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Pricing Credit Risk for Mortgages: Credit Risk Spreads and Heterogeneity across Housing Markets

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We develop a Monte Carlo procedure to project MSA-level house-price paths from 2013 to 2023. These price paths are applied to a fixed portfolio of synthetic mortgages in order to estimate credit risk spreads (CRS) for each MSA. Like the well-known annual percentage rate (APR)–which converts an array of fees into an all-encompassing annual measure of costs to borrowers–the CRS is a holistic measure that encompasses both expected losses from default plus the cost of capital (or unexpected credit losses) needed to cover losses in a stress scenario. We find variation in the CRS across MSAs, with the range spanning 37 basis points. This range spans 86 basis points for those carrying first-loss positions, such as private mortgage insurers. We conclude that, in order to accurately price credit risk, it is necessary to monitor more than borrower characteristics, but also local economic conditions.

Introduction

Federal policies involving mortgage lending do not, for the most part, account for local economic conditions.[1] If some markets are more prone to economic shocks than others, ignoring variation in local economic conditions implies that the true *risk-adjusted* borrowing rates will vary by location. Distorting the price of mortgage credit across locations subsidizes borrowing in high-risk locales at the expense of low-risk ones. In recent years, the government has considered taking further steps to account for variation across

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[1]Local-market characteristics are accounted for *indirectly*. For example, heterogeneity in local economic conditions results in heterogeneity in incomes and employment rates of prospective homebuyers across localities. Federal policies do account for income and employment status, but do not account directly for local factors, such as the local economy or volatility in the local housing market.

markets. Examples include the Federal Housing Finance Agency (FHFA), which, in 2013, announced plans to maintain an adverse market delivery charge (AMDC) of 25 basis points (bps) for mortgages that Freddie Mac and Fannie Mae guarantee in a handful of states with especially high costs associated with default–while discontinuing the AMDC for all other states.[2] Before implementation, the FHFA reopened the policy for discussion. After much input, FHFA ultimately decided against this proposal (FHFA 2015). The experiences surrounding the AMDC are reminiscent of the GSEs plan to use more stringent underwriting parameters (while not increasing fees) for new mortgages in declining markets. In this case, the policy change was implemented in January 2008, but discontinued in May of the same year. Hurst *et al.* (2016) document political pressure, which they conclude was a major factor in preventing these policies from taking hold.

The Federal Housing Administration's (FHA's) mortgage insurance premium (MIP) is another example of a policy that could incorporate spatial variation in credit risk. Under FHA policy, two otherwise identical borrowers will face the same borrowing costs independent of their location. Thus, the risk-adjusted borrowing costs for otherwise identical borrowers will vary by location, because some areas, for example, with higher economic growth that support stronger house-price growth, have a lower probability of default and of losses given default. Even if the premiums for guaranteeing loans covers overall credit losses, some lending markets must be subsidized while others are effectively taxed.[3] In fact, this is exactly what Hurst *et al.* (2016) find for GSE-backed loans. They estimate $14.5 billion in redistribution (measured in present value) through mortgage payments on GSE-backed mortgages originated between 2007 and 2009. When accounting for spillover effects in economic activity and increased house prices brought on by the first-order effects, cross-subsidization rises to $47 billion in present value on originations from 2007 to 2009.

Varying housing policies by local markets is also relevant for objectives other than efficiency or financial stability. The FHA and the GSEs do vary loan limits in light of the vast difference in housing costs across locations. Likewise, on December 22, 2017, President Trump signed into law the Tax Cuts and Jobs Act,[4] which, among other things, limits the deductibility of

[2]Although lenders set the interest rate on the mortgages they originate, loans sold to the GSEs with an ADMC of 25 bps raises borrowing costs by about 5 bps on an annualized basis (FHFA 2015).

[3]Adverse selection becomes a potential problem, since those in the subsidized markets will become relatively more likely to avail themselves of FHA-backed loans.

[4]The legislation is commonly referred to as the "Tax Cuts and Jobs Act," although this title was officially rejected before final passage.

mortgage interest, as well as state and local taxes, against federal income taxes. It is widely accepted that these tax changes will disproportionately increase housing costs for upper and upper-middle income groups living in high-cost and high-tax markets. The increase in post-tax home ownership costs could reduce the value of owner occupied homes in these high tax locations or reduce homeownership in favor of renting.

Although U.S. financial regulations generally do not account for local market conditions, the Canadian government now incorporates supplemental capital requirement on mortgages in certain metropolitan areas (Office of Superintendent of Financial Institutions 2017). For loans insured by regulated entities in Canada, additional capital requirements are triggered if metropolitan area house-price indices, as a share of area per capita income, exceed a set threshold. Although the rationale for the additional capital is not discussed in the regulatory advisory, it is consistent with policies aimed at attenuating house-price cycles. One year after the new regulations, Bloomberg reports "Toronto's housing market has fallen over the past few months as the government has tried to curb demand that had driven prices to record highs with harsher mortgage guidelines and regulations" (Wong and Hertzberg 2018).

Decomposing Mortgage Interest Rates

In addition to a 25-bps fee for loan servicing, interest rates on traditional fixed-rate mortgages can be decomposed into three key components: (1) the risk-free rate, (2) a spread for interest-rate risk and (3) an additional spread for credit risk from default. The rate on the 10 year Treasury note is a common proxy for the risk-free rate component of mortgages. The spread for interest-rate risk is driven by the probability that a borrower will prepay prior to the stated maturity, possibly refinancing at a lower interest rate. The spread for credit risk is driven by the probability that a borrower will default on the loan. These last two components are embedded options. The treatment of interest-rate risk is a call option allowing the borrower to pay off the mortgage at its amortized book value; when market interest rates decline, this option is in the money. The treatment of credit risk is a put option owned for the borrower. The put option allows the borrower to give up (*i.e.*, sell or "put") the house to the lender and in exchange is absolved from paying the remainder of the mortgage (both principal and interest). The term credit risk spread (CRS), as used in this article, refers to the annualized costs of the put. In many states, this option is not *de jure* and, even when it is, it is unlikely that the borrower will simply give up the house with impunity. For example, those exercising this option generally face borrowing impediments for a number of years.

Local Measures of Credit Risk

In this article, we examine how credit risk from default, as measured by the CRS, varies across markets. We simulate common foreclosure practices across states (see Pence 2006)–in order to isolate the effect of heterogeneity in house-price paths and stress scenarios on credit risk. To this end, we estimate CRSs by MSA for large portfolio of mortgages. The CRS can be thought of as an actuarially fair insurance premium for protection in the case of loss from default.

Our process is carried out in two stages. In the first stage we project house-price and stress scenarios by MSA. The house-price scenarios are based on an econometric model and use a variant of a Monte Carlo approach employed by Follain and Giertz (2011a and 2016). In the second stage, we evaluate the credit risk embodied in the price scenarios. Here, house-price scenarios for 50 MSAs are fed into the state-of-the-art model of mortgage default and prepayment developed within FHFA. For the nuts and bolts on the FMAP model, see Dunsky *et al.* (2014).[5] The output from this process and the focus of this article, is the CRS, which is–as described earlier and in more detail later–an annualized measure of the expected credit loss from mortgage default. By holding the set of mortgages constant (along with expected costs from default) when running price scenarios through FMAP, our CRS estimates isolate variation in mortgage credit risk due to MSA-specific economic conditions.

Our article is in the same vein as Hurst *et al.* (2016), who investigate essentially the same question, while focusing on the early 2000s through the Great Recession. Hurst *et al.* first document that mortgage rates on GSE-backed loans (at least for 2001–2009) do not incorporate location-specific risk. Next, they examine whether, *ex ante*, it is possible to incorporate location-specific credit risk into borrowing rates. In place of examining factors contributing to credit risk, they look to data on jumbo loans from the private market. The jumbo market consists of mortgages that exceed conforming loan limits applying to GSE-backed mortgages. Hurst *et al.* then compare borrowing rates on GSE-backed and jumbo loans by location. They control for a wide range of factors that contribute to individual-specific credit risk–*e.g.*, loan-to-value, credit scores, etc.[6]

[5]The model, or Mortgage Analytics Platform (FMAP), incorporates many of the complexities involved in mortgage finance, including nonlinearities between house-price declines and losses.

[6]Of course, the size of the loans cannot be perfectly controlled, since jumbo loans are by definition larger.

Our most important contributions stem from several important distinctions between our work and Hurst *et al.* First, we focus on mortgages originated in 2013, a period when the mortgage market is less volatile and underwriting standards are more consistent and robust. Second, we focus only on spatial variation in credit risk emanating from economic shocks, while holding constant variation in borrower characteristics and assuming a common state foreclosure practice. Therefore, our results are not driven by the varying foreclosure laws across the country. Third, as opposed to examining actual mortgage data, we simulate economic shocks and then employ a mortgage model to assess the credit risk from the estimated responses to our simulated shocks. Thus, even when the housing market and economy are tranquil, we find that *ex ante*, federal housing policy tends to cross-subsidize in favor of higher-risk locations.

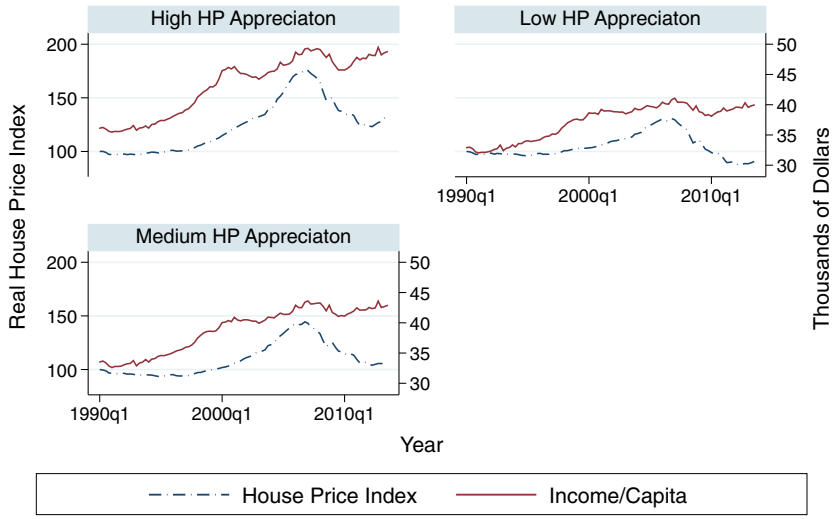
A key finding from our work is that, except when lending standards are extremely high (or loan originators only issue loans to super-prime borrowers), the wide variation in house-price scenarios across MSAs results in significant variation of CRS (even when holding constant both foreclosure processes across states and borrower characteristics). When holding the mortgage portfolio constant, CRS estimates range from 5 bps for Portland to 43 bps for Albuquerque. When we focus on the portion of credit losses typically covered by mortgage insurance the range is 86 bps, from 11 (Austin, Texas) to 97 bps (Albuquerque). The remaining credit risk (for the balance not backed by mortgage insurance and commonly guaranteed by the GSEs) ranges from 2 to 28 bps (or 26 bps).

Data and Trends

Several sources are used to create a pooled-time-series dataset for 97 large MSAs (population greater than 570,000 in 2000) beginning with 1990Q1 and extending through 2013Q3. We run house-price projections for 50 of these MSAs through FMAP to project credit losses from a synthetic set of newly originated mortgages.

Data are from publicly available sources, such as FHFA, the Census Bureau, Bureau of Labor Statistics (BLS) and Bureau of Economic Analysis (BEA). In many cases data were obtained via Moody's Analytics Economy.com Data Buffet. A feature that we use from the Data Buffet is Moody's out-of-sample forecasts produced under various economic scenarios, which we utilize in our house-price simulations. A key variable throughout the analysis is FHFA's purchase-only house price index (HPI). Other key variables include income per capita, employment and single-family home sales at the MSA level.

Figure 1 ■ Mean income and price trends by MSA group. [Color figure can be viewed at wileyonlinelibrary.com]



Note: Dollar values are in thousands and adjusted by the CPI-U with 2010 as the base year. House-price indices are set to 100 in 1990.

For our sample of 97 large MSAs, the average FHFA HPI (weighted by MSA employment) increased by 11% from 1990Q1 to 2013Q3. Real per capita household income over this same time period increased 26%, from $37,300 in 1990Q1 to $47,100 in 2013Q3. See Figure 1 house price and per capita income trends for three groups of MSAs. Employment increased by an average of more than 11%. Dollar values are in real 2010 terms (as adjusted by the Consumer Price Index for urban consumers), unless otherwise stated.

Table 1 presents summary statistics, including a breakdown by three MSA groups. MSA groups are of roughly equal size and are defined by total HPI change from 1990Q1 to 2013Q3. The low-growth group experienced real declines in their HPIs of at least 1% and had average price declines of 8%. The middle-growth group experienced net growth in their HPIs of between −1% and 17%, with an average increase of 9.5%. The high-growth group experience real HPI increases of at least 17%, with an average increase of 29%.

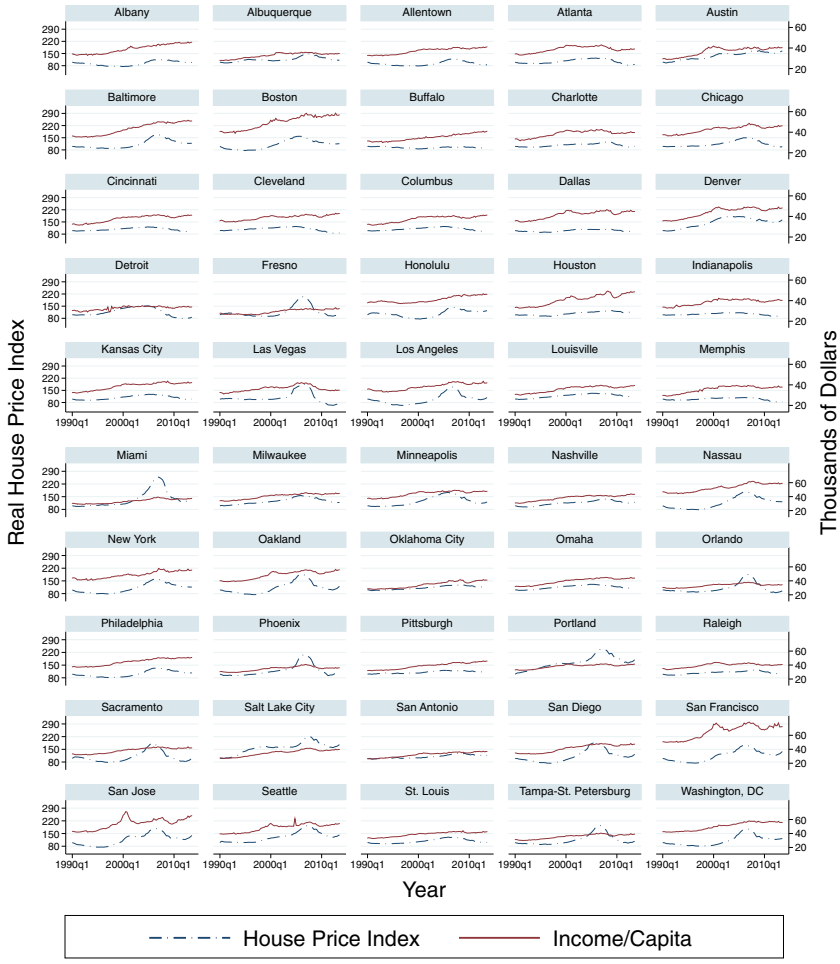
Trends, averaged over groups of MSAs, mask considerable variation across MSAs. Figure 2 present real HPI trends for the 50 MSAs whose projections serve as inputs for our CRS estimates. Table 2 shows HPI growth for each

Table 1 ■ Summary statistics for key variables: 1990Q1–2013Q3.

Low HPI Growth (31 MSAs)	Real HPI	Employment (000)	Income/capita	Single sales (000)	HPI Change, 1990–2013
Mean	107	1,915	39,486	62.6	−8.0%
Std. Dev.	20	1,482	6,683	47.6	0.06
Min	64	126	15,088	4.3	−23.6%
Max	185	4,694	84,086	202.3	−1.2%
Middle HPI Growth (34 MSAs)					
Mean	107	3,772	43,191	66.2	9.5%
Std. Dev.	25	2,856	7,030	43.3	0.06
Min	63	208	19,656	4.5	−0.9%
Max	221	9,651	62,268	180.3	16.9%
High HPI Growth (32 MSAs)					
Mean	122	1,619	45,369	44.6	29.2%
Std. Dev.	32	762	9,169	28.6	0.15
Min	67	48	24,749	0.6	18.1%
Max	258	3,381	78,857	163.1	79.4%
Total (97 MSAs)					
Mean	112	2,641	42,931	58.6	11.1%
Std. Dev.	27	2,310	7,984	41.7	0.17
Min	63	48	15,088	0.6	−23.6%
Max	258	9,651	84,086	202.3	79.4%

Notes: Authors' calculations based on data from FHFA, BEA and Census. Statistics are weighted by MSA employment (except for the employment variable).

Figure 2 ■ Mean income and price trends by MSA. [Color figure can be viewed at wileyonlinelibrary.com]



Note: Dollar values are in thousands and adjusted by the CPI-U with 2010 as the base year. House-price indices are set to 100 in 1990.

of the 50 MSAs over three periods: (1) From 2000Q1–2006Q3, which represents the approximate beginning of rapid house-price growth to the approximate house-price peak; (2) From 2006Q3–2013Q3, which spans from the approximate peak to our most recent data; (3) From 2001Q1–2013Q3, the full period, which includes both the bubble and bust. These dates are necessarily approximate, partly, because the date varies by MSA and some MSAs

Table 2 ■ Percent change in real house price index and the price cycle.

MSA	2000q1–2006q3	2006q3–2013q3	2000q1–2013q3	MSA	2000q1–2006q3	2006q3–2013q3	2000q1–2013q3
Detroit	−0.8	−36.6	−37.1	Pittsburgh	11.6	−2.5	8.8
Cleveland	1.2	−26.3	−25.4	Oklahoma City	15.1	−5.3	9.1
Atlanta	12.4	−28.6	−19.7	Salt Lake City	26.2	−13.2	9.4
Memphis	2.6	−21.7	−19.7	Buffalo	12.2	−2.4	9.5
Las Vegas	85.7	−56.7	−19.6	Fresno	119.7	−49.3	11.3
Cincinnati	5.3	−20.1	−15.8	San Antonio	18.9	−4.6	13.3
Indianapolis	0.8	−14.0	−13.4	Sacramento	95.7	−42.1	13.4
Columbus	5.2	−17.4	−13.1	Portland	46.0	−22.3	13.5
Chicago	35.9	−34.2	−10.6	Seattle	48.2	−23.2	13.8
Kansas City	11.3	−19.6	−10.5	Houston	13.9	0.9	14.9
Omaha	6.2	−13.4	−8.0	Boston	49.6	−23.0	15.2
Charlotte	8.7	−15.3	−7.9	Oakland	84.9	−34.1	21.8
Louisville	7.3	−12.3	−5.9	Austin	14.1	6.9	22.0
Raleigh	6.6	−10.5	−4.6	San Jose	55.9	−21.2	22.9
Milwaukee	24.7	−23.2	−4.2	Philadelphia	57.0	−19.7	26.0
St. Louis	22.8	−21.5	−3.7	Miami	127.3	−44.1	27.1
Orlando	88.5	−48.0	−1.9	Nassau	80.0	−29.3	27.3
Minneapolis	38.1	−28.1	−0.7	New York	72.3	−26.1	27.3
Dallas	5.6	−4.9	0.5	Baltimore	79.5	−28.3	28.7
Albuquerque	32.0	−22.9	1.8	San Francisco	60.8	−19.3	29.8
Denver	11.6	−7.5	3.2	Albany	50.8	−12.9	31.3
Nashville	15.3	−10.4	3.3	San Diego	96.5	−32.7	32.3
Phoenix	81.1	−42.6	4.1	Washington, DC	101.5	−29.0	43.0
Tampa	90.4	−44.0	6.7	Los Angeles	123.5	−35.2	44.7
Allentown	50.1	−28.1	7.9	Honolulu	83.1	−12.4	60.5

Note: Authors' calculations based on FHFA's MSA-Level House-Price Index.

(*e.g.*, Dallas and Memphis) do not experience rapid house-price growth; it is this heterogeneity that serves as a motivating theme of our work. A simple comparison of HPI levels over this time period shows that MSA-level house-price patterns vary greatly across MSAs. For example, 11 MSAs experienced house price growth of less than 9% from 2000Q1 to 2006Q3, with cumulative HPI appreciation for these 11 MSAs averaging 4.4% through the most recent data, 2013Q3.

MSAs experiencing no real price bubble include long-term declining cities such as Detroit and Cleveland, who despite not experiencing a bubble, were hit hard by the bust. See Follain (2010). This group (with no bubble to speak of) also includes MSAs that where only modestly hit by the bust, such as Dallas, Raleigh and Omaha.

A second set of 13 MSAs experienced real HPI growth during the bubble of between 11.3% and 26.2%. While this is strong house-price growth, it is not extraordinary for a seven year period. At the other end of the spectrum, 32 of our 50 MSAs experienced house-price growth of 50% or more over this seven year period. Seven of these 32 MSAs experienced price growth exceeding 90%, while four saw house prices more than double. At the extreme are Fresno, Los Angeles and Miami, where house prices rose by between 120% and 127%. Again, Figure 2 illustrates the great heterogeneity in the economic experiences across MSAs, comparing house prices and per capita income. For example, the three MSAs with the greatest price growth through 2006Q3 all show a sharp divergence with per capita income and all experience severe sharp house-price declines post-2006Q3. Many of the MSAs in our sample exhibit similar patterns, however, only relatively modest and gradual divergences or convergences between house prices and incomes are observed. This house price and income phenomenon is well documented. However, we argue that policymakers have all too often turned a blind eye to this variation, making the U.S. financial system more susceptible to systemic risk. That is, using national trends to price credit risk under prices risk in high-risk areas and over prices risk in low-risk areas. Moral hazard by borrowers may leave lenders or guarantors holding portfolios with greater risks.

Methodology

This section is divided into three parts. First, we present an autoregressive model used to estimate house-price growth. We explored including an error-correction equation and a multiequation vector autoregression (VAR) to project all of our MSA-specific variables. However, our projections are more robust and more plausible using a simpler approach, which relies on out-

of-sample predictions from Moody's for variables other than house prices.[7] Second, we review how the results from the autoregressive model are used to project both expected out-of-sample house-price paths, as well as stress scenarios. Third, we discuss our forecast of credit losses and the formulation of the CRS.

Autoregressive Model

We estimate a house-price equation in first differences and expressed such that

$$\begin{aligned}\Delta\log(HP_{it}) = \alpha_t + \alpha_{group} + \sum_{j=1}^{8}\left(\beta_{1j}\Delta\log\left(HP_{it-j}\right)\right)\\ + \sum_{j=1}^{8}\left(\beta_{2j}\Delta\log\left(Emp_{it-j}\right)\right) + \sum_{j=1}^{8}\left(\beta_{3j}\Delta\log\left(Inc_{it-j}\right)\right)\\ + \sum_{j=1}^{8}\left(\beta_{4j}\Delta\log\left(Sales_{it-j}\right)\right) + \delta_1(TB10_{t-4} - TB1_{t-4})\\ + \delta_2 TB10_t + \epsilon_{it}. \qquad (1)\end{aligned}$$

The log change in real house prices (*HP*) for MSA i in quarter t are regressed against lagged values of the location-specific variables, where j the number of quarters prior to t. Explanatory variables include log changes of employment (*Emp*), income per capita (*Inc*) and single-family home sales (*Sales*). Also included among the regressors is the 10 year Treasury rate (*TB*10) because it is strongly correlated with multiyear fixed rate mortgage interest rates and is exogenous–*i.e.*, not a function of borrower characteristics. Mortgage interest rates, by contrast, are not exogenous. An increase in mortgage interest rates could reflect a general increase in borrowing costs, driving house prices lower; or, it could reflect the fact that lenders have expanded credit to riskier borrowers, driving house prices higher. Additionally, a one year lag of the yield spread ($TB10_{t-4} - TB1_{t-4}$), where $TB1$ is the one year Treasury rate, is included because it has been shown to be a good predictor of real economic activity (*e.g.*, Estrella and Mishkin 1998, Gürkaynak and Wright 2012). Akaike information criterion (AIC) test statistics support the inclusion of eight quarterly lags for the four MSA-specific variables. Year

[7]Including a separately estimated error-correction term has conceptual advantages. However, in practice, *ad hoc* adjustments were often required to produce sensible house-price projections. Even with such adjustments, projections for a substantial minority of MSAs remained anomalous.

(α_t) and group (α_{group}) fixed effects measure the influence of unobservables not explicitly included in the estimation—and which often are not available in sufficient detail and spanning many years. In estimating credit risk, we focus on out-of-sample projections produced iteratively from the *HP* equation and, for the other variables, we use projections from Moody's Economy.com. More details are presented shortly.

Estimated coefficients on lagged growth in house prices and employment can help distinguish between markets characterized by price momentum and those characterized more by mean reversion. Positive estimated coefficients on the house-price lags suggest momentum (or self-reinforcing) effects. For example, all else equal, the more positive the momentum effect (or the sum of the lagged coefficient estimates), the more sensitive are projected price changes and thus the more fragile the housing market. In such markets, an initial negative shock suggests continued price declines. This could characterize price bubbles, where behavior such as speculation or weak underwriting standards can lead to periods of rapid price increases and, after peaking, rapid price decreases.[8]

Lags of other variables, such as employment and per capita income growth, are intended to capture more traditional changes in housing demand. National factors, such as interest rates and the lagged term structure, are part of the model, but much of their influence will be absorbed by the year fixed effects. Thus, these national variables estimate the residual influence of within-year variation in interest rates, etc.

We define bubbles as scenarios in which asset prices rise substantially above those dictated by economic fundamentals, or above prices consistent with the risk-adjusted present value of rents from a property. Note, however, that rapid declines in house prices could also result from unexpected events, even when agents are fully rational. Such events would have similar negative consequences for borrowers and guarantors. For example, suppose prices in an area are based largely on the strength of the oil industry. An unexpected shock to this industry could cause a sharp drop in house prices. This house-price scenario could look just like a bubble; however, it would not be driven by momentum effects or irrational elements. Our approach for projecting house-price paths and stress scenarios applies to "irrational" bubbles and busts as

[8]Other factors, sometime independent, but often interrelated contribute to momentum effects. For example, see Follain (2012) who shows the importance of distressed real estate in understanding house price changes mid crisis. Also, see Duca, Muellbauer and Murphy (2011) who emphasize the importance of credit constraints (or the supply of mortgage credit) after the bubble peak.

well as price swings due to unexpected shocks. In sum, credit risk is higher during bubbles, but also in rationally-priced markets that have a higher, but still low, probability of a negative price shock. Examples of the latter may include MSAs dominated by a single industry or those with greater risk of natural disaster or civil unrest, etc.

Simulating House-Price Paths

We use our regression results in conjunction with Moody's projections for other economic variables to produce out-of-sample house-price forecasts for each MSA. We employ a Monte Carlo simulation based on an approach developed by Follain and Giertz (2011a and 2016) to construct house-price stress scenarios. We project house prices out 10 years (40 quarters).

Each set of projections uses the estimated regression coefficients from the house-price-growth equation (Equation (1)). To generate an expected distribution of price paths, we also use Moody's baseline projections for the other lagged economic variables in our model, see Equation (2). To generate stress scenarios, we use Moody's most negative or "protracted slump" scenario for these other variables.[9] In each case, and for each MSA, 500 house-price paths are simulated. A random variable is added to each iteration (*i.e.*, for each quarter) of the house-price projection process, producing distributions of projected price scenarios. (Select price paths from the projected distributions are run through FMAP to estimate credit losses.) Thus, predicted (or projected) values, based on Equation (1), can be expressed such that

$$\begin{aligned}\log\left(\widehat{HP}_{it}\right) = \hat{\alpha}_t + \hat{\alpha}_{group} + \sum_{j=1}^{8}\left(\hat{\beta}_{1j}\Delta\log\left(HP_{it-j}\right)\right)\\ + \sum_{j=1}^{8}\left(\hat{\beta}_{2j}\Delta\log\left(Emp_{it-j}\right)\right) + \sum_{j=1}^{8}\left(\hat{\beta}_{3j}\Delta\log\left(Inc_{it-j}\right)\right)\\ + \sum_{j=1}^{8}\left(\hat{\beta}_{4j}\Delta\log\left(Sales_{it-j}\right)\right) + \hat{\delta}_1(TB10_{t-4} - TB1_{t-4})\\ + \hat{\delta}_2 TB10_t + N\left(0, \hat{\sigma}_t^2\right). \qquad (2)\end{aligned}$$

[9]It is possible that using external projections, in place of a full VAR, removes randomness from these other variables reducing the variation in our house-price projections. Ultimately, this depends on the interrelationship between the estimated equations from a VAR approach. For example, do the other equations in the system tend to offset the effect of shocks to the house-price equation? Do they tend to reinforce the shocks? Or, are the effects of the other equations independent of what happens with the house-price equation?

Over the 10-year horizon, Moody's baseline and protracted slump scenarios begin and end at roughly the same points. The main difference between the projected scenarios (for employment, income per capita and single-family home sales) is that the protracted slump scenarios begin with a negative shock persisting for roughly three years. This slump is followed by somewhat faster growth so that the protracted-slump and baseline scenarios begin to converge in the quarters following the slump.

Relying on Moody's for these endogenous variables removes the feedback mechanism between the equations. For example, with a multiequation system, a shock in employment in projection period 1 affects house prices, house sales, income and employment in period 2. In turn, the effect of the period 1 shock on all four of these variables in period 2 has additional effects on period 3 projections for each variable, plus the employment shock in period 1 also directly influences all period 3 projections, because it is a lag in each equation. As the projection proceeds, the channels of influence continue to grow to where it quickly becomes impossible to identify the driving factors underlying the projections.

Variation in the projected house-price paths (for each MSA) results from the last term in Equation (2), $N(0, \hat{\sigma}_t^2)$, which is a normally distributed random variable with mean 0 and a standard deviation equal to the standard error of the regression (or root-mean-square error, RMSE). The starting lagged values, used to project for the first out-of-sample quarter, are the actual historical values of the economic variables in the 8 quarters just prior to the end of the sample (*i.e.*, running through 2013Q3).

Alternative Approaches for Stress Scenarios

The approach that we propose for producing stress scenarios is one among many. For many years, historical house-price paths have been used to assess credit risk. This approach was dominant in the years leading up to the crisis. For example, consider the ALMO-based stress scenarios. ALMO stands for states Arkansas, Louisiana, Mississippi and Oklahoma. The ALMO stress test is based on the experiences of these states during the 1980s. ALMO did not perform well leading up to the 2008 crisis. However, this does not mean that it could not perform better with modifications (Follain and Giertz 2011a).

Yet another alternative, employed by Palmer (2015), uses an instrument for house price paths, where in-sample prices follow the same national price cycle, but the severity of the price cycles vary greatly based on historical MSA-specific price swings. These constructed price trends, which do not al-

low for market-specific shocks, are then compared to actual house-price paths. Deviations between the two paths are attributed to market-specific factors.

CRS: Modeling Credit Risk

The CRS is the annualized cost of default, expressed in bps–where 0.01 percentage points equals 1 basis point–as a share of the original loan balance. In the case of a mortgage portfolio, loan-level results are aggregated. While the measure is annualized, it captures credit losses occurring over the life of the mortgages, which we approximate as a 10 year period because nearly all credit losses on mortgages occur during this period. The CRS consists of two main components: expected annual credit losses (*EL*) plus the cost of capital held in reserve (*K*). The capital reserve equals the present value of stress losses minus expected losses.[10] The annualized cost of capital represents forgone returns from investing these reserve funds in a risk-free asset. Thus, the CRS can be expressed such that

$$\text{CRS} = \left(\frac{EL + (r - r_{rf})K}{debt} \right) \cdot 10,000, \tag{3}$$

where r is the normal return to investments by the lender and r_{rf} is the risk-free rate of return.[11]

While the CRS reflects the risk associated with mortgages, in many cases, a mortgage is backed by multiple entities. For example, in many instances, loans with original LTVs greater than 80% must include a credit enhancement, typically mortgage insurance.[12] The mortgage insurer is in a first-loss position (after homeowner equity), yet their loss is limited to foreclosure costs plus the mortgage insurance coverage percentage times the defaulted unpaid principal

[10]An alternative means of financing mortgage portfolios is directly via equity. In such an approach, investors would purchase equity stakes in the mortgage portfolios. Thus, debt financing with a capital reserve would be replaced with equity (or partial equity) financing. Direct-equity financing would not require capital reserves invested in risk-free assets, since the costs of a stress event would be borne by shareholders. Admati and Hellwig (2013) advocate this approach to mortgage finance, arguing that the current heavy reliance on debt financing is to a large degree the result of government policies that insulate debt holders from market risk. It is also well known that the U.S. tax system heavily favors corporate debt over equity (e.g., see Burnham 2014).

[11]Follain and Sklarz (2005) and Calem and Follain (2007) use this expression (i.e., Equation (3)) to compute credit risk spreads.

[12]Increasingly during the early 2000s, borrowers opted for second (or "piggyback") mortgages for borrowing that would have put them beyond the GSEs' LTV ceilings. MI is not required on piggyback mortgages, which are in the first-loss position and also not backed by the GSEs.

Table 3 ■ Mortgage pool: Loan counts.

	Credit-Score Groups				
Loan-to-Value Ratio	680–699	700–719	720–739	740–759	Total
80–85	1,593	2,249	2,841	161	6,844
85–90	7,804	10,340	13,596	764	32,504
90–95	11,213	15,982	22,618	1,319	51,132
Total	20,610	28,571	39,056	2,224	90,481

Note: Authors' calculations based on a synthetic loan pool.

balance. The most common mortgage insurance coverage percentage is 25%. Mortgage insurance covers the portion of property not held in equity (by the borrower) and in the case of default, proceeds from the mortgage insurance claim will reduce the bank or GSE credit losses.

The overall CRS does not reflect the risk to any one entity, because loans may be backed by multiple investors holding different loss positions. Should a loan default, MI providers, holding the first-loss position (after homeowner equity), bear considerably greater risk (per dollar insured) than the investors in the second-loss position (*e.g.*, GSEs, investors in GSE credit risk securities,[13] banks, etc.). Only if losses exceed the MI provider's coverage do investors in the second position incur losses. Thus, we decompose the CRS measure into two components, the first-loss component covered by a mortgage insurance company and the remaining losses.

We construct two sets of newly originated synthetic mortgages: one set is very low risk while the second set is comprised of higher risk loans. Both loan sets contain approximately 100,000 mortgages. The low-risk loan set generates very low CRS estimates and little variation across MSAs. This suggests that, when the quality of mortgages is very high, and economic conditions are sound (which was the case for GSE-originated loans in 2013), the efficiency gains from varying mortgage costs by location would be modest. This statement pertains only to variations in credit risk due to differences in house-price paths and stress scenarios across locations–and not to differences in individual characteristics or state foreclosure practices.

We focus on the riskier loan set summarized in Table 3. All of the loans in the riskier group are assumed to hold mortgage insurance and about 93% of

[13]Examples of GSE credit risk securities are Freddie Mac's Structured Agency Credit Risk (STACR) and Fannie Mae's Connecticut Avenue Securities (CAS).

loans in this pool have loan-to-value ratios (LTVs) between 85% and 95% and credit scores between 681 and 740. For 23% of borrowers, credit scores are between 680 and 700. No borrowers have credit scores under 680. While our mortgage pool is risky compared to the majority of loans acquired by the GSEs in 2014, it is likely less risky than comparable loans insured by the FHA during the same period.

In order to implement Equation (3), we calculate credit loss by discounting the sum of charge-offs and real-estate owned (REO) operations expenses (also called foreclosed property expenses), which are estimated within FMAP. Future values are discounted at the one month London Interbank Offered Rate (LIBOR). A charge-off occurs when the title of the property is transferred, for example, when foreclosure is completed, or the property is sold in a pre-foreclosure (or third party) sale. The amount of the charge-off is the difference between the defaulted unpaid principal balance and the expected house-price value on the charge-off date net of foreclosure, and ancillary disposition expenses. REO operations expenses are the monthly carry cost associated with REO properties after foreclosure and prior to sale; for example, maintenance, property taxes and insurance. Elements in the charge-off and REO operations expenses are mutually exclusive and reflect the values based on the projected house-price path. For our simulations, we held loan portfolios constant and built a common foreclosure and disposition timelines, so as to isolate credit losses due to the house price paths and other local economic conditions.

Results

This section includes (1) a discussion of the regression results used to generate the house-price scenarios; (2) an overview of the house-price projections; and (3) an overview of the implications that the house-price scenarios have for losses (from credit risk) for the mortgage portfolio discussed in the previous section. For estimates of a wider range of specifications and for subsets of the period included here, see Follain and Giertz (2011b and 2012).

Regressions Results, 1990Q1–2013Q3

Results from the house-price-growth equation, for the three groups, are presented in Table 4. On balance, the house-price lags show a strong positive and statistically significant association with current house prices. The relationship is similar across the three groups. The sum of the lagged coefficient estimates is about 0.72 for each group. Coefficient estimates on the first and third lags are always positive and much larger than for the other lags. These results suggest a momentum effect, where price increases beget further increases and declines beget further declines. By contrast, negative estimates would

Table 4 ■ Autoregression with eight lags. Dependent variable = Δlog (Nominal House Price Index).

HP Volatility:	Low	Medium	High
Δlog (Real House Price)			
qtr 1 lag	0.418	0.368	0.445
	(0.082)	(0.057)	(0.031)
qtr 2 lag	−0.093	−0.003	−0.069
	(0.038)	(0.039)	(0.043)
qtr 3 lag	0.326	0.334	0.364
	(0.026)	(0.028)	(0.027)
qtr 4 lag	0.137	0.117	0.060
	(0.066)	(0.067)	(0.040)
qtr 5 lag	0.002	−0.046	−0.068
	(0.035)	(0.029)	(0.042)
qtr 6 lag	−0.047	0.024	−0.007
	(0.021)	(0.021)	(0.029)
qtr 7 lag	0.003	−0.070	−0.007
	(0.015)	(0.021)	(0.021)
qtr 8 lag	−0.035	0.009	0.006
	(0.028)	(0.018)	(0.024)
Δlog (employment)			
qtr 1 lag	0.159	0.157	0.124
	(0.042)	(0.031)	(0.023)
qtr 2 lag	0.110	0.130	0.032
	(0.044)	(0.026)	(0.051)
qtr 3 lag	−0.059	−0.084	−0.092
	(0.039)	(0.038)	(0.051)
qtr 4 lag	−0.046	−0.093	−0.053
	(0.050)	(0.048)	(0.035)
qtr 5 lag	0.097	0.078	0.054
	(0.043)	(0.032)	(0.046)
qtr 6 lag	0.016	0.091	0.002
	(0.048)	(0.045)	(0.037)
qtr 7 lag	−0.074	−0.045	0.051
	(0.039)	(0.030)	(0.033)
qtr 8 lag	0.001	0.079	0.067
	(0.038)	(0.029)	(0.038)
Δlog (income/capita)			
qtr 1 lag	0.022	0.013	0.089
	(0.013)	(0.016)	(0.021)
qtr 2 lag	0.065	0.108	0.136
	(0.024)	(0.020)	(0.024)
qtr 3 lag	0.057	0.041	0.039
	(0.015)	(0.012)	(0.018)
qtr 4 lag	0.047	0.051	0.029
	(0.019)	(0.020)	(0.020)
qtr 5 lag	0.032	0.044	0.026
	(0.016)	(0.017)	(0.021)
qtr 6 lag	0.023	−0.023	0.018
	(0.015)	(0.023)	(0.020)

Table 4 ■ Continued.

HP Volatility:	Low	Medium	High
qtr 7 lag	0.037	0.092	0.058
	(0.018)	(0.019)	(0.022)
qtr 8 lag	0.039	−0.002	0.042
	(0.011)	(0.023)	(0.024)
Δlog (single home sales)			
qtr 1 lag	−0.001	0.004	0.007
	(0.004)	(0.003)	(0.003)
qtr 2 lag	0.018	0.017	0.019
	(0.006)	(0.006)	(0.003)
qtr 3 lag	0.018	0.024	0.020
	(0.006)	(0.004)	(0.003)
qtr 4 lag	0.013	0.018	0.006
	(0.006)	(0.005)	(0.003)
qtr 5 lag	0.003	0.004	0.003
	(0.005)	(0.005)	(0.003)
qtr 6 lag	0.002	0.005	0.003
	(0.005)	(0.004)	(0.003)
qtr 7 lag	0.014	0.013	0.012
	(0.005)	(0.005)	(0.003)
qtr 8 lag	0.012	0.008	0.005
	(0.003)	(0.004)	(0.003)
10−Yr Treas	−0.007	−0.004	−0.004
	(0.001)	(0.001)	(0.001)
Lagged Term Structure	−0.001	−0.001	−0.001
	(0.001)	(0.001)	(0.001)
Constant	0.042	0.020	0.022
	(0.007)	(0.007)	(0.008)
RMSE	0.011	0.010	0.011
Observations	2,494	2,408	2,287
R−squared	0.712	0.757	0.757

Notes: Robust standard errors are in parentheses. Year and quarterly dummies are included in all specifications.

suggest mean reversion. While positive coefficients are consistent with price bubbles, they could also reflect slow movements (due to frictions) between equilibriums. For example, a city in decline will be unlikely to experience a sharp drop in the housing stock but may rather experience persistent price declines over many years as the housing stock slowly depreciates.

Estimated coefficients for employment are positive and substantial for the first two lags. The sum of these lagged coefficients ranges from 0.12 for the smallest MSA group to 0.16 for the two larger groups.

The modest coefficient estimates for employment could be consistent with several scenarios. One, it could imply a weak link with what are traditionally considered core fundamentals. Two, it could imply that employment trends were accurately anticipated and previously incorporated into house prices. Three, it could imply that house supply is very elastic. Four, to a certain extent, the relationship between house prices and employment goes both ways. Employment growth drives up housing demand. But, house-price increases, all else equal, makes an area less desirable for worker and firms–because higher wages are presumably required to offset the higher cost of living.

Turning to income per capita, lagged growth has a much stronger relationship for the high-appreciation group than for the other two. For the high-appreciation group, the sum of lagged coefficients equals 0.44 and 0.32 the low and medium groups. While income is a core fundamental to the extent that it produces "rational" increases in demand, it can also contribute to bubbles, if short-term (and rational) income growth evolves into unreasonable expectations for long-term price growth. This phenomenon may play out with a other variables, in addition to income. With income, however, the effect is compounded if current income is a key determinant of individual borrowing limits. During price bubbles, some buyers may borrow at or near the limit allowed by creditors and not make home bids based on a rational estimation of the present value of long run returns (Shiller 2005).[14]

The sum of lagged coefficient estimates for single-family home sales are generally positive, with coefficient sums ranging from 0.08 for the low-appreciation group to 0.09 for the medium-appreciation group. Home sales captures a combination of supply and demand factors. The overall results are consistent with growth in home sales driven by demand and associated with rising prices. While the relationship is modest, it is consistent with simple trends, which generally show sales increasing with prices and plummeting during housing slumps.

The interest-rate is statistically significant while the lagged term structure is not. These variables do not vary across MSAs. Year and quarter dummies are

[14]One likely contributor to irrational expectations of future house-price appreciation was the Taxpayer Relief Act of 1997, which eliminated taxes on most capital gains from owner-occupied housing. In reference to the Act, Gjerstad and Smith (2014, p. 149) note: "any asymmetric reduction in taxes on homes implies that a larger fraction of capital will flow into home investment away from other forms of capital investment in pursuit of higher after-tax returns . . . [And,] in moving to that equilibrium, any increase in the expected rate of home price appreciation also would raise the short-run momentum demand for homes."

included to control for unobserved factors that are similar across MSAs but vary over time. Thus, year and quarter dummies absorb most of the variation in the national variables, which helps explain the small residual impact from the national interest rate measures.[15] Also, note that the regression standard errors are nearly identical across specifications. These standard errors are an important component of the Monte Carlo exercise.

House-Price Projections: 2013Q4–2023Q3

Out-of-sample house prices are projected for 50 MSAs for 2013Q4–2023Q3 using the regression estimates based on data extending through 2013Q3. While full monthly price paths are imputed, here we provide an overview by showing the cumulative change in projected house prices for each MSA at 3 points over the 10 year period.[16] For each MSA, house prices after year 3, 7 and 10 are divided by the HPI at month 1. Thus, ratios above 1 suggest real price appreciation, whereas, values less than 1 suggest real depreciation.

Table 5 highlights total price changes at the median of our distributions, as well as at the first percentile, which we view as stress scenarios.[17] As previously noted, we use our estimated house-price equation to project house prices but rely on projections from Moody's for our other economic variables. The stress scenarios are based on Monte Carlo simulations using Moody's protracted-slump scenarios, while our expected scenarios use Moody's baseline projections for the other economic variables.

As reported in Table 5, we project a 1% likelihood of an average nominal price decline of 14% (or 36% in real terms, assuming 2% annual inflation) after 10 years (column (5)). At the median, we project, on average, that house prices will roughly keep pace with overall inflation, rising by 25% in nominal terms (column (6)).

On average, after 10 years, median projected prices exceed stress prices by 39 percentage points (comparing columns (5) and (6)). The range (subtracting column (5) from column (6)) is from 8 (Boston) to 79 (Sacramento)

[15]If a dummy were included for every quarter, the effect of any national variable would be totally wiped out.

[16]House prices are projected at the quarterly level. A linear path is assumed for the intervening months between each quarterly projection. Monthly values are needed as input for FMAP.

[17]This is a bit of a simplification, in that first percentile in terms of price appreciation may not also be at first percentile in terms of credit loss. MSAs that, all else equal, experience price declines in the earlier quarters or have slower recoveries will have greater losses.

Table 5 ■ Nominal house price projections and credit risk spreads. House prices expressed as the future price divided by the October 2013 price.

	HP at 3 Years		HP at 10 Years		HP at 10 Years		CRS after 10 Years		
Percentile	0.01	0.50	0.01	0.50	0.01	0.50	Overall	GSEs	MIs
Albuquerque	0.75	0.93	0.65	0.89	0.69	0.94	43	28	97
Nassau-Suffolk	0.76	1.04	0.66	1.05	0.70	1.11	30	20	68
Chicago	0.78	1.10	0.64	1.10	0.68	1.16	29	20	61
Boston	1.05	1.08	1.02	1.10	1.08	1.16	25	15	59
Pittsburgh	0.79	1.01	0.79	1.00	0.83	1.06	25	14	66
Fresno	0.91	0.99	0.80	0.95	0.84	1.01	25	13	66
Charlotte	0.76	1.19	0.68	1.25	0.72	1.32	24	17	52
Seattle	0.76	1.20	0.70	1.23	0.74	1.30	24	16	53
Salt Lake City	0.74	1.23	0.69	1.26	0.73	1.34	23	16	51
Memphis	0.81	1.05	0.77	1.06	0.82	1.13	22	13	59
San Diego	0.75	1.27	0.72	1.31	0.76	1.39	22	15	48
Milwaukee	0.84	1.02	0.81	1.03	0.86	1.09	21	11	60
Phoenix	0.79	1.17	0.71	1.20	0.76	1.28	21	14	48
Miami	0.78	1.11	0.77	1.11	0.82	1.17	21	12	54
Philadelphia	0.92	1.00	0.82	1.00	0.87	1.06	21	11	58
Tampa	0.80	1.17	0.74	1.19	0.78	1.26	20	12	47
San Antonio	0.88	1.10	0.75	1.16	0.80	1.23	19	11	49
St. Louis	0.91	1.00	0.89	0.99	0.95	1.05	19	9	56
Cincinnati	0.82	1.11	0.79	1.14	0.84	1.21	18	10	49
Buffalo	0.83	1.18	0.76	1.21	0.80	1.29	18	11	45
Omaha	0.84	1.05	0.85	1.07	0.90	1.13	18	9	52
Dallas	0.80	1.20	0.78	1.28	0.83	1.35	18	11	44
Washington, DC	0.87	1.05	0.84	1.07	0.90	1.13	18	9	51

Table 5 ■ Continued.

	HP at 3 Years		HP at 10 Years		HP at 10 Years		CRS after 10 Years		
Percentile	0.01	0.50	0.01	0.50	0.01	0.50	Overall	GSEs	MIs
Los Angeles	0.79	1.19	0.71	1.20	0.76	1.27	17	14	29
Allentown	0.86	1.09	0.82	1.14	0.87	1.21	16	9	46
Houston	0.87	1.18	0.78	1.24	0.83	1.31	16	9	42
Sacramento	0.81	1.42	0.75	1.50	0.80	1.59	16	11	37
Kansas City	0.97	1.03	0.90	1.02	0.96	1.08	16	7	49
Denver	0.86	1.24	0.77	1.29	0.82	1.37	15	9	37
New York	0.95	1.05	0.87	1.06	0.92	1.12	15	7	45
Cleveland	0.84	1.12	0.86	1.14	0.91	1.21	15	7	43
San Francisco	0.94	1.22	0.78	1.22	0.83	1.29	14	8	37
Columbus	0.85	1.18	0.82	1.21	0.87	1.29	14	8	39
Baltimore	0.82	1.00	0.71	0.99	0.75	1.05	14	6	44
Honolulu	0.86	1.21	0.83	1.25	0.88	1.32	14	7	38
Detroit	0.87	1.16	0.86	1.13	0.91	1.20	14	7	39
Oklahoma City	0.96	1.12	0.82	1.18	0.87	1.26	13	7	38
Nashville	0.97	1.13	0.96	1.15	1.02	1.22	12	4	44
San Jose	0.83	1.37	0.82	1.43	0.86	1.52	12	7	31
Indianapolis	0.96	1.19	0.83	1.23	0.88	1.31	12	6	34
Louisville	1.08	1.07	0.90	1.08	0.95	1.15	12	5	38
Raleigh	0.88	1.26	0.84	1.36	0.89	1.44	12	6	32
Oakland	0.86	1.33	0.85	1.36	0.90	1.45	11	6	30
Minneapolis	0.96	1.13	0.90	1.15	0.96	1.22	11	5	33
Albany	0.92	1.18	0.90	1.22	0.95	1.29	10	5	31

Table 5 ■ Continued.

	HP at 3 Years		HP at 10 Years		HP at 10 Years		CRS after 10 Years		
Percentile	0.01	0.50	0.01	0.50	0.01	0.50	Overall	GSEs	MIs
Orlando	0.94	1.30	0.84	1.35	0.89	1.43	10	6	28
Atlanta	0.94	1.25	0.91	1.32	0.97	1.40	8	4	24
Las Vegas	0.96	1.48	0.93	1.60	0.98	1.70	6	3	19
Austin	0.92	1.21	0.89	1.29	0.94	1.37	6	5	11
Portland	1.10	1.17	1.09	1.20	1.16	1.27	5	2	19
Average	0.87	1.15	0.81	1.18	0.86	1.25	17	10	45
Std. Dev.	0.09	0.11	0.09	0.14	0.10	0.15	7	5	15

Notes: Authors' calculations. See the previous section for a discussion of the Monte Carlo simulation used to produce distributions of projected house-price paths. Percentiles for stress scenarios are based on cumulative price changes after 10 years. CRS measures are with respect to risk in force. It is assumed that 21% of initial outstanding debt is backed by parties holding a first-loss position (such as mortgage insurers). The remaining 79% is held in a second-loss position (by the GSEs or other parties). The overall CRS is a weighted sum of the MI and GSE CRS and not the simple sum of the two components.

percentage points. The small difference between Boston's median and stress scenarios is driven primarily by its mild stress scenario, which is the second mildest among the 50 MSAs. The extreme difference for Sacramento, on the other hand, is driven primarily by its strong median projection, which is second strongest among the 50 MSAs.

Focusing on the 1% scenarios, the steepest total price drop is for Chicago, where the cumulative effect of the 10 year stress scenario is a nominal 32% price (54% real) drop. Furthermore, Baltimore, Seattle, Salt Lake City, Charlotte, Nassau-Suffolk and Albuquerque all had 1% nominal declines in excess of 25%.

At the other extreme, Portland's 1% scenario shows a cumulative nominal price appreciation of just 16%, while Boston and Nashville show nominal appreciation of 8% and 2%, respectively. The median MSA has a 1% scenario with a 13% nominal price decline after 10 years.

Variation in projections across cities emanates from several factors. One factor is the estimating equation used for the projections. As discussed earlier, house-price growth equations are estimated separately for three groups of MSAs (see Table 4). On average, projections for MSAs in groups 1 and 2 are almost the same. However, median projections for group 2 MSAs are about 7% lower than for the other groups. Out of the 15 MSAs with the weakest median price paths, ten are from group 2.

Another important factor driving the projections is cross-MSA variation in the lagged (in-sample) observations used to start the projections. Quarterly house-price growth, in the 8 quarters prior to the first projection period, is directly correlated with stress severity and weak median projections. Chicago, Albuquerque and Nassau-Suffolk have the most severe stress scenarios, and all have nominal house-price growth in the eight quarters of in-sample data (fed into the model) that averages about 0. By contrast, average house-price growth across all 50 MSAs over these eight quarters (in nominal-annualized terms) is 3.7%. For the four MSAs with the least severe stress scenarios, lagged house-price growth averaged 5.4%.

For some MSAs, lags for the other economic variables and not lagged house prices, seem to dominate. For example, consider Fresno. Fresno has the second weakest median house-price projection, despite having nominal house-price growth averaging more than 6% (annualized) over the last eight quarters of in-sample data. However, Fresno's strong house-price growth leading into the projections was more than offset by weakness in other areas, such single-family home sales, which, for the eight quarters preceding the projections,

were the weakest among all 50 MSAs–declining by more than 22% per year on average.

Accuracy of Projections, 2013Q4–2016Q3. In Table 6, we compare our median projections to actual FHFA price data for the first three years of our projection period. On average, nominal prices rose 20% in the actual data and by 14% in the projected data. In a couple of cases, such as Seattle and Las Vegas, we projected rapid appreciation, far exceeding actual appreciation. However, more often than not, we projected slower appreciation that what actually occurred. We attribute this primarily to the unusually strong housing market over these few years. On an annual basis, we projected real price appreciation at a healthy 2.7% rate. By contrast, the actual experience was real growth at a 4.7% rate. For a handful of MSAs, our projections were tepid while actual appreciation was extremely rapid. These were our biggest misses. For example, (cumulative) nominal price appreciation ranged from 25% to 34% for Fresno, Salt Lake City, Cleveland, San Diego and Miami. Although, our projected price appreciation for these MSAs ranged from −2% to 12%.

Regressing actual against projected appreciation for this three year period yields an estimated coefficient of 0.2 with a t-statistics of 1.9. The coefficient of determination is 0.07. If we drop the biggest misses, leaving 42 states, our estimated coefficient and corresponding t-statistic double (to 0.4 and 3.9) and the coefficient of determination jumps to 0.28.

Comparing Stress Scenarios to the Post-2006 Crisis. For purposes of comparison, consider FHFA peak-to-trough price declines surrounding the post-2006 crisis and peak-to-trough declines from our projected stress scenarios (see Table 7). These MSAs reached a price nadir between 2008 and 2013, with an average peak-to-trough real decline of 30%. For comparison, the average peak-to-trough decline from our 1% stress scenario (for these same MSAs) for 2013–2023 was 31%. During the crisis, real peak-to-trough declines ranged from 8% to 66%. For our later projected stress scenario, real peak-to-trough declines range from 11% to 45%.

While the average peak-to-trough declines are nearly identical for our stress scenario and the post-2006 crisis, the crisis represents a more severe stress event for many of the hardest hit MSAs. In fact, nine MSAs have crisis declines exceeding the hardest hit for our stress scenario. However, this is counterbalanced by a number of MSAs for which the 2008 crisis did not represent a serious stress event. Thus, for cities such as Houston, Buffalo, Oklahoma City, Pittsburgh and Austin, we project 1% stress scenarios, even

Table 6 ■ Nominal HPI appreciation. Actual versus projected, 2013Q4 –2016Q3.

MSA	Actual	Projected	Projected–Actual
Seattle	12.5	35.4	22.9
Las Vegas	29.6	45.6	16.0
San Francisco	10.6	25.9	15.3
Raleigh	13.8	24.7	10.9
Oakland	21.4	31.4	10.1
Sacramento	30.6	39.9	9.3
Los Angeles	10.3	17.5	7.2
Indianapolis	13.3	18.3	5.0
Denver	18.2	23.0	4.7
Charlotte	13.7	18.3	4.6
Honolulu	15.1	19.6	4.4
Houston	14.4	17.0	2.6
Allentown	7.4	8.8	1.4
Portland	15.3	15.4	0.1
Dallas	19.8	19.0	−0.8
Columbus	18.0	17.0	−1.0
Minneapolis	13.8	12.5	−1.2
Orlando	29.9	28.6	−1.3
San Antonio	23.4	22.1	−1.3
Atlanta	26.5	23.8	−2.7
Chicago	12.2	9.0	−3.2
Albany	20.6	17.1	−3.5
Buffalo	20.4	16.8	−3.6
Nashville	15.6	11.8	−3.7
Boston	12.3	7.2	−5.0
Baltimore	6.0	−0.2	−6.1
Detroit	20.5	14.3	−6.2
Washington, DC	10.9	4.4	−6.5
Memphis	13.0	4.6	−8.4
Louisville	15.2	6.2	−9.0
Pittsburgh	10.3	0.5	−9.8
Cincinnati	21.3	10.9	−10.4
Austin	32.9	19.9	−13.0
Kansas City	15.7	1.9	−13.8
Philadelphia	14.0	−0.1	−14.0
Phoenix	29.7	15.6	−14.1
Oklahoma City	26.0	11.7	−14.3
Omaha	19.3	4.4	−14.9
San Jose	35.2	20.2	−14.9
Tampa	33.1	16.2	−16.9
Albuquerque	10.5	−7.2	−17.8
Nassau−Suffolk	21.4	3.5	−17.9
St. Louis	37.4	18.5	−19.0
New York	24.5	4.2	−20.4
Milwaukee	22.9	1.5	−21.4
Miami	32.2	10.4	−21.8

Table 6 ■ Continued.

MSA	Actual	Projected	Projected–Actual
San Diego	33.8	9.7	−24.0
Cleveland	36.8	11.8	−25.0
Salt Lake City	24.9	−0.2	−25.1
Fresno	29.9	−2.1	−32.0
Average	20.3	14.1	−6.2

Notes: Projected appreciation is the median projection from the Monte Carlo model. Actuals are from FHFA.

though the crisis was only a bump in the road for these MSAs (at least when measured by the HPI).

While it is instructive to compare our stress price declines to those from the crisis, note that we are not attempting to replicate the crisis. By contrast, our aim is to simulate a crisis given the conditions leading into 2013, as opposed to those leading up to the 2006 peak. This helps explain the relatively weak relationship between our stress declines and those during the crisis. For example, regressing peak-to-trough declines from the crisis against those from our stress scenario yields a positive estimated coefficient, but this estimate is small, 0.12, and not statistically significant. Another difference between our simulation and the crisis is that declines during the crisis were generally more protracted. All of our stress scenarios reach their trough prior to year 5.

For 22 MSAs, peak-to-trough stress scenarios are within 10 percentage points of actual post-2006 price declines. For the most part, MSAs with stress scenarios much more severe than for the crisis had only modest crisis declines. The most pronounced example is Buffalo (see Table 7) which experience a crisis real price decline of just 8% but a project 1% scenario decline of 36%. At the other extreme are MSAs hit especially hard during the crisis. The most pronounced example is Las Vegas, which has a projected 1% real price decline of 20% but an actual crisis real price decline of 66%.

The last two columns of Table 7 report estimated credit losses for the peak-to-trough house-price declines for both the projected and actual crisis numbers. Credit losses for the projected period are commensurate with the relative depth and duration of the house-price paths. For a given price decline, price drops that occur more quickly (following loan origination) tend to convey greater losses.[18] In cases where peak-to-trough paths are similar for the crisis

[18]An exception could be an instance where a sharp drop is followed a sharp price increase.

Table 7 ■ Peak-to-trough crisis real price declines versus post-2013 stress projections.

	Pre-2013: Actual Data			2013–2023: Stress Projections		Losses as % Original Balance	
	Peak Year	Trough Year	Peak-to-Trough Decline (%)	Peak-to-Trough Decline (%)	Projected less Crisis (%)	Pre-2013 Actual Path	Post-2013 Projected Path
Albany	2006	2014	19.0	23.1	4.1	1.1	1.8
Albuquerque	2006	2013	27.0	44.6	17.5	2.0	5.8
Allentown	2006	2013	31.5	31.4	−0.1	2.7	2.9
Atlanta	2006	2012	36.3	25.1	−11.2	3.4	1.6
Austin	2008	2011	10.8	22.1	11.3	1.0	1.0
Baltimore	2006	2012	31.8	16.5	−15.3	3.0	0.8
Boston	2005	2012	27.5	39.3	11.8	2.1	4.7
Buffalo	2006	2012	8.4	35.8	27.5	0.7	3.8
Charlotte	2007	2012	23.3	41.6	18.3	2.0	5.4
Chicago	2006	2012	37.7	45.4	7.7	3.9	5.8
Cincinnati	2005	2013	24.4	31.2	6.8	1.2	3.4
Cleveland	2003	2013	32.2	25.8	−6.4	1.3	2.6
Columbus	2005	2012	23.6	30.0	6.4	1.2	2.9
Dallas	2006	2012	13.9	33.7	19.9	0.9	3.9
Denver	2003	2011	21.7	34.4	12.7	0.8	3.3
Detroit	2003	2012	50.7	26.1	−24.6	4.4	2.4
Fresno	2006	2012	55.9	33.0	−23.0	8.1	2.9
Honolulu	2007	2012	18.5	28.0	9.5	1.5	2.9
Houston	2007	2011	9.4	33.3	23.9	0.7	3.4
Indianapolis	2003	2012	20.8	30.9	10.0	0.8	2.4
Kansas City	2006	2012	23.6	23.1	−0.5	1.7	1.7
Las Vegas	2006	2012	66.0	19.7	−46.3	10.5	1.6
Los Angeles	2006	2012	44.0	39.0	−5.0	6.5	3.7
Louisville	2006	2012	16.2	28.0	11.8	1.1	1.4
Memphis	2006	2012	25.0	32.2	7.1	1.8	3.7
Miami	2007	2012	53.2	32.9	−20.3	8.3	3.9
Milwaukee	2006	2013	26.9	31.1	4.2	2.1	3.1

Table 7 ■ Continued.

	Pre-2013: Actual Data			2013-2023: Stress Projections		Losses as % Original Balance	
	Peak Year	Trough Year	Peak-to-Trough Decline (%)	Peak-to-Trough Decline (%)	Projected less Crisis (%)	Pre-2013 Actual Path	Post-2013 Projected Path
Minneapolis	2005	2012	36.2	24.9	−11.3	3.2	1.7
Nashville	2006	2012	18.5	17.4	−1.0	2.5	2.0
Nassau-Suffolk	2006	2013	31.7	43.6	11.9	3.0	5.5
New York	2006	2013	30.7	26.0	−4.7	2.8	1.9
Oakland	2006	2012	47.7	25.7	−22.0	6.6	2.6
Oklahoma City	2007	2011	11.3	32.3	21.0	0.8	2.4
Omaha	2005	2013	17.7	25.8	8.1	0.9	2.6
Orlando	2006	2012	55.3	29.1	−26.2	8.4	2.3
Philadelphia	2006	2012	21.0	31.2	10.2	1.4	2.6
Phoenix	2006	2011	57.0	39.3	−17.6	8.7	4.5
Pittsburgh	2006	2012	9.1	31.5	22.4	0.7	3.7
Portland	2006	2012	33.0	11.0	−21.9	3.1	0.5
Raleigh	2007	2012	17.3	26.1	8.8	1.4	2.6
Sacramento	2005	2012	55.6	34.8	−20.8	8.0	4.0
Salt Lake City	2006	2013	24.9	23.3	−1.6	3.2	5.4
San Antonio	2007	2012	29.4	40.6	11.2	0.9	3.7
San Diego	2007	2012	12.1	36.1	23.9	5.7	5.1
San Francisco	2005	2012	44.2	35.7	−8.5	2.9	3.0
San Jose	2006	2011	32.4	32.8	0.4	4.2	2.9
Seattle	2006	2012	35.1	32.3	−2.9	4.1	5.2
St. Louis	2007	2012	34.5	39.0	4.6	1.8	2.0
Tampa	2006	2012	50.9	39.3	−11.6	7.6	4.1
Washington, DC	2006	2012	34.5	26.2	−8.3	4.0	2.6

Notes: Data from the crisis are measured from peak-to-trough. Stress projections are measured over the first 48 months. The last two columns show credit total credit losses as a percentage of outstanding loan balances.

and the projected 1% scenario, estimated credit losses are also similar. Note that the duration of the crisis price declines varies across MSAs, while the durations for our 1% price declines are similar across MSAs.

Projected (*i.e.*, post 2013) stress scenarios that were milder than their crisis counterparts (*e.g.*, see Baltimore or Portland) tended to have smaller credit losses. The reverse is also true; MSAs where stress scenarios were more severe than their crisis counterparts tended to have larger credit losses (*e.g.*, see Albuquerque or Charlotte). However, credit losses are not always proportional to price declines. Credit losses are a nonlinear function of house-price declines, with credit loss accelerating when price declines push house values below outstanding debt. Furthermore, economic variables also play a role in the capital model (in addition to their role in our model for house-price projections). Differences in these economic variables, across the two time periods, also led to differences in estimated credit losses. This notwithstanding, when comparing credit losses for the two sets of scenarios, the credit-loss model yields estimates consistent with our expectations.

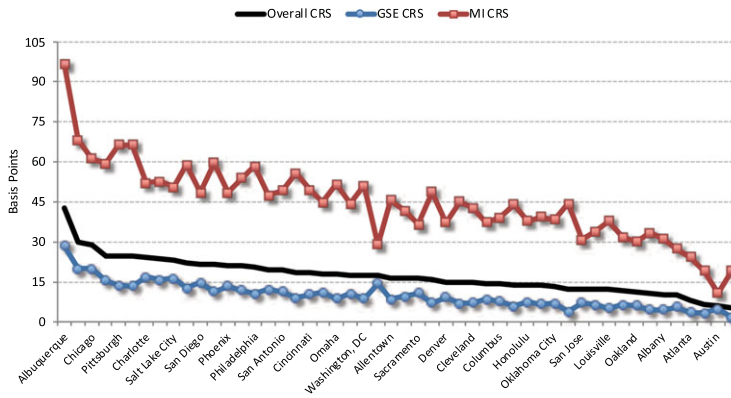
CRS by MSA

Recall that the CRS is the annualized loss from default, expressed in bps as a share of the initial loan balance for the portfolio. The two components that make up the CRS are expected annual credit losses (*EL*) and the cost of capital, which equals the forgone returns from investing economic capital (equal to the difference between estimated losses in a 1% stress scenario and expected losses) in risk-free assets. See Equation (3).

To isolate variation in credit losses resulting from the house-price scenarios only, we hold the mortgage portfolio constant across MSAs. To be clear, one would want to vary borrower characteristics in the mortgage-portfolio in order to estimate the actual CRS by MSA. However, our goal is not to produce MSA-specific CRSs, but to show how heterogeneity in projected house-price paths and stress scenarios affect CRS measures, holding other factors constant. That is, we are interested in the effects of heterogeneity in local-market conditions on CRS, as opposed to the effects heterogeneity in borrower characteristics on CRS.

CRS estimates for the MSAs are plotted in Figure 3 and presented in Table 5. MSAs are reported in descending order based on the overall CRS. For each MSA, we report the (1) overall CRS, (2) GSE CRS and (3) MI CRS. The overall CRS is measured per dollar of the original loan amount. The GSE component is measured per dollar of the GSE guaranteed original loan amount. The MI CRS is measured per dollar of the insured original loan

Figure 3 ■ Credit risk spreads by MSA (annualized basis points). [Color figure can be viewed at wileyonlinelibrary.com]



Source: Author's calculations using data from various government sources and FHFA's FMAP model. See the previous section for details.

amount (or risk in force). Conceptually, the three measures of CRS should be ordered, such that the overall MI CRS is the highest, with the GSE CRS the lowest, and the overall is a weighted average of these two components. Albuquerque has the highest overall CRS at 43 bps, while Portland, Oregon, has the smallest overall CRS at just 5 bps (for a range of 38 bps). The average CRS among these MSAs is 17 bps, while the overall CRS for the median MSA is 16 bps.

The overall CRS estimates, for this relatively risky loan portfolio, supports some variation in fees to account for heterogeneity in credit risk across locations. Breaking the CRS down into a first-loss component ascribed to the MI coverage (MI CRS) and a second-loss component for the GSEs (or other credit investors net of mortgage insurance coverage), Table 5 shows variation across MSAs for both groups. As expected, MI CRS is greater than GSE CRS because the level of loss severity on the defaulted balances covered by the mortgage insurers is greater than the loss severity of the GSE-CRS guaranteed portion of the loan. The MI CRS also reveals greater range and standard deviation across the MSAs than the MI GSE measure. The MI CRS component has a standard deviation of 15 bps and a range of 86 bps while the GSE CRS has a standard deviation of 5 bps with a range of 27 bps. The greater variation in MI CRS across MSAs suggests that the MIs would benefit from MSA-level premium pricing more than the GSEs would from varying G-fees by MSA. Recall that Hurst *et al.* (2016) reports that MIs in fact do vary prices by location; however, this variation may be driven by variation in

state foreclosure practices across states, as well as susceptibility to negative price shocks.

Using a portfolio comprised of high down-payment loans with credit scores in the mid-700s yields much less variation in credit risk across MSAs. For this low-risk loan portfolio, and given current economic conditions, efficiency concerns do not warrant varying guarantee fees across MSAs. However, if the government were to pursue policies to combat price bubbles or excessive credit risk, doing so at a subnational level offers many advantages over policies that do not allow for variation across markets.

Recall that the variation in CRS estimates that we report is driven only by differences in projected house-price paths–both expected paths and stress scenarios. Other factors, such as the mortgage portfolio and borrower characteristics are held constant. Our results suggest that for two identical borrowers purchasing the same home with the same mortgages, the borrower in Seattle (higher credit risk due to house prices) is subsidized by the borrower in Austin (lower credit risk due to house prices). If mortgage credit were priced at the MSA level, the borrower in Austin would be paying less than her identical twin in Seattle.

Note, varying policies by local markets can combat either localized price bubbles or excessive credit risk. The correlation between price bubbles and credit risk is often strong, but not always. For example, with riskier loan sets, the prospects of sharp price drops following bubbles implies substantial credit risk. However, with low-risk loan sets (namely, low LTV loans), credit risk may increase only slightly with a bubble, because a substantial drop in house prices will be unlikely to wipe out homeowner equity. As a case in point, the fact that stock investors were not highly leveraged, may help explain why the bursting of the tech bubble of the late 1990s was associated with little disruption in financial markets.

Conclusion

Follain and Sklarz (2014) examine monthly house-price data on 90 million properties spanning 5,500 ZIP codes and in so doing "help debunk the notion of a national housing market." In comparing price per square foot of housing for their ZIP codes to a national index, they find about 15% to 20% of local markets deviate from the national index by more than 50%. They also show great variation in house-price growth rates across ZIP codes (from 2005 to 2013). This variation is great across states, but they also note substantial within state variation. It is thus not surprising that we find variation across markets in other aspects of housing markets, including price

paths, stress scenarios and credit risk from large negative shocks to house prices.

When examining a large pool of mortgages, we find that the susceptibility to a negative price shock results in substantial differences in credit risk across markets. The exception is when down payments are high, in which case, mortgage credit risk remains low in all markets. In the presence of heterogeneity in credit risk across markets, the mortgage market tends to subsidize housing in high-credit risk areas, while penalizing it in low-credit risk areas.

We demonstrate that credit risk can vary widely across local housing markets when incorporating local house-price projections and stress scenarios, as opposed to relying on a national economic scenario that is invariant across markets. Table 5 points to an average CRS of 17 bps over 50 MSAs with the range extending from a high of 43 bps (Albuquerque) to a low of 5 bps (Portland). Results from our econometric model for projecting house-price scenarios are consistent with some key aspects of the recent boom and bust; that is, wide variation in the impact of the bubble and bust among metropolitan areas. Thus, it is critical to pay closer attention to credit risk entailed in local markets, particularly when LTVs rise, or borrower credit scores decline.

A system that incorporated this variation in credit risk into prices (for mortgages, for example), investors' required return on equity, or even regulatory capital, would mitigate local price bubbles, instead of fueling them. At the same time, varying policy across markets would not cause collateral damage to stable markets by raising borrowing costs across the board. A variety of policy tools could be tweaked to achieve this objective. These policies would result in higher borrowing or funding costs in housing markets where house-prices are expected to decline (*e.g.*, markets more susceptible to large price drops or to a stagnant job market), and lower borrowing (or funding) costs in markets where house prices are supported by stronger fundamentals. One policy for accounting for variation in credit risk is to require higher amounts of capital for loans originated in riskier metropolitan areas (or at riskier times) and vice versa. We do not explicitly report those capital ratios in this article, but they underlie the calculations of the CRS. In cases where variation in credit risk across locations is small, then risk-based policies would call for little or no variation in the price of credit, conditional on borrower characteristics. However, in such situations, it is important to continually monitor risk, as both the riskiness of mortgage portfolios and the susceptibility to negative price shocks change over time.

These results are relevant for the ongoing debate about how to combat house-price bubbles and more generally towards the design of macroprudential policies to reduce systemic risk. Follain and Giertz (2013) support the view that it is prudent for borrowing costs (or lender capital required for loans) to rise in areas where the threat of a bubble and bust are more pronounced. For example, increases in capital in the Sand States (Arizona, California, Florida and Nevada) in the years prior to the bust would have slowed the growth in the demand for housing and the rate of house-price appreciation. Not doing so fueled the bubble to ever greater heights. More recently, Canada implemented policies designed to stem rapid increases in house-prices. As a result, strong price momentum in Toronto was quickly reversed (Wong 2018). The new rules require all Canadian homebuyers to undergo a stress test before taking out a loan. Other measures make explicit adjustments for local market conditions.

In sum, an important lesson from our work is that variation in local-market conditions is a critical feature of the US housing market. Policies targeting systemic risk or stress scenarios should take account of local-market conditions. One size surely does not fit all markets.

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