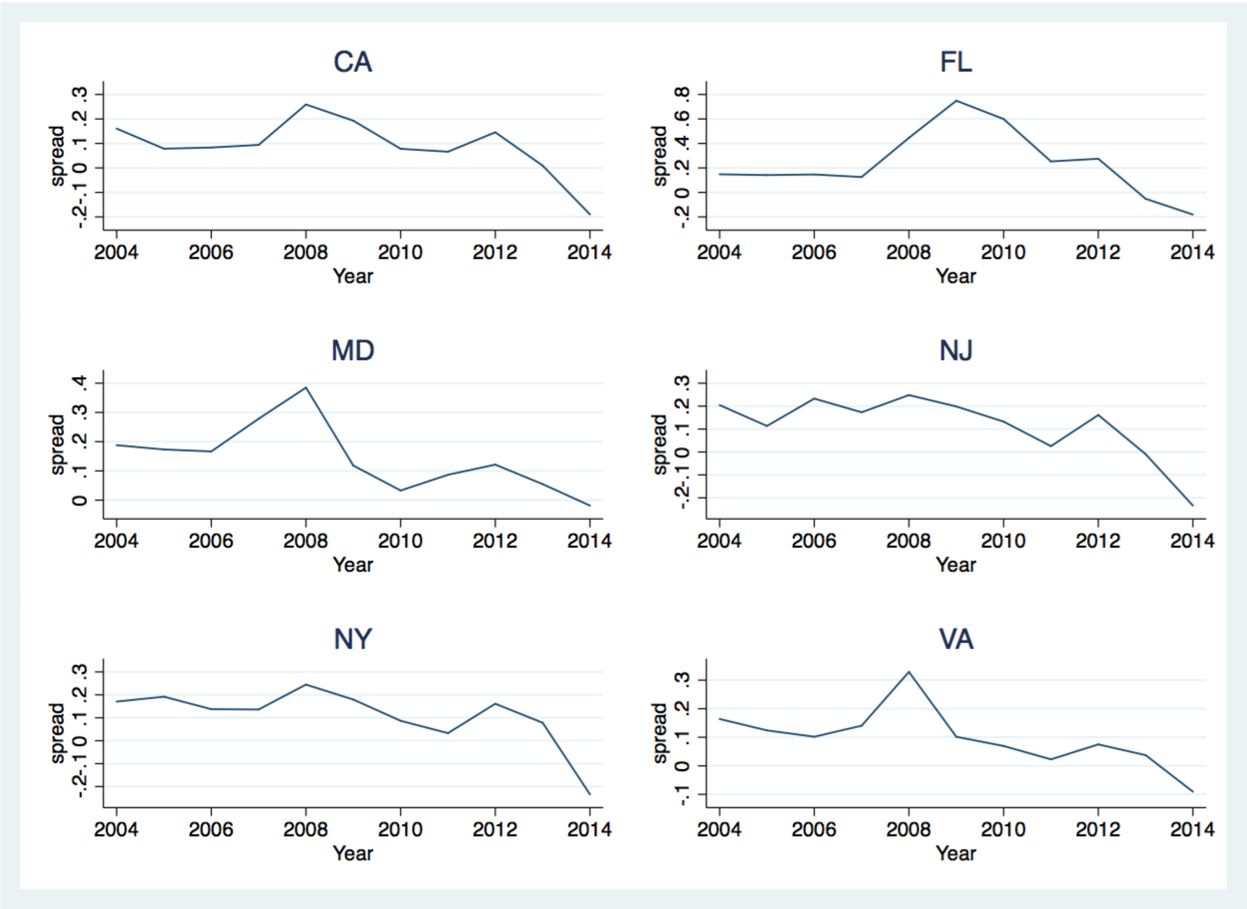

Figure 4: Jumbo/conforming spread in 6 major MSAs

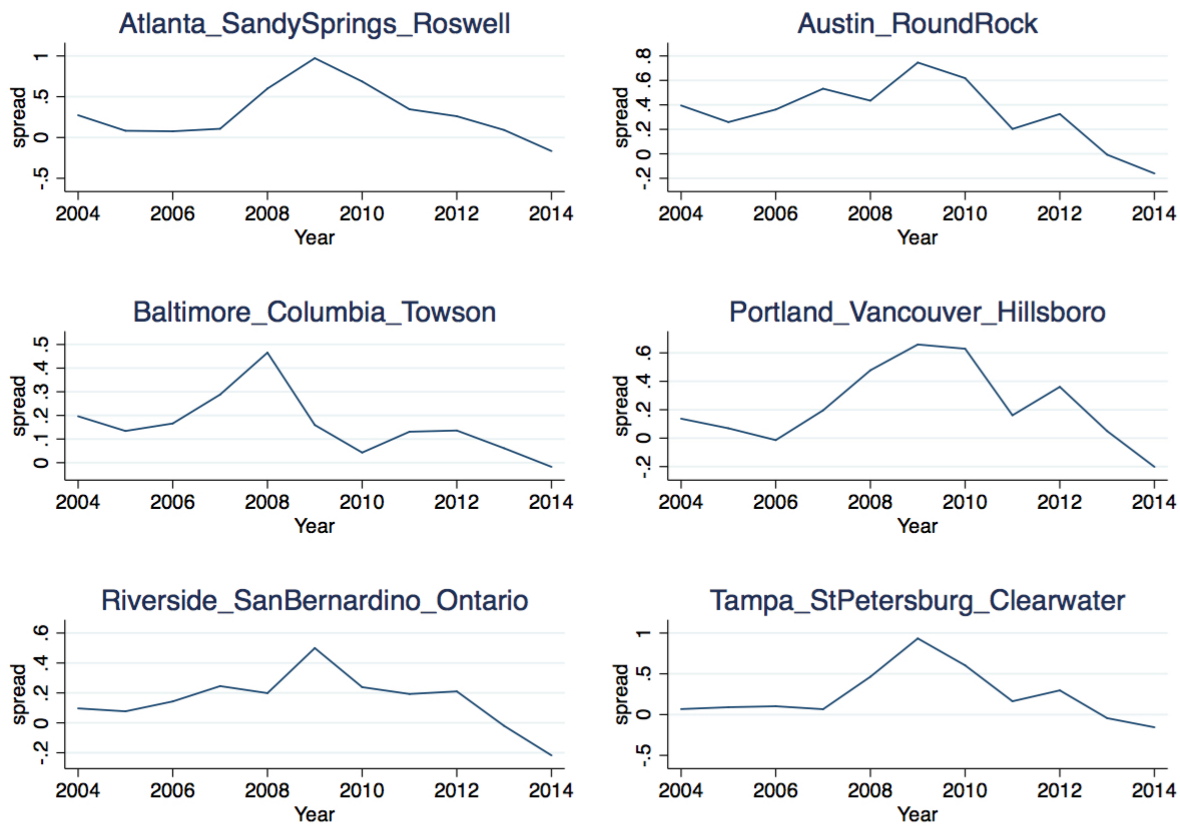

Table A.1: Jumbo Loan Contract Rate Spatial Distribution

State	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014
AK	6.12			5.88		5.88			3.81	3.50	
AL	5.96	6.00	6.64	6.42	6.88		5.69	5.20	3.54	3.94	4.33
AR			6.66	6.88	8.00	5.88	5.25	5.12	4.50	3.99	4.27
AZ	6.09	6.17	6.70	6.53	6.68	6.00	5.40	5.00	4.09	3.96	4.07
CA	6.04	6.02	6.67	6.48	6.29	5.20	4.88	4.72	3.88	4.04	4.17
CO	6.07	6.01	6.72	6.45	6.45	5.56	5.26	4.72	3.94	3.96	4.08
CT	6.03	5.98	6.59	6.46	6.43	5.25	4.97	4.72	3.92	3.98	4.10
DC	6.05	5.93	6.61	6.44	6.26	5.11	4.81	4.67	3.86	4.03	4.27
DE	6.43	6.29	6.73	6.75	6.68	5.88	5.65	4.69	3.97	3.98	4.21
FL	6.16	6.29	6.86	6.64	6.68	5.89	5.49	4.99	3.95	3.97	4.26
GA	5.98	5.97	6.62	6.48	6.61	5.91	5.43	4.91	3.86	3.91	4.13
HI	5.91	5.98	6.47	6.58	6.23	5.10	4.93	4.71	4.03	4.15	3.98
IA	5.88	6.00	6.06	6.25	6.67	4.88	5.15	4.83	4.00	3.81	4.02
ID	5.83	5.85	6.53	6.63	6.17	5.50	5.38	5.00	3.99	4.27	4.12
IL	6.11	6.10	6.72	6.56	6.77	5.93	5.39	4.94	4.03	3.91	4.12
IN	6.25	6.13	6.72	6.88			5.44	4.65	3.80	3.94	3.88
KS	5.99	5.72	6.22	6.27	6.04	5.21	5.15	4.72	3.75	3.87	4.15
KY	5.94	6.10	6.74	6.72	7.06		5.62		4.21	3.86	4.11
LA	5.88	5.98	6.69	6.53			4.88	4.88	4.26	4.01	4.14
MA	6.20	5.96	6.62	6.45	6.48	5.34	4.95	4.75	4.00	3.90	4.06
MD	6.21	6.24	6.77	6.69	6.45	5.12	4.82	4.73	3.82	4.04	4.29
ME	6.25	6.08	6.53	6.64	6.67	5.83		4.92	3.99	4.00	4.32
MI	6.10	6.12	6.98	6.50	6.25	5.83	5.42	4.74	4.06	3.99	4.03
MN	5.96	5.76	6.43	6.34	6.35	6.15	5.25	4.74	3.86	3.93	4.00
MO	5.98	5.95	6.67	6.58	6.43	5.61	5.55	4.88	4.07	3.90	3.95
MS	6.12	6.25	6.62	6.56					3.87		4.54
MT	5.75	6.20	6.58	6.48	7.44		5.41	4.75	4.12	3.97	3.85
NC	5.95	5.96	6.68	6.55	6.49	5.84	5.47	4.87	3.98	3.98	4.14
ND		5.94	6.38	6.88			5.50				5.30
NE		6.21	6.75	6.67	6.25		5.53	5.38	4.38	4.25	4.25
NH	6.29	5.98	6.69	6.59	7.09	5.69	5.06	5.12	4.19	4.08	4.14
NJ	6.17	6.02	6.76	6.55	6.29	5.21	4.89	4.69	3.88	3.96	4.10
NM	6.08	5.96	6.58	6.60	6.96		5.50	5.09	3.89	4.08	4.18
NV	6.24	6.04	6.71	6.43	6.89	5.77	5.46	5.17	3.88	4.01	4.09
NY	6.19	6.07	6.65	6.56	6.34	5.24	4.91	4.70	3.92	4.01	4.12
OH	6.03	6.12	6.74	6.50	6.38	5.71	4.96	4.70	3.92	4.02	4.03
OK	6.00	6.00	6.69	6.42	6.88	5.95	5.25	4.92	4.12	3.88	4.03
OR	6.02	5.94	6.58	6.48	6.55	5.72	5.38	4.72	3.92	4.11	4.10
PA	6.22	6.16	6.79	6.63	6.78	5.83	5.23	4.76	4.01	3.92	4.15
RI	6.40	5.93	6.70	6.49	7.06	5.75	5.12	4.81	3.83	4.04	4.12
SC	6.03	6.02	6.60	6.60	6.98	6.01	5.63	4.95	4.06	3.91	4.26
SD	6.00	5.62							4.38	4.38	4.00
TN	6.02	6.15	6.80	6.54	6.65	6.04	5.65	4.87	4.06	3.95	4.15
TX	6.17	6.09	6.67	6.50	6.67	5.82	5.35	4.94	4.03	3.98	4.04
UT	5.95	6.04	7.10	6.58	6.20	5.16	4.89	4.74	3.91	4.10	4.08
VA	6.08	6.14	6.64	6.50	6.32	5.08	4.83	4.68	3.83	4.01	4.23
VT		6.29	6.67	6.94			5.25	4.75	4.20	4.13	4.18
WA	5.96	5.95	6.63	6.44	6.31	5.27	4.88	4.65	3.86	3.98	4.09
WI	6.08	5.93	6.59	6.66	6.44	5.92	5.42	4.65	4.20	4.04	4.00
WV	6.38	6.16	7.03	6.83			5.12	5.50	3.75		4.25
WY	6.00	6.00	6.12	6.58		5.12	5.12	4.75	4.23	4.00	4.15

Table A.2: Conforming Loan Contract Rate Spatial Distribution

State	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014
AK	5.94	5.95	6.59	6.41	6.11	5.00	4.81	4.73	3.80	4.10	4.37
AL	6.24	6.22	6.78	6.56	6.17	5.04	4.89	4.74	3.91	4.17	4.45
AR	6.16	6.18	6.66	6.56	6.26	5.05	4.90	4.82	3.99	4.18	4.42
AZ	6.05	6.08	6.67	6.53	6.19	5.22	4.97	4.83	3.95	4.08	4.44
CA	5.99	5.97	6.66	6.49	6.17	5.15	4.92	4.79	3.93	4.13	4.45
CO	5.96	5.97	6.56	6.42	6.10	5.08	4.86	4.75	3.88	4.13	4.41
CT	6.06	5.95	6.62	6.52	6.20	5.05	4.87	4.72	3.89	4.09	4.47
DC	6.10	6.03	6.63	6.43	6.10	5.02	4.90	4.70	3.84	4.05	4.42
DE	6.10	6.12	6.63	6.49	6.12	5.07	4.79	4.68	3.73	4.08	4.36
FL	6.14	6.18	6.81	6.59	6.25	5.18	4.96	4.81	3.88	4.12	4.44
GA	6.04	6.11	6.71	6.47	6.16	5.00	4.84	4.77	3.88	4.06	4.39
HI	5.83	6.00	6.51	6.34	5.97	5.00	4.94	4.76	3.83	3.97	4.47
IA	6.03	5.96	6.58	6.45	6.20	5.06	4.85	4.72	3.78	4.07	4.39
ID	6.07	6.01	6.54	6.44	6.06	5.09	4.89	4.81	3.91	4.08	4.37
IL	6.13	6.09	6.70	6.65	6.30	5.21	4.94	4.78	3.93	4.13	4.42
IN	6.23	6.22	6.80	6.71	6.37	5.27	4.95	4.82	3.93	4.27	4.45
KS	6.06	5.96	6.55	6.43	6.14	5.11	4.90	4.65	3.79	4.01	4.31
KY	6.15	6.13	6.72	6.58	6.26	5.21	4.95	4.77	3.89	4.14	4.47
LA	6.06	6.10	6.63	6.61	6.33	5.10	4.93	4.84	4.00	4.17	4.44
MA	6.00	5.91	6.54	6.51	6.19	5.10	4.90	4.77	3.90	4.11	4.40
MD	6.07	6.07	6.66	6.48	6.14	5.06	4.82	4.70	3.79	4.08	4.37
ME	6.17	6.15	6.75	6.65	6.22	5.09	4.87	4.75	3.92	4.04	4.42
MI	6.09	6.09	6.84	6.77	6.31	5.22	5.01	4.77	3.92	4.16	4.43
MN	5.92	5.84	6.47	6.38	6.07	5.02	4.84	4.71	3.79	4.08	4.37
MO	6.18	6.08	6.64	6.61	6.30	5.20	4.98	4.82	3.97	4.06	4.42
MS	6.17	6.14	6.83	6.73	6.46	5.24	5.00	4.84	4.03	4.28	4.49
MT	5.99	5.93	6.52	6.46	6.12	5.04	4.86	4.72	3.79	4.04	4.37
NC	6.00	6.04	6.58	6.43	6.12	5.02	4.84	4.73	3.82	4.04	4.41
ND	5.93	5.74	6.44	6.31	5.94	4.96	4.77	4.67	3.82	4.06	4.35
NE	6.07	6.01	6.58	6.45	6.21	5.16	4.98	4.80	3.88	4.02	4.41
NH	6.10	5.98	6.68	6.60	6.26	5.11	4.88	4.79	4.01	4.15	4.38
NJ	6.07	5.99	6.67	6.51	6.16	5.08	4.85	4.71	3.84	4.05	4.39
NM	6.07	6.03	6.66	6.54	6.23	5.15	4.94	4.77	3.91	4.16	4.49
NV	6.09	6.00	6.58	6.47	6.14	5.22	4.99	4.92	4.08	4.23	4.52
NY	6.08	5.98	6.62	6.56	6.18	5.10	4.85	4.67	3.83	4.07	4.38
OH	6.12	6.09	6.66	6.57	6.17	5.14	4.87	4.76	3.90	4.19	4.42
OK	6.26	6.20	6.69	6.63	6.33	5.17	4.97	4.81	3.92	4.13	4.41
OR	6.01	5.97	6.59	6.43	6.08	5.02	4.84	4.77	3.91	4.10	4.42
PA	6.16	6.09	6.64	6.55	6.19	5.14	4.85	4.71	3.79	4.11	4.39
RI	5.99	5.94	6.60	6.46	6.23	5.06	4.98	4.70	4.03	4.13	4.44
SC	6.02	6.01	6.58	6.47	6.16	5.03	4.85	4.72	3.85	4.10	4.41
SD	5.93	5.88	6.47	6.37	6.03	4.99	4.77	4.70	3.70	4.04	4.38
TN	6.10	6.12	6.70	6.51	6.18	5.02	4.86	4.72	3.90	4.09	4.38
TX	6.10	6.20	6.69	6.57	6.23	5.09	4.89	4.74	3.87	4.10	4.39
UT	6.01	6.02	6.61	6.50	6.14	5.06	4.91	4.80	3.85	4.08	4.43
VA	6.09	6.07	6.64	6.46	6.10	5.03	4.83	4.72	3.84	4.06	4.39
VT	6.24	6.11	6.82	6.68	6.29	5.14	4.88	4.75	3.93	4.08	4.40
WA	5.96	5.94	6.55	6.44	6.07	5.04	4.85	4.71	3.89	4.08	4.42
WI	6.02	6.00	6.64	6.54	6.24	5.15	4.90	4.78	3.88	4.08	4.40
WV	6.20	6.22	6.82	6.69	6.23	5.13	4.87	4.89	3.91	4.10	4.42
WY	6.02	5.96	6.57	6.43	6.17	5.03	4.86	4.73	3.73	4.08	4.45

Table A.3: Jumbo/Conforming Spread, 2004-2014

State	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014
AK	0.112	.	.	-0.432	.	0.991	.	.	-0.0633	-0.300	.
AL	0.279	0.169	0.303	0.186	0.886	.	0.994	0.607	1.732	-0.136	-0.0251
AR	.	.	0.188	0.438	.	0.842	.	0.507	0.568	-0.112	-0.0582
AZ	0.0983	0.123	0.0740	0.0872	0.387	1.055	0.574	0.337	0.345	0.0126	-0.258
CA	0.161	0.0786	0.0832	0.0940	0.259	0.193	0.0780	0.0663	0.145	0.00953	-0.190
CO	0.197	0.145	0.314	0.114	0.460	0.644	0.509	0.158	0.277	-0.0938	-0.213
CT	-0.000568	0.147	0.143	0.0723	0.208	0.250	0.145	0.0629	0.151	0.161	-0.242
DC	0.0367	0.0412	0.0774	0.190	0.253	0.197	0.0126	0.153	0.123	0.0600	-0.0199
DE	0.0689	0.141	0.192	0.329	0.620	0.887	0.822	0.243	0.405	0.0217	-0.140
FL	0.148	0.141	0.147	0.126	0.446	0.749	0.599	0.253	0.275	-0.0518	-0.181
GA	0.210	0.0952	0.0690	0.114	0.610	1.007	0.657	0.350	0.285	0.101	-0.184
HI	0.201	0.224	0.0868	0.305	0.350	0.0523	0.120	0.117	0.144	0.0629	-0.316
IA	0.219	0.234	-0.153	0.00400	0.773	0.0399	0.581	0.147	0.424	-0.0803	-0.288
ID	-0.00626	-0.154	0.117	0.249	-0.00507	0.643	0.575	0.353	0.478	0.150	-0.162
IL	0.147	0.155	0.154	0.0995	0.404	0.884	0.610	0.275	0.308	0.0279	-0.176
IN	0.279	0.285	0.195	0.544	.	.	0.536	0.215	0.0871	0.0397	-0.336
KS	0.183	0.0369	-0.0535	0.107	0.0307	0.126	0.219	0.131	0.247	0.128	-0.113
KY	0.222	0.282	0.127	0.444	1.328	.	0.762	.	0.602	0.00517	-0.127
LA	0.115	0.114	0.286	0.0204	.	.	-0.0236	0.191	0.590	-0.00898	-0.0548
MA	0.178	0.0720	0.139	0.0593	0.250	0.207	0.150	0.174	0.292	-0.0604	-0.206
MD	0.188	0.173	0.167	0.278	0.385	0.118	0.0329	0.0867	0.121	0.0548	-0.0187
ME	0.181	0.132	0.0480	0.181	0.488	0.730	.	0.402	0.300	-0.256	0.0224
MI	0.295	0.145	0.274	0.0572	0.158	0.634	0.518	0.305	0.510	0.0639	-0.241
MN	0.259	0.0961	0.105	0.129	0.455	1.268	0.585	0.194	0.277	0.0516	-0.250
MO	0.0881	0.179	0.135	0.172	-0.180	0.473	0.652	0.357	0.545	0.0837	-0.271
MS	0.341	.	0.148	0.101	.	.	.	.	.	.	.

State	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014
MT	0.340	0.450	0.0119	0.202	1.452	.	0.834	0.0977	0.379	0.0894	-0.352
NC	0.150	0.113	0.175	0.267	0.367	0.875	0.600	0.227	0.348	0.0598	-0.226
ND	.	0.332	0.0940	.	.	.	1.185	.	.	.	1.241
NE	.	0.624	0.333	0.156	0.205	.	0.709	0.679	0.553	0.107	-0.0359
NH	0.311	0.151	0.329	0.153	0.444	0.677	0.312	0.572	0.499	0.0844	-0.206
NJ	0.204	0.113	0.233	0.173	0.248	0.199	0.132	0.0255	0.161	-0.00951	-0.234
NM	0.212	0.188	0.105	0.0124	0.888	.	0.852	0.468	0.296	-0.134	-0.172
NV	0.212	0.0168	0.165	0.0926	0.963	0.770	0.606	0.473	0.0843	-0.161	-0.226
NY	0.171	0.192	0.138	0.136	0.245	0.179	0.0868	0.0332	0.161	0.0782	-0.234
OH	0.134	0.167	0.204	0.106	.	0.763	0.409	0.346	0.0895	0.116	-0.271
OK	0.121	0.227	0.287	0.0346	.	1.330	0.413	0.261	0.517	0.114	-0.192
OR	0.0988	0.0625	0.105	0.144	0.464	0.749	0.777	0.101	0.360	0.0586	-0.236
PA	0.201	0.161	0.273	0.219	0.382	0.831	0.438	0.137	0.297	-0.0270	-0.182
RI	0.411	0.0322	0.149	0.130	-0.166	.	0.187	0.0808	-0.0336	-0.0429	-0.281
SC	0.235	0.238	0.122	0.236	0.639	1.099	0.696	0.355	0.353	0.0446	-0.122
SD	0.406	0.0741	.	-0.0859	.	.	.	.	.	0.248	-0.310
TN	0.317	0.359	0.237	0.235	0.602	1.088	0.838	0.216	0.387	0.0747	-0.172
TX	0.344	0.223	0.250	0.126	0.470	0.871	0.592	0.330	0.361	-0.00114	-0.198
UT	0.0789	0.0824	0.371	0.0550	0.328	0.0213	0.0654	0.195	0.186	0.0698	-0.115
VA	0.164	0.124	0.102	0.140	0.329	0.102	0.0693	0.0226	0.0749	0.0373	-0.0908
VT	.	0.321	-0.00133	0.401	.	.	0.294	0.164	0.162	0.181	-0.132
WA	0.150	0.0875	0.160	0.0974	0.273	0.292	0.175	0.0787	0.218	0.00301	-0.191
WI	0.137	0.139	0.173	0.306	0.550	0.895	0.400	0.228	0.602	0.124	-0.205
WV	0.186	0.169	0.258	0.436	.	.	0.214	.	0.0779	.	0.0479
WY	0.444	0.348	-0.361	0.478	.	0.138	0.173	0.0695	0.436	0.202	-0.101

Table A.4: Housing Price Prediction with Different Sample Selection

(a) Panel A: State-level

	$\Delta log(HPI)$, Full Sample		$\Delta log(HPI)$, Restricted Sample	
Variables	(1)	(2)	(3)	(4)
Lag Spread	-0.0212	-0.0253	-0.0438*	-0.0536**
	(0.0173)	(0.0166)	(0.0229)	(0.0221)
Lag Income		-1.03e-05**		-1.15e-05**
		(4.59e-06)		(5.46e-06)
Lag Population		4.15e-09		1.20e-09
		(7.05e-09)		(8.13e-09)
Lag Unemployment Rate		-0.0181***		-0.0196***
		(0.00544)		(0.00624)
Constant	0.112***	0.649***	0.126***	0.763**
	(0.0104)	(0.234)	(0.0133)	(0.287)
Observations	430	430	320	320
R-squared	0.674	0.718	0.697	0.745
# of States	51	51	32	32
State FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES

(b) Panel B: MSA-level

	$\Delta log(HPI)$, Full Sample		$\Delta log(HPI)$, Restricted Sample	
Variables	(1)	(2)	(3)	(4)
Lag Spread	-0.0163**	-0.0179**	-0.0454***	-0.0508***
	(0.00744)	(0.00759)	(0.0138)	(0.0138)
Lag Income		-1.70e-05***		-1.87e-05***
		(3.58e-06)		(6.17e-06)
Lag Population		7.90e-09*		1.32e-08***
		(4.68e-09)		(4.79e-09)
Lag Unemployment Rate		-0.0137***		-0.0204**
		(0.00515)		(0.00834)
Constant	0.141***	0.906***	0.156***	0.965***
	(0.00622)	(0.172)	(0.0109)	(0.318)
Observations	1,271	1,271	580	580
R-squared	0.624	0.667	0.668	0.715
# of MSAs	243	243	58	58
MSA FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES

Loans with a contract rate more than 100 basis points below the monthly median interest rate are excluded from the jumbo/conforming loan spread estimation spread to circumvent loan type misclassification or avoid interest rate outliers.

Table A.5: Housing Price Prediction with Lagged Housing Price

VARIABLES	$\Delta log(HPI)$, Full Sample				$\Delta log(HPI)$, Restricted Sample			
	OLS	FE	FE	System GMM	OLS	FE	FE	System GMM
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Lag Δ log(HPI)	0.715***	0.657***	0.708***	0.603***	0.703***	0.660***	0.699***	0.584***
	(0.0378)	(0.0161)	(0.0343)	(0.0371)	(0.0436)	(0.0170)	(0.0370)	(0.0421)
Lag Spread	-0.0173***	-0.0262***	-0.0317***	-0.0520***	-0.0274***	-0.0326***	-0.0435***	-0.0650***
	(0.00643)	(0.00604)	(0.00663)	(0.0170)	(0.00915)	(0.00920)	(0.00967)	(0.0195)
Lag Income			-4.42e-06*	-7.74e-07***			-5.03e-06*	-9.51e-07***
			(2.52e-06)	(2.31e-07)			(2.92e-06)	(2.41e-07)
Lag Population			5.42e-11	-2.31e-10			-1.84e-09	-3.10e-10
			(5.53e-09)	(2.40e-10)			(6.27e-09)	(2.44e-10)
Lag Unemployment Rate			0.0140***	0.00421*			0.0138**	0.00428
			(0.00505)	(0.00231)			(0.00559)	(0.00263)
Constant	0.00520*	0.0594***	0.182	0	0.00650	0.0664***	0.242	0.0383*
	(0.00305)	(0.00623)	(0.127)	(0)	(0.00402)	(0.00771)	(0.151)	(0.0193)
Observations	429	429	429	429	320	320	320	320
R-squared	0.614	0.832	0.854		0.608	0.842	0.863	
State FE	NO	YES	YES	YES	NO	YES	YES	YES
Year FE	NO	YES	YES	YES	NO	YES	YES	YES
Hansen Test p-value				0.995				1
Number of state	51	51	51	51	32	32	32	32

Table A.6: Housing Price Prediction with Lagged Housing Price_Continued

VARIABLES	$\Delta log(HPI)$, Full Sample				$\Delta log(HPI)$, Restricted Sample			
	OLS	FE	FE	System GMM	OLS	FE	FE	System GMM
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Lag Δ log(HPI)	0.705***	0.638***	0.677***	0.613***	0.689***	0.605***	0.632***	0.581***
	(0.0241)	(0.0187)	(0.0250)	(0.0392)	(0.0364)	(0.0176)	(0.0267)	(0.0317)
Lag Spread	-0.000689	-0.00804	-0.00917*	-0.0866***	-0.0159	-0.0252**	-0.0305***	-0.0633***
	(0.00510)	(0.00536)	(0.00521)	(0.0161)	(0.0104)	(0.0106)	(0.0102)	(0.0168)
Lag Income			-7.42e-06***	-1.05e-06***			-8.04e-06**	-1.08e-06***
			(2.18e-06)	(2.01e-07)			(3.64e-06)	(2.55e-07)
Lag Population			6.39e-09*	-4.62e-10***			9.73e-09**	-2.88e-10*
			(3.27e-09)	(1.38e-10)			(3.83e-09)	(1.70e-10)
Lag Unemployment Rate			0.0211***	0.0119***			0.0205***	0.0122***
			(0.00338)	(0.00217)			(0.00509)	(0.00274)
Constant	0.00146	0.0770***	0.224**	-0.00245	0.00375	0.0888***	0.211	0
	(0.00248)	(0.00487)	(0.109)	(0.0207)	(0.00438)	(0.00791)	(0.187)	(0)
Observations	1,260	1,260	1,260	1,260	570	570	570	570
R-squared	0.535	0.766	0.797		0.527	0.795	0.824	
MSA FE	NO	YES	YES	YES	NO	YES	YES	YES
Year FE	NO	YES	YES	YES	NO	YES	YES	YES
# of MSA	243	243	243	243	57	57	57	57

Lagged housing price appreciation rate is added in the regression as one of the independent variables to account for autoregressive behavior of housing price change.

Table A.7: Correlation between Spread and Fundamentals

(a) Panel A: State-level

	Spread, Full Sample		Spread, Restricted Sample	
	(1)	(2)	(3)	(4)
Lag $\Delta log(HPI)$	0.255	0.819*	0.194	0.650
	(0.356)	(0.449)	(0.390)	(0.487)
Income		8.31e-06		4.10e-06
		(6.56e-06)		(6.72e-06)
Population		-1.56e-08		-2.26e-08
		(1.46e-08)		(1.73e-08)
Unemployment Rate		0.0980***		0.0843**
		(0.0337)		(0.0386)
Constant	0.127***	-0.634	0.114***	-0.324
	(0.0278)	(0.415)	(0.0326)	(0.477)
Observations	430	430	320	320
R-squared	0.581	0.594	0.635	0.646
State FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
# of States	51	51	32	32

(b) Panel B: MSA-level

	Spread, Full Sample		Spread, Restricted Sample	
	(1)	(2)	(3)	(4)
Lag $\Delta log(HPI)$	0.00584	0.0565	0.121	0.333
	(0.168)	(0.200)	(0.191)	(0.233)
Income		3.28e-07		3.75e-07
		(6.69e-06)		(6.22e-06)
Population		-2.45e-08		-1.97e-08
		(1.55e-08)		(1.54e-08)
Unemployment Rate		0.0127		0.0561
		(0.0310)		(0.0345)
Constant	0.151***	0.365	0.118***	0.123
	(0.0223)	(0.431)	(0.0259)	(0.466)
Observations	1,260	1,260	570	570
R-squared	0.376	0.377	0.525	0.529
MSA FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
# of MSAs	243	243	57	57

Table A.8: Housing Price Prediction with Effective Interest Rate Spread

(a) Panel A: State-level

	$\Delta log(HPI)$, Full Sample		$\Delta log(HPI)$, Restricted Sample	
Variables	(1)	(2)	(3)	(4)
Lag Spread	-0.0290	-0.0339**	-0.0493*	-0.0569**
	(0.0180)	(0.0168)	(0.0264)	(0.0247)
Lag Income		-1.06e-05**		-1.15e-05**
		(4.72e-06)		(5.49e-06)
Lag Population		4.25e-09		1.59e-09
		(6.98e-09)		(8.03e-09)
Lag Unemployment Rate		-0.0184***		-0.0195***
		(0.00568)		(0.00625)
Constant	0.114***	0.661***	0.128***	0.755**
	(0.0108)	(0.242)	(0.0140)	(0.289)
Observations	429	429	320	320
R-squared	0.677	0.722	0.700	0.746
# of States	51	51	32	32
State FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES

(b) Panel B: MSA-level

	$\Delta log(HPI)$, Full Sample		$\Delta log(HPI)$, Restricted Sample	
Variables	(1)	(2)	(3)	(4)
Lag Spread	-0.0111	-0.0130*	-0.0410***	-0.0465***
	(0.00676)	(0.00687)	(0.0146)	(0.0141)
Lag Income		-1.70e-05***		-1.87e-05***
		(3.63e-06)		(6.19e-06)
Lag Population		8.19e-09*		1.28e-08**
		(4.76e-09)		(4.95e-09)
Lag Unemployment Rate		-0.0139***		-0.0205**
		(0.00528)		(0.00854)
Constant	0.140***	0.901***	0.157***	0.966***
	(0.00634)	(0.176)	(0.0116)	(0.317)
Observations	1,258	1,258	570	570
R-squared	0.622	0.665	0.667	0.713
# of MSAs	242	242	57	57
MSA FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES

The spread is estimated by using effective interest rate as the dependent variable in the first stage estimation.