University of Pretoria
Department of Economics Working Paper Series

Spillover of Mortgage Default Risks in the United States: Evidence from Metropolitan Statistical Areas and States

Qiang Ji
Chinese Academy of Sciences
Rangan Gupta
University of Pretoria
Festus Victor Bekun
Eastern Mediterranean University
Mehmet Balcilar
Eastern Mediterranean University and Montpellier Business School
Working Paper: 2018-50
August 2018

Department of Economics
University of Pretoria
0002, Pretoria
South Africa
Tel: +27 12 420 2413

Spillover of Mortgage Default Risks in the United States: Evidence from Metropolitan Statistical Areas and States

Qiang Ji [a, b*], Rangan Gupta [c], Festus Victor Bekun [d] and Mehmet Balcilar[c, d, e]

[a] Center for Energy and Environmental Policy Research, Institutes of Science and Development, Chinese Academy of Sciences, Beijing, 100190, China

[b] School of Public Policy and Management, University of Chinese Academy of Sciences, Beijing, 100049, China

[c] Department of Economics, University of Pretoria, Pretoria, 0002, South Africa

[d] Department of Economics, Eastern Mediterranean University, Famagusta, via Mersin 10, Northern Cyprus, Turkey

[e] Montpellier Business School, Montpellier, France

Abstract: This paper offers a new perspective to the analysis of spillover transmission in the housing market, specifically dealing with mortgage default risks. To do this, the recently developed generalized forecast error variance decomposition (FEVD) methodology proposed by Diebold and Yilmaz (2014) is utilized to investigate the degree of interconnectedness of mortgage default risks in metropolitan statistical areas (MSAs) and states of the U.S. The empirical findings, based on a real-time mortgage default risks index, reveals complex interconnectedness across twenty MSAs and forty-three states. Our study reveals that Chicago, New York, and Los Angeles are net transmitters of spillover effects to other regions in the housing market investigated. This study also corroborates with the central place theory (CPT), as Washington DC serves as a key player in the housing market among the MSA's. Amongst the states, Minnesota, followed by Arizona, Pennsylvania, New York and New Hampshire, are found to be the main source of mortgage default risks spillovers.

Keywords: Mortgage default risk; connectedness network; centrality; metropolitan statistical area, states, United States
JEL Codes: C32, R30

[*] Corresponding author: jqwxnjq@163.com (Qiang Ji).

1. Introduction

The U.S. subprime mortgage crisis was at the epicenter of the financial meltdown which rocked the world in 2007-08. Mortgage defaults rose rapidly after house prices had started falling in some U.S. states, triggering panic in mortgage-backed security and connected financial instruments markets. As housing price dynamics and mortgage lending practices differed widely between U.S. states, it is interesting to investigate the diffusion of mortgage defaults across the country. This is an important line of research, since if these risks across regions are indeed interrelated, then a particular region can be influenced by the negative impacts of external risk shocks originating from other regions. At the same time, an increase in risks in a particular region is likely to have prolonged effects on the economy of another region through risks feedbacks. Finally, more interconnected the regions are in terms of their mortgage default risks spillovers, more likely it is for these risks to affect all regions, and in the process the entire economy, without being restricted to a particular region. Naturally, a better understanding of risk spillovers is of great importance for risk management by investors, regulators and policymakers.

Mortgage defaults can spillover through different channels. They can accelerate falls in house prices, which have a major impact on defaults (Calomiris et al., 2013). They affect the wider economy and therefore incomes and jobs, and hence the ability of households to repay their mortgages. As defaults rise, lenders tighten their lending conditions. Berrospide et al., (2016) show that during the financial crisis, banks operating in several markets reduced lending in some markets in response to rising mortgage delinquencies in other markets. Tighter credit conditions both weigh on house prices and affect the ability of borrowers to refinance their mortgages, heightening the risk of default. Falls in house prices and refinancing constraints

reinforce each other as negative equity prevents refinancing.

Against this background, this paper examines information spillovers of mortgage default risks across twenty metropolitan statistical areas (MSAs) and states of the U.S. Understandably, for our purpose, we need a measure of such risks at the regional level. While aggregate financial risk has been captured by an array of generalized market indices (such as the VIX, for instance), none of these measures provided timely insights that are specific to mortgage default risks during run-up to the crisis. In addition, the few available measures of mortgage default risks only captured information known to lenders or financial market participants and thus neglected potentially sensitive information on mortgage distress emanating directly from households. Given this, Chauvet et al., (2016) use Google search query data to develop broad-based and real-time index of mortgage default risks (MDRI) for the U.S. Unlike established indicators, the MDRI developed by these authors directly reflects households'concerns regarding their risk of mortgage default. The MDRI is shown to predict housing returns, mortgage delinquency indicators, and subprime credit default swaps, both within and out-of-samples, and across various data frequencies. Chauvet et al., (2016) has now extended their original aggregate-level analysis, and developed MDRIs at state- and MSA-levels, which is the data that we use in our analysis.

While there are some studies that have studied spillovers of mortgage default risks, primarily at the micro (neighbourhood)-level in the U.S. (see for example, Lin et al., (2009), Agarwal et al., (2018), Ambrose and Diop (2014), Chomsisengphet et al., (2018), and Gupta (forthcoming)), to the best of our knowledge, this is the first attempt to analyze the same at a wider regional level based on a newly-developed index which provides the most timely information on mortage default risks. For our purpose, a network approach based on Diebold and Yilmaz's (2014) connectedness framework is

applied to information spillover and market integration of regional mortgage default risk, shedding light on risk diffusion and information linkages in U.S. housing markets. In addition, some network indicators are developed to provide a comprehensive analysis on centrality, direction and intensity of risk spillovers across regional housing markets in the U.S.

The remainder of the paper is organized as follows: Section 2 discusses the methodology, while Section 3 presents the data and results, with Section 4 concluding the paper.

2. Methodology

2.1 Risk spillover connectedness modeling

Referring to Diebold and Yilmaz (2014), we use generalized forecast error variance decomposition (FEVD) based on VAR model to measure the risk spillover connectedness of the U.S. housing market system. Therefore, a VAR model is first constructed as follows:

$$R_t = \mu + \sum_{i=1}^{p} \Phi_i R_{t-i} + \varepsilon_t \tag{1}$$

where R_t is the vector of logarithmic difference of mortgage default risk index in the regional housing markets in the U.S. Φ_i is the matrix of autoregressive coefficients and ε_t is the vector of error terms that are assumed to be serially uncorrelated.

Equation (1) can be rewritten as an infinite moving average process given that the VAR system is a stationary covariance. Then, $R_t = \sum_{j=0}^{\infty} A_j \varepsilon_{t-j}$. The coefficient matrix A_j can be interpreted intuitively as the so-called impulse response (Sims, 1980). Thus, the *H*-step-ahead generalized forecast error variance from market *j* to market *i* can be presented as follows (Koop et al., 1996; Pesaran and Shin, 1998):

$$\theta_{ij}(H) = \frac{\sigma_{jj}^{-1}\sum_{h=0}^{H-1}\left(e_i' A_h \sum e_j\right)^2}{\sum_{h=0}^{H-1}\left(e_i' A_h \sum A_h' e_i\right)} \qquad (2)$$

where $\theta_{ij}(H)$ is the variance contribution of variable j to variable i, e_i is a selection vector with ith element unity and zeros elsewhere. Σ is the covariance matrix of the shock vector in the non-orthogonalized VAR and σ_{jj} is the standard deviation of the error term of the jth equation. Therefore, a risk spillover connectedness matrix is constructed based on generalized variance as $\theta(H) = [\theta_{ij}(H)]$, where each element represents the variance contribution of one variable to the other variable. Because sums of forecast error variance contributions are not necessarily unity, we further normalize the $\theta(H)$ matrix to make sure the row sum is equal to 1 by $\tilde{\theta}_{ij}(H) = \frac{\theta_{ij}(H)}{\sum_{j=1}^{N}\theta_{ij}(H)}$. Then, $\tilde{\theta}(H) = [\tilde{\theta}_{ij}(H)]$ is used to investigate the risk spillover connectedness in the empirical results section.

2.2 Connectedness networks

To analyse different network characteristics of the housing market system, two different networks are constructed.

(1) Centrality connectedness network

A centrality connectedness network is constructed based on the sum of pairwise connectedness. This network is an undirected weighted network in which each market represents a node and each pairwise nodes i and j has an undirected edge. The off-diagonal elements in the network's adjacency matrix are $\tilde{\theta}_{ji} + \tilde{\theta}_{ij}$ and the diagonal elements are zeros.

Therefore, in this network, we only focus on the linkage intensity of the housing market. Furthermore, two centrality indicators are calculated to measure the central

status of one market in the network, referring to Yang and Zhou (2017). First is degree centrality which is the average of column sum of the off-diagonal weight in the network's adjacency matrix. Second is eigenvector centrality which is defined as the principal eigenvector of the network's adjacency matrix.

(2) Directional net connectedness network

A directional net connectedness network is constructed based on pairwise net connectedness. In this network, each market is set as a node, and the condition in which a directional edge from i to j exists in the network if and only if $\tilde{\theta}_{ji} - \tilde{\theta}_{ij} > 0$. Using this network, the structure of risk spillover and the direction of information flow can be well identified and the risk origin of the housing market can be detected.

3. Data and empirical analysis

3.1 Data

In this paper, we collect mortgage default risk index (MDRI) as the measure of the U.S. housing market risk. Monthly data of MDRI for twenty MSAs in the U.S. are obtained from MDRI database[1], ranging from February 2004 to September 2017. As mentioned earlier our study uses data from the MDRIs developed by Chauvet et al. (2016). These authors using Google data, collect sensitive information directly from individuals seeking assistance via internet search on issues of mortgage default and home foreclosure. Specifically, Chauvet et al. (2016) aggregate Google search queries for terms like "foreclosure help" and "government mortgage help" to compile a novel MDRI in real-time. Furthermore, we also analyze MDRI data of forty-three states in the U.S. (obtained from the same source) to investigate the risk spillover of housing market in the state level.

3.2 Empirical results

[1] The data can be accessed at: https://chandlerlutz.shinyapps.io/mdri-app/.

3.2.1 Analysis for the MDRI MSA network

According to the minimizing Bayesian information criteria (BIC), the optimal lag in the VAR model is 1. Then, we can obtain the pairwise connectedness measure based on 10-step-ahead forecasting error variance decomposition results.

Firstly, we construct a centrality connectedness network and the weight of network edges, and the values of two network centrality indicators are shown in Table 1. The first 20 rows of the Table 1 present the pairwise spillover intensity which is calculated as the sum of the two directional pairwise connectedness: ($\tilde{\theta}_{ji} + \tilde{\theta}_{ij}$). It can measure the spillover magnitude and strength of information linkages across areas. From Table 1, it can be observed that information interdependence present across areas is quite different. For example, the pairwise spillover intensity between San Francisco and Washington DC is largest at 30.2%, which means that more than 30% risk of the mentioned two areas can be explained by each other. On the contrary, the pairwise spillover intensity of Atlanta-Las Vegas and New York-Las Vegas are smallest with 0.5%, indicating the risk spillover across these areas can be ignored. Furthermore, the values of two network centrality indicators namely, degree centrality and eigenvector centrality introduced in section 2.2, are presented in the last two rows in Table 1, which in turn, are good reflection of the core status of each MSA in the U.S. housing market system. These two indictors show similar evidence in the sense that Chicago, New York and Los Angeles rank as the top 3, confirming their central status in the housing market network. Both centrality measures for Las Vegas are the smallest, indicating its fringe status in the network.

[INSERT TABLE 1]

The centrality connectedness network can measure well the central position of each regional market, but it provides limited evidence for the spillover direction across

markets. Therefore, we further construct a directional net connectedness network based on pairwise net connectedness measure, as shown in Figure 1. In the figure, the information flow and structure of regional mortgage default risk transmission can be intuitively identified. Generally, the connectedness network indicates that there exists complex risk spillover across the regional housing markets. Similar to the centrality connectedness network, New York, Chicago and Los Angeles plays the core role in risk spillover in the directional net connectedness network, implying that the information on mortgage default risks in the U.S. housing market usually originates from these MSAs to other regions. Moreover, besides the above MSAs, Washington DC also plays an important role in risk spillover in the network. This finding is consistent with the central place theory of regional economics in the sense that, commercial central and capital of the country often play the leading role in information diffusion taking into account its importance in the national economy, politics and transportation. In addition, risk spillover presents a certain regional connection properties, in which the risk spillover across metropolitan areas that have close economic and spatial distance.

[INSERT FIGURE 1]

3.2.2 Analysis based on state-level data

In this section, we include forty-three states in our analysis. The directional net connectedness network for the state-level MDRIs is depicted in Figure 2. Interestingly, the findings for the state-level risk spillover are not fully consistent with that in the metropolitan-based network. Figure 2 shows clearly that Minnesota is at the core of the network, followed by Arizona, Pennsylvania, New York and New Hampshire. While, Idaho, Iowa, West Virginia, Rhode Island and Oregon show the lowest level of

involvement in terms of the spillover of mortgage default risks.[2]

[INSERT FIGURE 2]

4. Conclusions

As observed during the recent housing and financial crisis, elevated mortgage delinquencies and defaults can wreak havoc on the macroeconomy and financial markets. In this regard, an important question is the spillover of mortgage default risks across MSAs and states of the U.S. Thus, the current study explores the interconnectedness across MSAs and states in terms of mortgage default risks. Using a newly-developed real time index of mortgage default risks, using the novel methodology of Diebold and Yilmaz (2014) built on the VAR framework, we find that there exist complex interconnectedness networks among twenty MSAs and forty-three states. At the state-level, the network analysis reveals that Minnesota is at the core alongside Arizona and Pennsylvania, while for the MSAs, Chicago, New York, and Los Angeles serve as transmitters of mortgage default risks spillover. In sum, our results indicate that, in terms of mortgage default risks, major MSAs and states of the U.S. are indeed interrelated in a complex manner to each other within their respective categories, with shocks originating from New York and Minnesota likely to have the strongest impact on other MSAs and states respectively. This information is of course important to investors, regulators and policymakers aiming to manage such risks, while making their respective optimal decisions.

While this paper is the first attempt to analyze spillover of mortgage default risks, which we show to exist, future analysis should be aimed at determining the underlying factors that drive the nature of the networks derived here. Moreover, what would be

[2] Complete details involving the analysis on the network centrality of connectedness for the MDRI of the forty-three states have been suppressed due to presentation issues associate with a 43×43 matrix, and to save space, but is available upon request from the authors.

interesting to analyze are the possible determinants of the common movement in these mortgage default risks, by identifying national, local and idiosyncratic factors, as in Gupta et al., (2018).

Acknowledgement

The first author acknowledges the support from the National Natural Science Foundation of China under Grant No. 71774152, 91546109; and the Youth Innovation Promotion Association of the Chinese Academy of Sciences (Grant No. Y7×0231505). The authors would also like to thank Christophe André at the Organisation for Economic Co-operation and Development (OECD) for many helpful comments.

References

Agarwal, S., Ambrose, B.W., Chomsisengphet, S., and Sanders, A.B. (2012). Thy Neighbor's Mortgage: Does Living in a Subprime Neighborhood Affect One's Probability of Default? Real Estate Economics, 40(1), 1-22.

Ambrose, B. W., and Diop, M. (2014). Spillover effects of subprime mortgage originations: The effects of single-family mortgage credit expansion on the multifamily rental market. Journal of Urban Economics, 81, 114-135.

Berrospide, J.M., Black, L.K., and Keeton, W.R. (2016). The cross-market spillover of economic shocks through multimarket banks". Journal of Money, Credit and Banking 48(5), 957-988.

Calomiris, C.W., Longhofer S.D., and Miles, W.R. (2013). The foreclosure–house price nexus: A panel VAR model for U.S. states, 1981–2009. Real Estate Economics 41(4), 709-746.

Chomsisengphet, S., Kiefer, H., and Liu, X. (2018). Spillover effects in home mortgage defaults: Identifying the power neighbor. Regional Science and Urban Economics. DOI: 10.1016/ j.regsciurbeco.2018.07.011.

Chauvet, M., Gabriel, S., and Lutz, C. (2016). Mortgage default risk: New evidence from internet search queries. Journal of Urban Economics 96, 91-111.

Diebold, F.X., and Yilmaz, K. (2014). On the network topology of variance decompositions: Measuring the connectedness of financial firms. Journal of Econometrics 182, 119-134.

Gupta, A. (Forthcoming). Foreclosure Contagion and the Neighborhood Spillover Effects of Mortgage Defaults. Journal of Finance.

Gupta, R., Ma, J., Risse, M., and Wohar, M.E. (2018). Common business cycles and volatilities in US states and MSAs: The role of economic uncertainty. Journal of Macroeconomics, 57, 317-337.

Koop, G., Pesaran, M.H., and Potter, S.M. (1996). Impulse Response Analysis in Nonlinear Multivariate Models. Journal of Econometrics, 74 (1), 119–147.

Lin, Z., Rosenblatt, E., and Yao, V. W. (2009). Spillover effects of foreclosures on neighborhood property values. The Journal of Real Estate Finance and Economics, 38(4), 387-407.

Pesaran, M.H. and Yongcheol, S. (1998). Generalized Impulse Response Analysis in Linear Multivariate Models. Economics Letters, 58, 17-29.

Sims, C.A. (1980). Macroeconomics and Reality. Econometrica, 48, 1–48.

Yang, Z., and Zhou, Y. (2017). Quantitative easing and volatility spillovers across countries and asset classes. Management Science 63(2), 333-354.

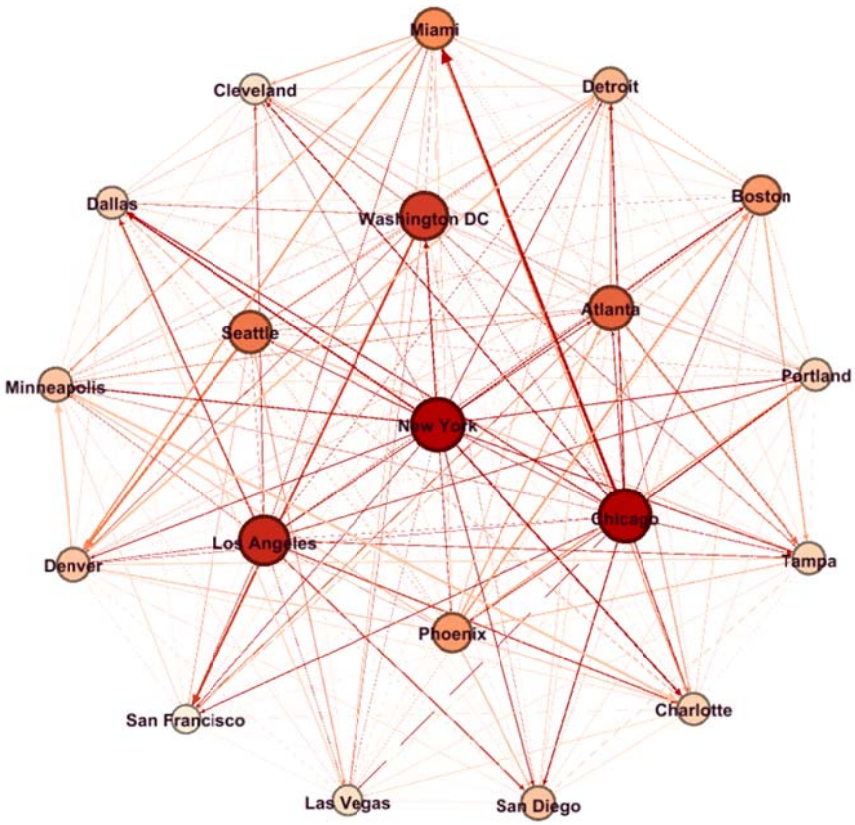

Figure 1. Directional net connectedness network for the MDRI of MSAs

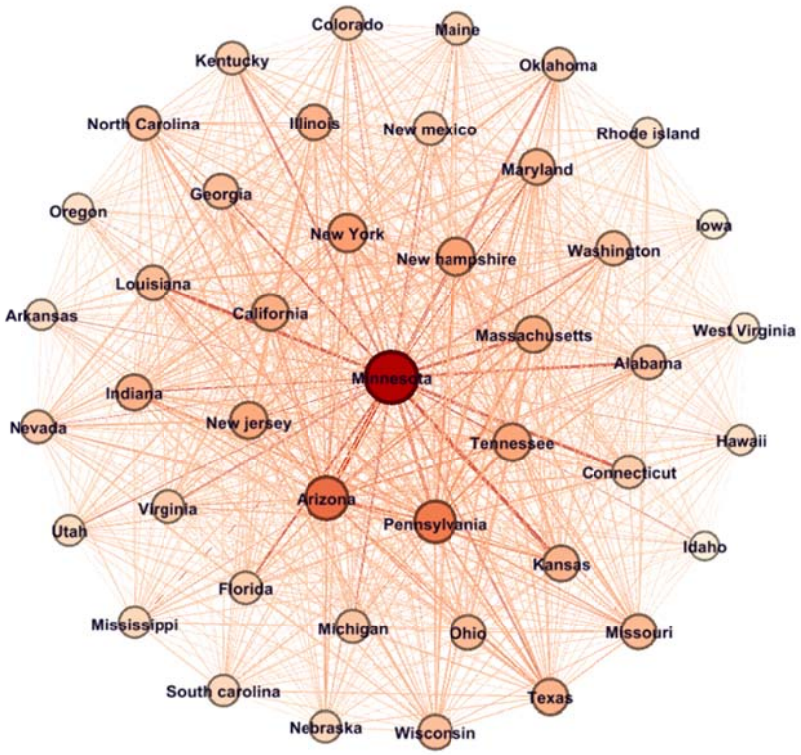

Figure 2. Directional net connectedness network for the MRDI of states sample

Table 1. Network centrality of connectedness for MDRI of MSAs

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
1	0																			
2	13.0	0																		
3	3.6	2.9	0																	
4	11.3	12.0	4.1	0																
5	5.0	2.5	4.5	10.9	0															
6	4.5	7.3	4.6	9.5	4.9	0														
7	5.0	2.4	0.9	1.7	6.5	6.4	0													
8	15.5	7.0	1.7	9.6	1.9	1.5	6.8	0												
9	0.5	3.0	3.6	1.5	0.9	3.6	1.0	0.6	0											
10	9.7	7.0	7.8	12.2	8.3	15.2	7.2	5.3	2.1	0										
11	4.3	8.1	4.8	19.3	5.8	2.6	5.9	4.3	1.7	6.7	0									
12	12.0	7.6	6.0	7.7	3.3	5.1	11.3	7.0	0.8	6.4	3.5	0								
13	10.3	18.2	7.8	15.1	3.7	11.5	6.6	7.1	0.5	16.7	7.0	9.9	0							
14	9.5	7.2	6.8	14.7	8.4	12.9	3.0	8.8	0.6	9.8	5.0	5.1	10.8	0						
15	6.2	2.6	2.2	8.4	5.6	1.9	3.8	6.0	2.9	9.3	6.3	6.3	8.3	13.0	0					
16	4.5	3.2	3.5	8.8	9.1	2.3	1.8	12.9	3.7	9.4	7.9	0.8	6.0	8.9	6.4	0				
17	10.1	6.2	4.5	7.7	5.8	5.2	2.2	2.5	1.6	5.7	2.2	2.7	4.8	4.4	3.7	6.3	0			
18	10.1	9.6	2.6	12.1	2.2	6.9	5.2	7.9	2.9	9.3	6.9	2.6	10.3	11.2	10.9	3.0	8.5	0		
19	8.5	6.1	4.2	4.9	2.2	5.3	9.4	8.2	2.2	7.3	4.0	6.0	6.6	5.2	2.4	5.3	4.6	4.6	0	
20	8.1	9.5	7.8	8.2	5.5	7.0	7.6	1.2	1.2	8.7	2.1	4.7	13.5	7.6	3.8	2.9	30.2	11.9	8.9	0
Degree centrality	**8.0**	**7.1**	**4.4**	**9.5**	**5.1**	**6.2**	**5.0**	**6.1**	**1.8**	**8.6**	**5.7**	**5.7**	**9.2**	**8.0**	**5.8**	**5.6**	**6.3**	**7.3**	**5.6**	**7.9**
Eigenvector centrality	**0.27**	**0.25**	**0.15**	**0.31**	**0.17**	**0.21**	**0.16**	**0.20**	**0.06**	**0.28**	**0.19**	**0.19**	**0.31**	**0.27**	**0.20**	**0.18**	**0.21**	**0.25**	**0.18**	**0.26**

Note: This table measures network centrality for MDRI MSA market. In the table, the off-diagonal elements are calculated by the sum of pairwise 10-day-ahead forecast error variance (in percentage points) and diagonal elements are zeros. 1=Atlanta, 2=Boston, 3=Charlotte, 4=Chicago, 5=Cleveland, 6=Dallas, 7=Denver, 8=Detroit, 9=Las Vegas, 10=Los Angeles, 11=Miami, 12=Minneapolis, 13=New York, 14=Phoenix, 15=Portland, 16=San Diego, 17=San Francisco, 18=Seattle, 19=Tampa, 20=Washington DC.