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Alex Bogin
LaRhonda Ealey
Kirsten Landeryou
Scott Smith
Andrew Tsai

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Working Paper 23-02

FEDERAL HOUSING FINANCE AGENCY
Division of Bank Regulation
Credit Risk Modeling Branch
400 7th Street SW
Washington, DC 20219, USA

Please address correspondence to Alex Bogin (alexander.bogin@fhfa.gov). We would like to thank Will Doerner, Anju Vajja, Andrew Davenport, Marianne Gerrard, Nataliya Polkovnichenko, Alice Sheehan, and Vivian Wong for their contributions to the paper.

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Abstract

We explore the impact of geographic disaggregation of house price stress paths on single-family credit risk measurement. Specifically, we focus on the value added of moving from national, to state-level, to core-based statistical area (CBSA)-level house price paths on estimates of mortgage credit related stress losses. To ensure the robustness of our results, we estimate losses across two different loan portfolios and three credit models. We find that CBSA-level paths provide additional insight on localized credit risk and can be reliably constructed using quarterly house price indices. Further, the variation in results across credit models suggests an implicit confidence interval around any one stress loss estimate. Accounting for this uncertainty through a model risk add-on could potentially offer a more conservative view of portfolio credit risk.

Key words: geographic aggregation • credit modeling • countercyclical

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Alex Bogin
Federal Housing Finance Agency
Division of Bank Regulation
400 7th Street SW
Washington, DC 20219, USA
alexander.bogin@fhfa.gov

LaRhonda Ealey
Federal Housing Finance Agency
Division of Bank Regulation
400 7th Street SW
Washington, DC 20219, USA
larhonda.ealey@fhfa.gov

Kirsten Landeryou
Federal Housing Finance Agency
Division of Bank Regulation
400 7th Street SW
Washington, DC 20219, USA
kirsten.landeryou@fhfa.gov

Scott Smith
Federal Housing Finance Agency
Division of Bank Regulation
400 7th Street SW
Washington, DC 20219, USA
scott.smith@fhfa.gov

Andrew Tsai
Federal Housing Finance Agency
Division of Bank Regulation
400 7th Street SW
Washington, DC 20219, USA
andrew.tsai@fhfa.gov

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1. Introduction

Risk managers calculate credit risk for single-family mortgages by running a portfolio of loans through a prepayment-default model, which estimates lifetime losses conditional on a macroeconomic scenario. The macroeconomic scenario consists of two primary components – a series of house price paths and interest rate projections. The house price paths are key to estimating credit-related stress losses because defaults and hence credit losses only materialize to the extent that house prices decline by more than any equity or credit support attached to the mortgage loan.[1] House price indices (HPIs) are available at different levels of regionalization. This paper explores the implications of incorporating different levels of regionalization on the severity of stress loss estimates. Specifically, we focus on the value added of moving from national, to state-level, to core-based statistical area (CBSA)-level house price paths on estimates of mortgage credit related stress losses.[2]

Additional geographic granularity allows for a given macroeconomic scenario to capture variation in house price dynamics within most states. For example, instead of assuming the same house price path across Texas, we can craft a macroeconomic scenario with a different price trajectory in a large city like Houston versus a smaller city like El Paso. This additional flexibility allows us to more accurately capture localized house price dynamics and the underlying credit risk associated with loans in each area.

We produce a series of regional stress paths by leveraging the scenario construction methodology that Smith and Weiher (2012) originally developed, and Smith et al. (2016) further tested, hereafter referred to as the Countercyclical Mortgage Asset Stress Test (CMAST).[3] CMAST is a framework by which we can develop stress scenarios using only historical house prices while preserving the regional level of granularity. In other words, if we input historical state-level HPIs, the CMAST framework will generate state-level house

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[1] For purposes of single-family credit risk measurement, house price movements are the primary driver of stress losses. Interest rate projections, which determine borrower refinance incentives, are the second major driver. Macroeconomic scenarios may include additional projections for other economic variables such as gross domestic product (GDP) and unemployment, but these generally have a tertiary effect on losses (Tajik et al., 2015; Jones and Sirmans, 2015).

[2] A CBSA is a geographic area consisting of one or more counties that is anchored to an urban center of at least 50,000 people. We currently use the Census Bureau delineations the Office of Management and Budget provides in Bulletin No. 20-01 (released in March 2020).

[3] The state-level framework has been tested additionally using a theoretically based statistical technique to identify a conservative lower bound (Bogin, Bruestle, Doerner, 2017).

price stress paths. Alternately, if we input historical CBSA-level HPIs, the CMAST framework will generate CBSA-level house price stress paths.[4] This same flexibility is not available in other commonly used approaches such as the Federal Reserve's Comprehensive Capital Analysis and Review (CCAR).[5,6] CMAST is also rules-based and dynamically adjusts to current market conditions, making it particularly well suited because of its ability to automatically rescale based upon the granularity of the included inputs.

Using the CMAST framework to generate stress scenarios, we estimate losses across two dissimilar U.S. loan portfolios and three credit models. We employ multiple portfolios and models to examine the robustness of the results. We find that the magnitude of stress loss estimates can vary considerably across both loan portfolios and credit models, but the rank order of losses with respect to the geographic disaggregation of the associated house price stress paths remains the same. Specifically, we observe the lowest level of stress losses when applying the same national house price path to all loans. Estimated losses then monotonically increase as we move to state- and then CBSA-level house price paths.[7] We find that these CBSA-level paths, which we can reliably construct using quarterly HPIs, provide a more accurate measure of localized credit risk.[8] In Section 2, we describe why disaggregated stress paths are more likely to result in larger stress loss estimates, and subsequently verify this result in our findings.

Finally, examining variation in stress losses across credit models provides an estimate of one component of model risk. This variation suggests an implicit confidence interval around any stress loss estimate generated from a single model. We can account for this additional source of uncertainty through a model risk-add on, which could provide a more conservative view of portfolio credit risk

We structure the remainder of the paper as follows. In the next section we motivate the research. In the third section, we discuss scenario construction, and in the fourth section we describe our loan data. The fifth section introduces the magnitude of loss estimates across geographies. The sixth section presents

[4] The major concern with using more geographically disaggregate HPIs is that the number of transactions underlying each index estimate may decrease to the point where there are too few observations to estimate a particular index value reliably. This form of estimation error can be significantly mitigated through more aggressive temporal aggregation. Specifically, instead of estimating a series of monthly indexes, we can move to a series of quarterly indexes, which allows us to aggregate three months of sales and refinance data, thus increasing the sample size used to estimate each index value.
[5] Additional information on the use of CCAR in stress testing is available in Clark and Ryu (2013).
[6] The analysis we provide in this paper and the mortgage stress test we will describe would be applicable to any housing market that is structured similarly to the United States.
[7] This monotonic increase is a result of the non-linearity of the borrower default with respect to house price declines, which is described in additional detail in section 2.
[8] In future research, we hope to explore other forms of disaggregation such as constructing house price stress paths based upon property characteristics or home price tiers.

differences in loss estimates across credit models, which provides a measure of potential model risk. We conclude in the final section.

2. Motivation

The frequency and amplitude of house price cycles can vary significantly across locations. During the Great Financial Crisis (GFC), inflation-adjusted or real house prices fell by 31.6 percent nationally between their peak in Q4 2006 and their trough in Q1 2012.[9,10] We observed even larger price decreases in states like California, where real house prices fell by 54.0 percent, and Nevada, where real house prices fell by 64.9 percent. In contrast, the crisis had a muted effect in states like Texas where real house prices fell just 12.4 percent.

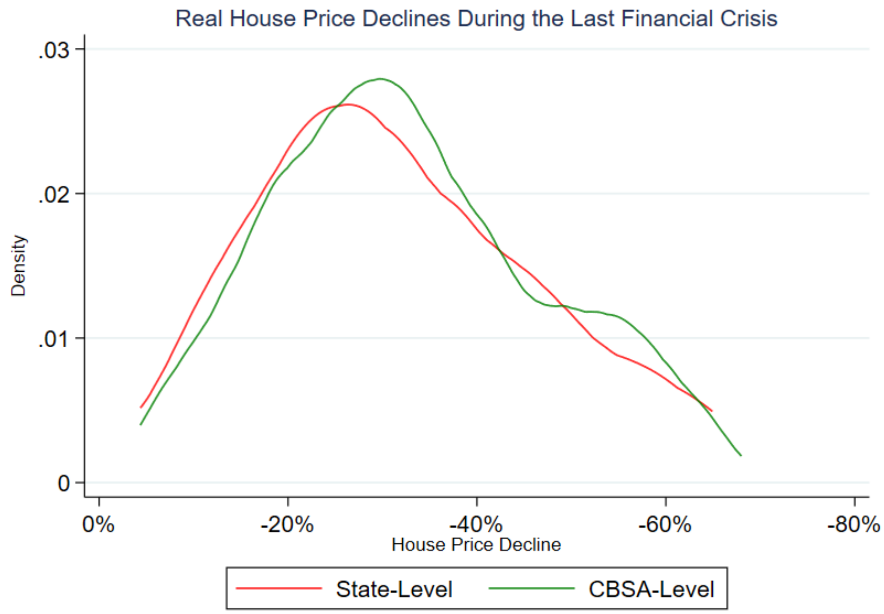
We also observe substantial variation within states when we examine CBSA-level prices. For example, within California, real house prices fell by 38.7 percent in San Jose, 46.0 percent in San Diego, 47.2 percent in Los Angeles, and 58.7 percent in Riverside. In other words, within the same state, we observed a range of house price declines as large as 20 percent. When measuring credit risk on a portfolio of loans only using a state-level house price path, we fail to account for potentially substantial variation within states.[11]

The additional information contained within CBSA-level house price movements is further evidenced in Figure 1, which shows the historical distribution of price declines at the state- and CBSA-levels during the GFC.[12] The median price decline across CBSA-level paths is 31.1 percent while the median price decline across state-level paths is 29.1 percent. The CBSA-level distribution is also characterized by a fatter right-hand tail indicating more probability mass associated with large house price declines. The 95th percentile of the CBSA-level distribution is associated with a price decline of 58.1 percent while the 95th percentile of the state-level distribution is associated with a price decline of 54.0 percent. Under the CMAST

[9]According to the National Bureau of Economic Research, the U.S. economy was in recession from December 2007 through June 2009. This period of recession was subsequently followed by an unusually slow economic recovery.
[10] We base the underlying HPIs we use to calculate these declines upon a set of hybrid indices that we discuss in Section 3 of the paper. The HPIs are constructed based upon transactions for single-family properties involving conforming, conventional mortgages purchased or securitized by Fannie Mae or Freddie Mac. The loan sample excludes condominiums, cooperatives, multi-unit properties, and planned unit developments.
[11] Gyourko and Voith (1992), Abraham and Hendershott (1996), Fratantoni and Schuh (2003), Gu (2002), and Hill (2004) discuss the importance of local house price dynamics in predicting future house price movements.
[12] The state-level data consists of information on all 50 states and the District of Columbia. The CBSA-level data includes state net of CBSA paths, which we construct based upon price declines associated with geographies outside of the included CBSA metro areas. In constructing the HPI distributions, we weigh both the CBSA- and state-level data based upon existing housing stock.

framework, larger historical CBSA-level house price declines lead to more severe localized stress paths, which provide a more accurate measure of credit risk for loans in the affected areas.[13]

Figure 1: Distribution of House Price Declines During the Last Financial Crisis



Everything else held equal, an increase in the severity of the stress path will lead to larger stress loss estimates, but the effect is non-linear. Specifically, as the size of the down shock increases, the magnitude of the stress loss estimate increases at an increasing rate. We can attribute this non-linearity in the loss function to the presence of borrower equity at origination. In addition, the significant transaction costs associated with default can also translate into a non-linearity with respect to mark-to-market loan-to-value (MTM LTV) in the borrower's decision to default.[14] We show an example of this non-linearity in Table 1, which displays state-level stress loss estimates for a synthetic pool of loans under increasingly large house price declines.[15]

[13] Bogin, Doerner, and Larson (2019) construct a credit model and find that mark-to-market loan-to-value ratios constructed using city-level HPIs lead to the most accurate modeled estimates of historical loan performance.
[14] Moving costs, penalties that limit future access to credit, and social stigma are all factors contributing to the non-linearity of the decision to default (Foote, Gerardi, and Willen, 2008; Elul, Souleles, Chomsisengphet, Glennon, and Hunt, 2010; and Foote and Willen, 2018).
[15] The synthetic pool of loans consists of 30-year fixed, purchase-only mortgages, each associated with a FICO score of 720, an LTV of 80 percent, and an interest rate of 5.00 percent. The loss estimates represent an average across a sample of 10 states characterized by a variety of economic conditions.

Table 1: The Non-Linear Relationship between Price Declines and Stress Losses

House Price Decline	Stress Loss Estimate	Change in Stress Loss Estimate
10%	1.35%	N/A
20%	1.57%	0.25% points
30%	2.98%	1.41% points
40%	6.61%	3.63% points

3. Scenario Construction

To begin our analysis, we build a series of HPIs measuring historical appreciation at three different levels of geographic aggregation – national, state-level, and CBSA-level. We construct the HPIs using a variant of the repeat-sales index Bailey, Muth, and Nourse (1963) first proposed and Case and Shiller (1987, 1989) later extended.[16] We can estimate a repeat-sales index using purchase only transactions, or a combination of purchase and refinance transactions (all transactions). Because house prices derive from the same property repeatedly transacted, the repeat-sales methodology closely approximates a constant quality index.[17]

We have sufficient data on historical property transactions to build national and state-level indices reliably using purchase-only data. Unfortunately, in less populated areas, it is difficult to build purchase-only indices at the CBSA-level.[18] This is because of an insufficient number of transactions in certain periods, which leads to small sample sizes, increased estimation error, and more period-to-period volatility in index estimates. To address this concern, we estimate our indices using a hybrid sample—purchase and refinance transactions prior to 1991 and then just purchase transactions post-1991.[19,20] We also move from a series of monthly HPIs to a series of quarterly HPIs.[21] This allows us to group transactions across time to abate the problem of small sample sizes.[22]

[16] FHFA's methodology can be found at http://www.fhfa.gov/PolicyProgramsResearch/Research/PaperDocuments/1996-03_HPI_TechDescription_N508.pdf
[17] Because of renovations, particularly substantial rehabilitation, and demolition followed by new construction, it is possible that the value of a property at the same address transacting on different dates will not reflect pure house price appreciation (Bogin and Doerner, 2019).
[18] Traditionally, FHFA has only published quarterly, purchase-only indices for 100 metropolitan statistical areas (MSAs). In contrast, FHFA publishes quarterly, all-transactions indices for over 400 MSAs.
[19] The underlying house price indices used to construct CMAST paths are non-public. They are distinct from the HPIs published by FHFA and publicly available on the Agency's website.
[20] To ensure comparability across geographies, our national, state, and CBSA-level indices are constructed using this same hybrid approach.
[21] Smith and Weiher originally used monthly indices to construct state-level CMAST paths.
[22] Another option for bolstering sample size would be to move to an all-transactions index, but this has problems as well. Specifically, during periods of rapid house price growth, growth in assessed values, which are used in

After constructing HPIs at the national, state, and CBSA levels, we input them into the CMAST framework. CMAST, which is relatively simple in concept, is determined by two factors: (1) where house prices are relative to their long-term trend; and (2) the extent to which prices can fall below this trend (depth of trough).[23] Constructing CMAST house price stress paths only require a historical HPI series for each geographic region. From the HPI series, we observe a current house price level, and generate a long-term trend and trough (or a lower bound). Trend is based on HPI as a function of time, estimated using only data from completed HPI cycles, and trough is established as a percentage of trend (e.g., 75 percent) based on the lowest level of HPI observed below trend in the historical house price series. Based upon these two components, we construct shock time paths using a 3-4-3 pattern: three years from current HPI to trough, four years at trough, and three years for HPI to return to long-term trend.[24,25] We base these shock time paths on historical house price dynamics.[26,27]

The very long-term stability of housing expenditures as a percent of GDP supports the CMAST assumption that HPI will be cyclically mean reverting, resulting in a stress path for HPI initiated at its current price level, dropping to trough, and then reverting back to trend.[28] Thus, CMAST is rules based, dynamic, and countercyclical by adjusting the severity of the HPI down shock to the extent that current HPI is above or below trend, where the stress is increasing as HPI rises above trend, and then decreasing as HPI approaches

refinances, tends to lag growth in purchase prices. This is largely a function of the backward-looking nature of assessments, which generally rely on previous sales in the same area, and which are used as comparable transactions (Fisher, 2005).

[23] The CMAST framework also includes a set of national-level interest rate projections which are intended to mirror the Federal Reserve's response to a housing market downturn such as occurred during the GFC. In future research, we would like to explore using the CMAST framework to produce other stressors such as borrower income shocks. This alternate source of stress could potentially enter a credit model through debt-to-income shocks.

[24] See Smith et al. (2016) for a thorough analysis of the time path assumption. The authors conclude that the 3-4-3 is conservative. Based upon our review of recent cycles, we find that there is no cause to revisit their time path assumption at the time of this writing.

[25] One potential critique of the CMAST trend line is that it doesn't capture structural breaks. We acknowledge that this a limiting factor, but believe it's a necessary feature of a truly rules-based approach to house price stress path construction. When present, the impact of structural breaks could potentially be muted by moving to a series of more localized CPI deflators which would allow us to at least partially account for changes in regional economic conditions.

[26] See Smith and Weiher (2012) for additional details.

[27] FHFA produces CMAST stress paths at both the state and CBSA-level on a quarterly basis. These CMAST paths can be downloaded at https://www.fhfa.gov/DataTools/Downloads/Pages/Countercyclical-Mortgage-Asset-Stress-Test.aspx.

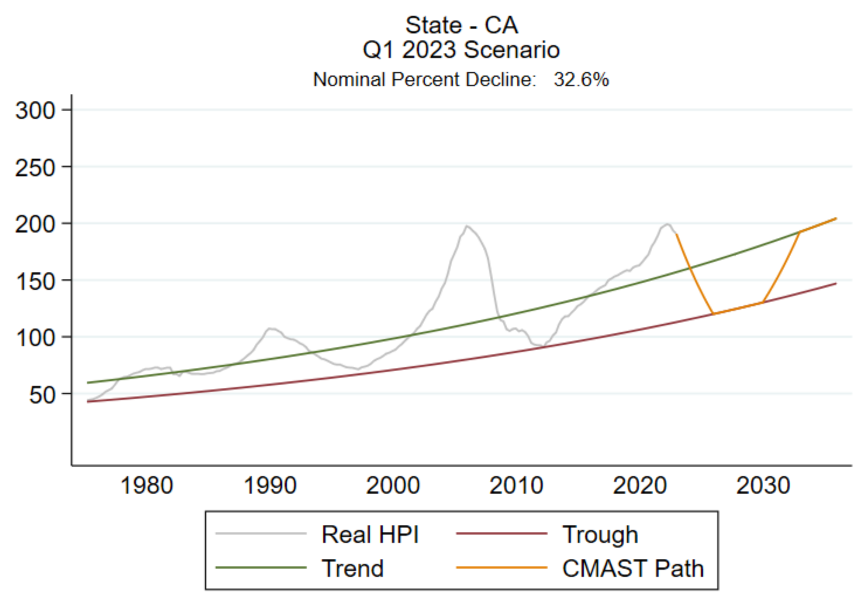
[28] Abraham and Hendershott (1996) use a variant of this first component, the difference between actual and equilibrium price levels, to estimate the magnitude of future price declines absent a change in market fundamentals. Wheaton and Torto (1988) consider a similar adjustment mechanism in commercial real estate. Both these approaches assume a mean-reverting process as discussed with respect to the rent-price ratio in Campbell, Davis, Gallin, and Martin (2009) and Plazzi, Torous, and Valkanov (2010).

the trough.[29] The fact that we construct CMAST scenarios using these same rules at each level of geographic aggregation ensures that our analysis is a properly controlled test of the impact of different levels of house price stress geographic aggregation.

Figure 2a illustrates a sample CMAST path for California, Figure 2b illustrates a sample CMAST path for San Jose, and Figure 2c illustrates a sample CMAST path for Riverside. The CMAST path for California is associated with an initial house price decline of 32.6 percent. In contrast to the state-level path, the CMAST path for San Jose is associated with a significantly smaller price drop of 18.6 percent. Alternately, the CMAST path for Riverside is associated with a substantially larger price drop of 49.4 percent.

As illustrated in Figures 2a through 2c, if we were to apply a state path to all loans in California, we would overstate credit risk in San Jose, but understate it in Riverside. By using the CBSA-level paths, we leverage information on localized house price dynamics to capture credit risk more accurately.

Figure 2a: Real HPI, Trend, Trough, and CMAST Path for California



[29] CMAST stress paths are countercyclical because the trough is invariant to the current cycle peak. Smith et al. (2016) examine this feature of CMAST in depth and find it robust. The supporting economic logic is that housing investors will reenter a depressed housing market once HPI is a certain amount (20 to 25 percent typically) below trend regardless of prior cycle peaks.

Figure 2b: Real HPI, Trend, Trough, and CMAST Path for San Jose

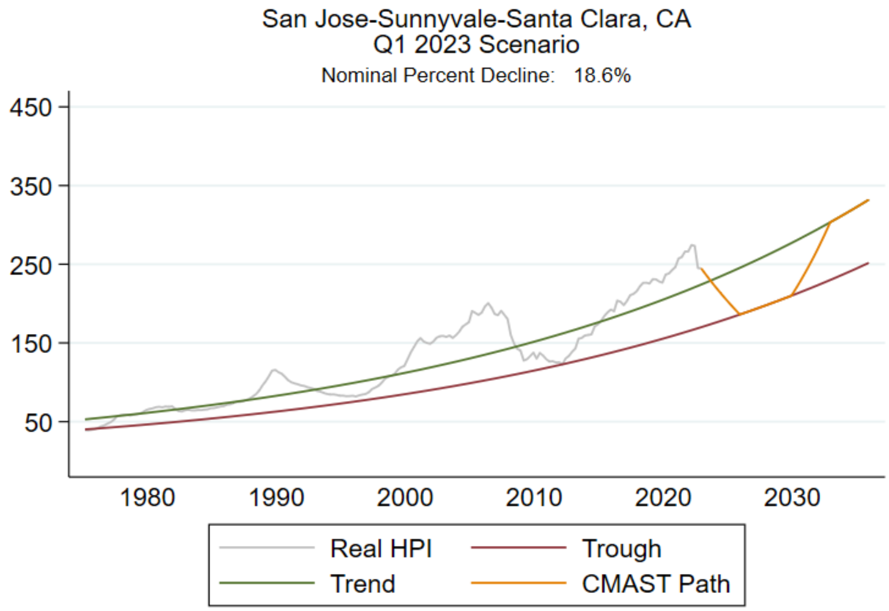
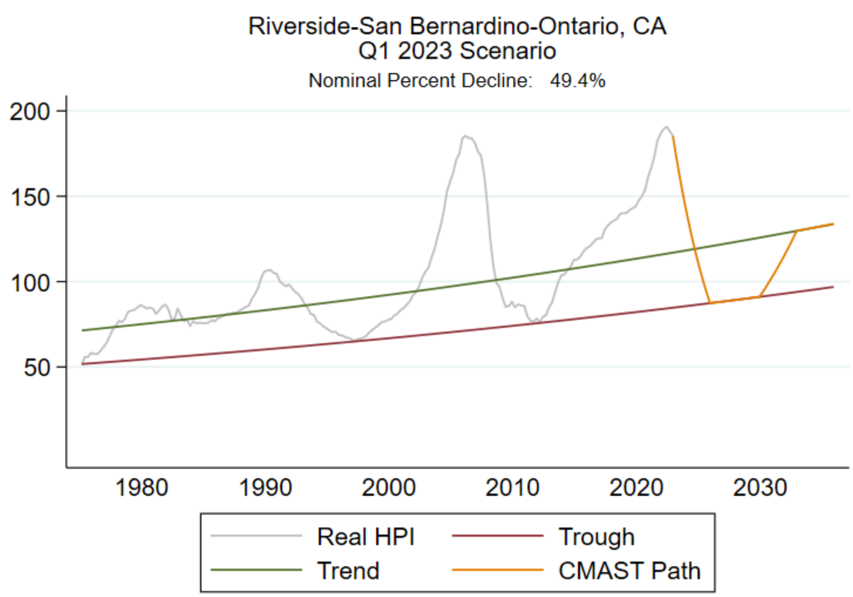


Figure 2c: Real HPI, Trend, Trough, and CMAST Path for Riverside



4. Portfolio Data

We base our analysis upon two different single-family mortgage portfolios containing conforming, conventional loans. The first portfolio consists of mortgage loans the Federal Home Loan Banks acquired under their Acquired Member Assets (AMA) program.[30] We drew the AMA sample as of Q4 2019 and it consists of approximately 406,000 active loans representing mortgage originations from 1997 to 2019. The second portfolio consists of single-family loans Fannie Mae acquired that were included in 2020 Connecticut Avenue Security (CAS) issuances, which are part of the Enterprise's credit risk transfer effort.[31][32] The CAS data represents only 2019 originations and consists of approximately 436,000 loans.[33] Between the two samples, the CAS loans are more representative of nationwide originations, whereas AMA loans reflect each Federal Home Loan Bank's participation in the AMA program, membership, and region of activity. The primary focus of our comparison is AMA and CAS loans originated in 2019, which are analyzed as new originations. Alternately, the full AMA sample represents a seasoned portfolio of loans with lower unpaid principal balances (UPBs) and a larger percentage of rate-term refinances.

As we show in Table 2, the average UPB associated with the full sample of AMA loans is $166,888. When we confine the sample to 2019 originations, this figure rises to $236,513. In contrast, the CAS loans, again all 2019 originations, are associated with a slightly higher UPB of $262,551. The weighted average FICO score for the full sample of AMA loans is 760.1. This score drops to 758.2 when examining just 2019 originations. The weighted average FICO associated with the CAS sample is approximately 11.8 points lower at 746.3. The higher credit quality of the AMA loans is partially a function of the AMA program requirement that members selling loans to the Federal Home Loan Banks must credit enhance those loans. Hence, such members have an incentive to provide loans associated with lower levels of credit risk to lessen their credit enhancement obligation.

[30] The Federal Home Loan Bank AMA programs support member housing finance activity through acquiring high quality, conforming residential mortgage loans from FHLBank members. It structures these programs such that members bear a substantial portion of the associated credit risk on acquired loans. AMA loan-level data is non-public.

[31] The CAS program is designed to allow investors to share credit risk on Fannie Mae's single-family conventional guaranty book of business. The CAS loan-level data we examined is publicly available. Freddie Mac has a similar credit risk sharing program called Structured Agency Credit Risk (STACR). STACR loan-level data is also publicly available and very similar in nature to the CAS data. Given the similarities between Fannie Mae and Freddie Mac loan acquisitions we felt there was a limited amount of added value including a STACR, as well as a CAS, dataset in our analysis.

[32] The lowest level of geography available in the public CAS data is three-digit ZIP Codes, which are similar in size to CBSAs in medium to smaller cities. The absence of additional geographic granularity precludes the possibility of studying the effects of further disaggregation such as five-digit ZIP Code or census tract house price stress paths. Further, in order to reliably create indices at this level of geographic detail, we would need to group transactions by the year as opposed to the quarter. This level of frequency can prevent an accurate estimate of trough.

[33] We chose to cut off our data in 2019 to only reflect pre-COVID originations.

Table 2: Summary Statistics for AMA and CAS Loans

Field	AMA Loan Data		CAS Loan Data
	Full Sample	**2019 Originations**	**2019 Originations**
Observations	406,234	81,729	436,191
Average UPB	$166,888	$236,513	$262,551
Weighted Average FICO	760.1	758.2	746.3
Weighted Average LTV	74.23	74.24	83.6
Weighted Average Coupon	4.07	3.91	4.44
% Purchase	41.7%	42.8%	70.3%
% Rate-Term Refinance	51.9%	26.5%	15.1%
% Cash-Out	6.4%	30.6%	14.7%

One of the most striking differences across the AMA and CAS samples is weighted average LTV. Among AMA loans (both the full sample and just the 2019 originations), the weighted average LTV rounds to 74.2 percent. In contrast, the weighted average LTV among CAS loans is 9.4 percentage points higher at 83.6 percent. Everything else held equal, the CAS portfolio's lower weighted average FICO score and significantly higher weighted average LTV should lead to larger loss estimates relative to the AMA sample (Jones and Sirmans, 2015).

We also observe a significant difference in the percentage of purchase loans across the two samples. Among the AMA portfolio, the percent of purchase loans is 41.7 percent in the full sample and 42.8 percent among 2019 originations. Alternately, the CAS portfolio is made up of 70.3 percent purchase loans. The AMA portfolio is made up of 6.4 percent cash-out loans in the full sample and 30.6 percent cash-out loans among 2019 originations. In contrast, the CAS portfolio is made up of 14.7 percent cash-out loans. Generally, cash-out loans perform worse than purchase or rate-term refinances (Jones and Sirmans, 2015; Kim, Cho, and Ryu, 2018), but, ultimately, the impact of loan purpose on losses depends on the loan performance data used to calibrate the credit model.

The other striking difference across the two loan portfolios is the geographic concentration of loans. Among the full sample of the AMA loans, the top three most represented states are Ohio at 11.88 percent, Indiana at 8.08 percent, and Kansas at 6.43 percent.[34] We see a slight shift when we focus on 2019 originations where the top three most represented states are Wisconsin at 12.09 percent, Ohio at 8.02 percent, and Illinois at 7.07 percent. Among the CAS portfolio, the top three most represented states are California at 11.51 percent, Texas at 7.67 percent, and Florida at 7.34 percent.

[34] We calculate measures of geographic concentration based upon sample loan count.

Table 3 details the severity of the three-year peak-to-trough CMAST state-level house price stress path in each aforementioned state. As detailed in the table, the most represented states in the CAS pool are where HPI has risen excessively above trend, translating into larger CMAST house price declines than the most represented states in either the AMA full sample or the AMA 2019 originations. Ex ante, this pronounced difference in severity suggests that portfolio-level estimated stress losses for the CAS sample are likely to exceed portfolio-level estimated stress losses for either AMA sample.

Table 3: Severity of Q4 2019 CMAST House Price Decline Among States with the Largest Geographic Concentration of Loans

Geographic Concentration	CMAST State-Level Paths
	Initial House Price Decline
AMA Loans Full Sample	
Ohio (11.88%)	25.8%
Indiana (8.08%)	25.5%
Kansas (6.43%)	30.2%
AMA Loans 2019 Originations	
Wisconsin (12.09%)	17.5%
Ohio (8.02%)	25.8%
Illinois (7.07%)	8.6%
CAS Loans	
California (11.51%)	29.3%
Texas (7.67%)	41.3%
Florida (7.34%)	38.6%

5. Results

We produce results using three commonly used and market-tested credit models (denoted as Models A, B, and C).[35,36] We present stress loss estimates for the AMA and CAS portfolios in Table 4. Each row represents a particular loan portfolio-credit model combination, and, as we move from left to right, we observe loss estimates under increasingly geographically granular stress paths. The same pattern of losses emerges across all rows. Loss estimates are lowest when applying a national house price stress path. As we move to state-level house price stress paths, loss estimates increase. Moving to CBSA-level house price paths leads to even larger loss estimates although the change is muted relative to the increase observed when moving from a national to a state-level house price path.

[35] For loans with origination LTVs greater than 80, we adjust for mortgage insurance.
[36] The use of three models serves as a robustness check on the effects of stress testing at different levels of geographic disaggregation.

Table 4: Portfolio-Level Stress Loss Results

Portfolios analyzed as of Q4 2019

Portfolio/Credit Model	National CMAST Path	State-Level CMAST Paths	CBSA-Level CMAST Paths	
CAS Loans - 2019 Originations			**Top 50 CBSAs**	**Top 100 CBSAs**
Model A	1.03%	1.68%	1.91%	1.97%
Model B	2.12%	2.67%	2.86%	2.91%
Model C	1.59%	2.13%	2.45%	2.54%
AMA Loans - 2019 Originations			**Top 50 CBSAs**	**Top 100 CBSAs**
Model A	0.81%	0.99%	1.21%	1.27%
Model B	1.11%	1.31%	1.36%	1.40%
Model C	1.36%	1.49%	1.65%	1.66%
AMA Loans - Full Sample			**Top 50 CBSAs**	**Top 100 CBSAs**
Model A	0.64%	0.78%	0.81%	0.85%
Model B	0.72%	0.79%	0.82%	0.85%
Model C	0.98%	1.02%	1.11%	1.12%

We include two sets of CBSA-level paths. The first includes house price stress paths for the top 50 CBSAs by housing stock.[37] All loans outside of these CBSAs receive a state net of CBSA (or balance of state) path, which we construct using housing transactions outside of all included metro areas.[38] The second set of paths includes house price stress paths for the top 100 CBSAs by housing stock. Again, all loans outside of these CBSAs receive balance of state paths. Moving from the top 50 to the top 100 CBSAs generally increases losses, but the change is minor compared to the increase in loss estimates when moving from a national path to state-level paths or from state-level paths to the top 50 CBSAs. Focusing on the AMA full sample, we see increases of one basis point (bp) to four bps depending on the credit model. It is important to note that while this is a small increase, it represents a portfolio-level aggregate. If we were to focus on the stress loss estimates associated with a state with multiple CBSAs (with a cohort in the top 50 and another in the top 100), we are likely to observe a larger differential. For instance, focusing on AMA loans originated in the state of California, we see an increase in the associated stress loss estimate of 14 bps when moving from the top 50 to the top 100 CBSAs.[39]

[37] Housing stock is calculated based upon 2019 county-level data, which we then aggregate to the CBSA-level. We include a list of the top CBSAs by housing stock in Appendix A.
[38] We invoke the same general methodology that FHFA uses in its public indexes to construct our balance of state paths.
[39] California has six CBSAs in the top 50 and an additional three CBSAs in the top 100.

Next, we explore stress loss estimates across individual geographies. For purposes of exposition, we focus on CAS and AMA 2019 originations run through Model C.[40] As we show in Table 5, we observe significant variation in stress loss results within California, Florida, and Texas. For AMA loans in California, stress losses range from a low of 0.67 percent in San Jose to a high of 3.67 percent in Riverside. In contrast, for AMA loans, we estimate state-level stress losses at 1.08 percent. For CAS loans in California, stress losses range from a low of 1.38 percent in San Jose to a high of 4.14 percent in Riverside. Alternately, for CAS loans, we estimate state-level stress losses at 1.71 percent. The results across both portfolios again indicate that state-level results can understate risk for loans in certain regions (e.g., Sacramento, Riverside), while at the same time overstating risk in other regions (e.g., San Jose). Without this additional level of geographic disaggregation, we lose information on these complexities. We observe a similar dynamic in both Florida and Texas.

Table 5: Region-Level Stress Loss Results

Portfolios analyzed as of Q4 2019

Region	CAS Loans - 2019 Originations	AMA Loans - 2019 Originations
California	**1.71%**	**1.08%**
Los Angeles-Long Beach-Anaheim	2.15%	1.44%
Riverside-San Bernardino-Ontario	4.14%	3.67%
Sacramento-Roseville-Folsom	3.05%	2.46%
San Diego-Chula Vista-Carlsbad	1.57%	1.54%
San Francisco-Oakland-Berkeley	2.02%	1.10%
San Jose-Sunnyvale-Santa Clara	1.38%	0.67%
Florida	**4.39%**	**3.55%**
Jacksonville	3.39%	3.18%
Miami-Fort Lauderdale-Pompano Beach	5.13%	3.90%
Orlando-Kissimmee-Sanford	5.59%	5.45%
Tampa-St. Petersburg-Clearwater	5.18%	4.08%
Texas	**3.98%**	**3.12%**
Austin-Round Rock-Georgetown	4.60%	3.88%
Dallas-Fort Worth-Arlington	4.16%	3.44%
Houston-The Woodlands-Sugar Land	5.58%	4.10%
San Antonio-New Braunfels	4.77%	4.06%

[40] We chose to focus on results from Model C because the underlying behavioral model was subject to several in-depth sensitivity analyses. Model A and B yield comparable results.

6. Model Risk

A dual benefit of incorporating results from three different credit models is the ability to explore several facets of model risk. We must acknowledge that the results reflect a snapshot in time and the rank order of results may vary as different portfolios are examined and models are updated. The primary intent of this analysis is to provide a calibration of potential model risk or the extent to which stress loss estimates can vary across credit models.

We focus our analysis on stress loss estimates associated with AMA loans.[41] For this use case, we define model risk as the difference in loss estimates across models when holding constant both the pool of loans and the included CMAST stress path. Table 6 illustrates the variation in loss estimates across these fixed portfolios and CMAST stress path combinations.

Table 6: Portfolio-Level Model Risk

Portfolios analyzed as of Q4 2019

Portfolio/Credit Model	National CMAST Path	State-Level CMAST Paths	CBSA-Level CMAST Paths	
AMA Loans - Full Sample			**Top 50 CBSAs**	**Top 100 CBSAs**
Model A	0.64%	0.78%	0.81%	0.85%
Model B	0.72%	0.79%	0.82%	0.85%
Model C	0.98%	1.02%	1.11%	1.12%
Range	**0.64% to 0.98%**	**0.78% to 1.02%**	**0.81% to 1.11%**	**0.85% to 1.12%**
AMA Loans - 2019 Originations			**Top 50 CBSAs**	**Top 100 CBSAs**
Model A	0.81%	0.99%	1.21%	1.27%
Model B	1.11%	1.31%	1.36%	1.40%
Model C	1.36%	1.49%	1.65%	1.66%
Range	**0.81% to 1.36%**	**0.99% to 1.49%**	**1.21% to 1.65%**	**1.27% to 1.66%**

As detailed, the range of loss estimates is wider when examining AMA 2019 originations. This is because, under the CMAST framework, the stress shock on loans is maximized at origination and then declines with loan age. This leads to larger loss estimates and more opportunity for variation across models.[42] Looking down each column of Table 6, we see the same rank order of losses. For the AMA portfolio, Model A

[41] We focus on the AMA sample because it allows us to compare model performance across both new and seasoned loans.
[42] See Smith and Weiher (2012) for additional details.

produces the smallest loss estimates, followed closely by Model B, with Model C producing the largest loss estimates.[43]

While the range in loss estimates is relatively constrained in absolute terms (conditional on the same portfolio and macroeconomic stress path, variation across models never exceeds 55 bps), we observe large proportional differences across models. The average percentage difference between Model A and Model B results is 11.70 percent. Alternately, the average percentage difference between Model A and Model C is 34.32 percent. To measure model risk extent more accurately, we next condition our analysis on a series of loan and borrower attributes using a regression framework.

Table 7 shows results for a linear regression model that we calibrate using loan-level loss estimates. We generate the loss estimates by applying the top 50 CBSA paths to AMA 2019 originations and running the loans through Models A, B, and C.

Table 7. Stress Loss Estimates Across Credit Models

LHS: Stress Loss Estimate	Full Sample	Purchase	Rate-Term	Cash-Out
Model A	-0.0048 ***	-0.0025 ***	-0.0054 ***	-0.0085 ***
	(0.0001)	(0.0002)	(0.0002)	(0.0002)
Model B	-0.0015 ***	0.0056 ***	-0.0086 ***	-0.0061 ***
	(0.0001)	(0.0002)	(0.0002)	(0.0002)
Loan Attributes and Borrower Characteristics	X	X	X	X
State FE	X	X	X	X
N	184,706	90,015	44,819	49,872
RMSE	0.0215	0.0244	0.0142	0.0200
Adjusted R2	0.3342	0.3358	0.3790	0.3396

The omitted category in the regression is Model C. We provide standard errors in parentheses; * p<0.1, ** p<0.05, and *** p<0.01.

The first column (*Full Sample*) of Table 7 shows results across purchase, rate-term refinance, and cash-out loans.[44] Controls include state-level fixed effects, indicator variables for mortgage purpose and mortgage amount, and continuous variables for LTV ratio, credit score, and mortgage interest rate.[45] The coefficient

[43] It is important to note that the rank order of losses may change as we evaluate alternate portfolios. Similarly, we may see a different ordering as each of models is updated to better reflect new market conditions.
[44] *Full Sample* represents all 2019 AMA originations. We then stack Loss estimates for each credit model.
[45] We explore different functional forms for LTV and credit score including bringing the variables in as linear terms, quadratics, and splines. The results are qualitatively similar across specifications.

estimate attached to the Model A indicator equals -0.0048 and is statistically significant at the one percent level. It indicates that, conditional on a suite of controls, Model A produces loss estimates 48 bps lower than Model C. The coefficient attached to the Model B indicator equals -0.0015 and is also statistically significant at the one percent level. It indicates that, conditional on the same set of controls, Model B produces loss estimates 15 bps lower than Model C.

The second column (*Purchase*) of Table 7 applies the same specification, but only to purchase loans. Interestingly, the coefficient attached to the Model B indicator switches signs while remaining statistically significant at the one percent level. It indicates that, when evaluating only purchase loans, Model B produces loss estimates 56 bps higher than Model C. In contrast, we find the same negative relationship between losses generated from Model A and losses generated from Model C as observed in the full sample. This suggests that for portfolios skewed towards a larger percentage of purchase loans, Model B may produce the largest loss estimates across all three credit models.

In columns 3 and 4, we limit our analysis to rate-term refinances and cash-out refinances, respectively. When evaluating only rate-term refinances, the rank order of losses changes (relative to the full sample results) with Model B now generating the smallest loss estimates (86 bps lower than Model C) followed by Model A (54 bps lower than Model C). In contrast, when evaluating only cash-out refinances, we return to the same rank order of losses as estimated using the full sample.[46,47]

The results from Table 7 show a significant degree of variation in loss estimates across credit models depending on loan purpose. This suggests that portfolio composition plays a large role in determining the extent to which loss estimates differ across models. More broadly, variation in loss estimates across credit models suggests an additional source of uncertainty when measuring credit risk. This uncertainty can potentially be accounted for through a model risk add-on, which should be updated periodically and would provide a more conservative measure of portfolio credit risk.

[46] We get qualitatively similar results when running the full sample with a series of interaction terms between credit model and loan purpose.

[47] As an additional exercise, we also explore variation in loss estimates across credit models for judicial versus non-judicial states. In non-judicial states, the difference in loss estimates across models shrinks. Specifically, when confining our analysis to non-judicial states, the coefficient attached to the Model A indicator is equal to -0.0015 (statistically significant at the one percent level) and the coefficient attached to the Model B indicator is equal to 0.0005 (statistically significant at the five percent level). In contrast, when confining our analysis to judicial states, the coefficient attached to the Model A indicator is equal to -0.0083 (statistically significant at the one percent level) and the coefficient attached to the Model B indicator is equal to -0.0035 (statistically significant at the one percent level).

7. Conclusions

Leveraging the CMAST framework, we examine how portfolio losses vary across stress paths constructed at three different levels of geographic aggregation. We explore results across two loan portfolios and three credit models and find that, while the magnitude of stress loss estimates varies across both loan portfolios and credit models, the rank order of losses with respect to the geographic disaggregation of the associated house price stress paths remains the same. Specifically, we observe the lowest level of stress losses when applying the same national house price path to all loans. Estimated losses then monotonically increase as we apply more geographically disaggregated house price paths.

From a policy perspective, these results suggest that moving to CBSA-level stress paths could improve credit risk measurement. We can reliably produce CBSA-level house price indices by moving them to a quarterly frequency. These CBSA-level results provide a more accurate measure of localized risk and allow for more informed risk management. From a model risk perspective, it is important to understand the extent to which stress loss estimates can vary across credit models, even when evaluating the same portfolio using the same macroeconomic scenario. This variation suggests an implicit confidence interval around any stress loss estimate generated from a single model, and accounting for this uncertainty through a model risk add-on could potentially offer a more conservative and fulsome view of portfolio credit risk.

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Appendix A

Top 100 CBSAs by Housing Stock

Ranking	CBSA Code	CBSA Name
1	35620	New York-Newark-Jersey City, NY-NJ-PA
2	31080	Los Angeles-Long Beach-Anaheim, CA
3	16980	Chicago-Naperville-Elgin, IL-IN-WI
4	19100	Dallas-Fort Worth-Arlington, TX
5	26420	Houston-The Woodlands-Sugar Land, TX
6	33100	Miami-Fort Lauderdale-Pompano Beach, FL
7	37980	Philadelphia-Camden-Wilmington, PA-NJ-DE-MD
8	47900	Washington-Arlington-Alexandria, DC-VA-MD-WV
9	12060	Atlanta-Sandy Springs-Alpharetta, GA
10	14460	Boston-Cambridge-Newton, MA-NH
11	38060	Phoenix-Mesa-Chandler, AZ
12	19820	Detroit-Warren-Dearborn, MI
13	41860	San Francisco-Oakland-Berkeley, CA
14	42660	Seattle-Tacoma-Bellevue, WA
15	40140	Riverside-San Bernardino-Ontario, CA
16	33460	Minneapolis-St. Paul-Bloomington, MN-WI
17	45300	Tampa-St. Petersburg-Clearwater, FL
18	41180	St. Louis, MO-IL
19	41740	San Diego-Chula Vista-Carlsbad, CA
20	19740	Denver-Aurora-Lakewood, CO
21	12580	Baltimore-Columbia-Towson, MD
22	38300	Pittsburgh, PA
23	16740	Charlotte-Concord-Gastonia, NC-SC
24	36740	Orlando-Kissimmee-Sanford, FL
25	38900	Portland-Vancouver-Hillsboro, OR-WA
26	17460	Cleveland-Elyria, OH
27	17140	Cincinnati, OH-KY-IN
28	28140	Kansas City, MO-KS
29	29820	Las Vegas-Henderson-Paradise, NV
30	40900	Sacramento-Roseville-Folsom, CA
31	41700	San Antonio-New Braunfels, TX
32	12420	Austin-Round Rock-Georgetown, TX
33	18140	Columbus, OH
34	26900	Indianapolis-Carmel-Anderson, IN
35	34980	Nashville-Davidson--Murfreesboro--Franklin, TN

Ranking	CBSA Code	CBSA Name
36	47260	Virginia Beach-Norfolk-Newport News, VA-NC
37	39300	Providence-Warwick, RI-MA
38	41940	San Jose-Sunnyvale-Santa Clara, CA
39	33340	Milwaukee-Waukesha, WI
40	27260	Jacksonville, FL
41	36420	Oklahoma City, OK
42	32820	Memphis, TN-MS-AR
43	39580	Raleigh-Cary, NC
44	35380	New Orleans-Metairie, LA
45	31140	Louisville/Jefferson County, KY-IN
46	15380	Buffalo-Cheektowaga, NY
47	40060	Richmond, VA
48	25540	Hartford-East Hartford-Middletown, CT
49	13820	Birmingham-Hoover, AL
50	40380	Rochester, NY
51	46060	Tucson, AZ
52	35840	North Port-Sarasota-Bradenton, FL
53	46140	Tulsa, OK
54	41620	Salt Lake City, UT
55	24340	Grand Rapids-Kentwood, MI
56	10580	Albany-Schenectady-Troy, NY
57	15980	Cape Coral-Fort Myers, FL
58	24860	Greenville-Anderson, SC
59	10740	Albuquerque, NM
60	36540	Omaha-Council Bluffs, NE-IA
61	28940	Knoxville, TN
62	49340	Worcester, MA-CT
63	14860	Bridgeport-Stamford-Norwalk, CT
64	12940	Baton Rouge, LA
65	19430	Dayton-Kettering, OH
66	35300	New Haven-Milford, CT
67	17900	Columbia, SC
68	46520	Urban Honolulu, HI
69	10900	Allentown-Bethlehem-Easton, PA-NJ
70	16700	Charleston-North Charleston, SC

Ranking	CBSA Code	CBSA Name
71	24660	Greensboro-High Point, NC
72	23420	Fresno, CA
73	30780	Little Rock-North Little Rock-Conway, AR
74	19660	Deltona-Daytona Beach-Ormond Beach, FL
75	10420	Akron, OH
76	34820	Myrtle Beach-Conway-North Myrtle Beach, SC-NC
77	29460	Lakeland-Winter Haven, FL
78	45780	Toledo, OH
79	49180	Winston-Salem, NC
80	21340	El Paso, TX
81	12540	Bakersfield, CA
82	19780	Des Moines-West Des Moines, IA
83	45060	Syracuse, NY
84	17820	Colorado Springs, CO
85	31540	Madison, WI
86	44140	Springfield, MA
87	37100	Oxnard-Thousand Oaks-Ventura, CA
88	14260	Boise City, ID
89	32580	McAllen-Edinburg-Mission, TX
90	37340	Palm Bay-Melbourne-Titusville, FL
91	20500	Durham-Chapel Hill, NC
92	38860	Portland-South Portland, ME
93	48620	Wichita, KS
94	39100	Poughkeepsie-Newburgh-Middletown, NY
95	42540	Scranton--Wilkes-Barre, PA
96	12260	Augusta-Richmond County, GA-SC
97	49660	Youngstown-Warren-Boardman, OH-PA
98	41540	Salisbury, MD-DE
99	25420	Harrisburg-Carlisle, PA
100	27140	Jackson, MS