

Convergence in U.S. Metropolitan Statistical Areas

Ghassen El-Montasser.

Ecole supérieure de commerce de Tunis, University of Manouba, Tunisia

Rangan Gupta* and Devon Smithers

Department of Economics, University of Pretoria, South Africa

Abstract

In this paper, the convergence of income per capita across U.S. metropolitan statistical areas (metros) are examined over the period between 1969 and 2011. We initiate the analysis with multivariate tests for stability, and the existence of unit roots. The analysis is complemented by the use of the panel stationarity test accounting for structural changes, as proposed by Carrion-i-Silvestre et al. (2005). The study of convergence is important for both economists, as a means to test growth theories and distinguish between different models, as well as policy makers who seek to maximize the utility of their constituents by making use of all information available to them. We find that that in the 384 U.S. metros there is a divergence of per capita income, which is dissimilar to other empirical literature that has dealt with convergence using older time periods and data.

Keywords: Panel data; Income convergence; Structural breaks; Unit root test

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* To whom correspondence should be addressed. Email: rangan.gupta@up.ac.za

1. Introduction

Convergence is defined as poorer regions or countries growing faster than rich regions or countries, so that the gap in relative incomes between the two will become smaller over time. Much empirical work has been done on this concept over the past 25 years. This is due to the fact that data on growth - over many countries - has been highly dissimilar over the last 3 decades. The empirical studies have been done to ascertain whether or not the convergence phenomenon is indeed valid, or merely a theoretical prediction of the seminal Solow (1956) model. The study of convergence is also important in order to analyse the determinants of growth, and why certain regions/countries tend to grow faster than others.

There are numerous empirical works testing the convergence hypothesis, with varying results. The main methodology used in the literature involves fitting cross-country regressions, where convergence is confirmed if there is a negative relationship between the average growth rate and initial income of a specific country, i.e. the higher the initial income, the slower the average growth rate. Studies by the pioneering Baumol (1986), as well as those by Barro and Sala-i-Martin (1991, 1992), and Mankiw et al. (1992) all find that convergence exists among OECD/industrial countries, as well as the regions within them.

For illustration, Barro and Sala-i-Martin (1991) make use of per capita income data for the U.S. states for the time period 1840 – 1990. They find significant evidence for the existence of convergence across the U.S. states for the time period. They then compare their original results for the U.S. to a cross country sample, using real GDP per capita from 1985 – 1990 for 85 countries, including industrialised as well as non-industrialised countries. Again they find significant evidence for the convergence of income.

The above mentioned methodology has been criticized for its simplicity, and other techniques applied to the convergence hypothesis. In contrast to the cross-sectional studies above, Quah (1993), making use panel data, and Bernard and Durlauf (1995), using a univariate form of cointegration tests that defines convergence as a stochastic process, cannot confirm convergence across a large sub-section of countries.

Time series methodologies appear to hold weight, as recently the study by Strazicich et al. (2002) makes use of a time series approach, utilizing a minimum Lagrange multiplier unit root test which endogenously determines two structural breaks in level and trend. This approach is not subject to restrictions on the null hypothesis, as many other tests are. Strazicich et al. empirically find that incomes are stochastically converging across 15 OECD countries for the time period 1870 - 1994. This means that the shocks to each country analysed are temporary, and do not affect incomes in the long run. They find two structural breaks for all countries, most often around the period of the two World Wars. These results contrast with other time series tests that did not allow for structural breaks, which gives weight to the inclusion of structural breaks in our analysis.

Further evidence of the validity of the inclusion of structural breaks are provided by Carlino and Mills (1996) as well as by Loewy and Papell (1996), who utilize one-break exogenous and endogenous unit root tests, respectively, and find support for convergence among the U.S. regions in the period 1920 - 1990. Fleissig and Strauss (2001) examine OECD countries with a variety of panel unit root tests and find, in general, support for convergence only in the post-WWII period.

Other methods that find support for convergence include spatial econometrics, which incorporates regional factors into the analysis, as well as Instrument Variable approaches making use of 2SLS. Rey and Montouri (1999) use a spatial econometric approach, in which they incorporate effects specific to their region of study, such as geography, to test convergence of the U.S. region relative incomes. They revealed strong evidence of spatial autocorrelation in the levels of state per capita incomes over the sample period of 1929 - 1994. They further found that state income growth rates had a high degree of autocorrelation. This implies that, while states may be converging in relative incomes, they do this together, i.e. not independently, but rather tend to display similar movements to that of their regional neighbours.

As far as the IV approach goes, Higgins, Levy and Young (2003) use 2SLS - making use of instrumental variables - to study growth determination and the speed of income convergence across the U.S. They find that the U.S. states are converging, as confirmed by both methodologies. However, they further emphasize that convergence rates are not constant across the U.S., for example, the counties in the Southern states converge at a rate that is more than two and half times faster than the counties located in the New England states. Further, the authors confirm that large presences of both finance, insurance, real estate industry and entertainment industry are positively correlated with growth.

Finally, in line with this papers methodology, Fousekis (2007) makes use of relative stochastic convergence and specifically, stationarity tests on panel data to analyse convergence of per capita incomes for the period 1929 – 2005 in US state data. This covers the period just before the global crisis of 2008, and gives a good indication of convergence pre-crisis in the U.S. region. The author discovers that not all states were stationary for every sub-period after the 1960's (which is when the data is considered to become free of any deterministic or stochastic trends). This implies that there is some degree of divergence in state per capita income, although more than 80% of the states have converged, or reached their steady-state equilibrium values.

Thus, considering the importance of testing convergence, and in light of the recent turmoil that engulfed the world economy in the form of the global crisis, this paper will investigate the convergence hypothesis for the U.S., using metro regions in the period subsequent to the crisis.

In order to achieve this, we make use of multivariate tests for stability, and the existence of unit roots, as used in the literature by Abuaf and Jorion (1990), and more recently by Harvey and Bates (2003). The stationarity tests are used to conclude whether the regions have converged, while the unit root tests come in handy to conclude whether the regions are converging. We account for the presence of structural breaks in the series, due to the highly volatile nature of the economy over the period of study, considering our data the recent global crisis, as well as numerous other possible structural breaks. Further accounting for potential breaks in our data, we conclude our empirical analysis with the panel stationarity test that accounts for structural changes, as proposed by Carrion-i-Silvestre, Del Barrio-Castro and López-Bazo [CBL] (2005).

We make use of U.S. data for studying convergence in a post-crisis world, due to the fact that we have a vast resource of data for over 40 years, on what is similar to over 384 separate economies, spread over 50 US states. There is substantial heterogeneity among the U.S. metros, in both terms of wealth, income, regulatory institutions, geographical location, and income per capita. The economies are also very open, which allows for high mobility of capital, labour and technology – all cornerstones of neo-classical models on which the idea of convergence is based. Exchange rate fluctuations are eliminated, as all the regions use the same currency. Price variations in consumer goods across countries also tend to be smaller than in a cross country analysis. We thus use the U.S as a benchmark, for what may be observed across the world. Additionally, due to our methodology, as Bernard and Durlauf (1996) mention “time series tests of convergence are not appropriate for those countries positioned far from the steady state as occurs with developing countries, in this case, the data would not be characterised by well-defined population moments, since the data are far from their limiting distribution.”

The rest of the paper is structured as follows: Section 2 discusses the methodology we employ, after which we detail the data we use in section 3. The empirical results are outlined in section 4. Finally we conclude in section 5.

2. Methodology

We study a group of metros, attempting to identify if the metro’s income per capita trend is stationary – indicating convergence. For this we make use of multivariate tests for stability. We take cognizance of the fact that there are probable structural breaks in our data, and due to this we make use of the Carrion-i-Silvestre et al. (2005) test, which appreciates structural changes. All unit root tests we perform, excluding the KPSS, have a null hypothesis of a unit root, meaning that a rejection of null indicates convergence. The KPSS test has the opposite null of no unit root. The Hadri Lagrange multiplier (LM) test that we make use of has as the null hypothesis that all the panels are (trend) stationary.

2.1 Multivariate tests for stability and unit roots

Multivariate tests are appropriate, if the aim is studying across a group of observations. Let x_t be n vector of contrasts between each of the metros, and a benchmark, e.g. $x_t' = (y_t^1, y_t^2, \dots, y_t^N)$. The simplest multivariate convergence model is the zero mean VAR(1) process:

$$x_t = \alpha x_{t-1} + \omega_t, \quad (3)$$

where α is a $N \times N$ matrix and ω_t is N dimensional vector of martingale differences innovations with constant variance Σ_ω . The model is said to be homogeneous if $\alpha = \varphi I_N$. Following Abuaf and Jorion (1990), Harvey and Bates (2003) propose the use of the multivariate unit root test from the homogeneous model. Specifically, they used the Wald-type statistic on $\rho = \varphi - 1$, that is

$$\psi_0(N) = \frac{\sum_{t=2}^T x_{t-1}' \tilde{\Sigma}_\omega^{-1} \Delta x_t}{(\sum_{t=2}^T x_{t-1}' \tilde{\Sigma}_\omega^{-1} x_{t-1})^{0.5}} \quad (4)$$

and referred to as the multivariate homogeneous Dickey-Fuller (MHDF) statistic. $\tilde{\Sigma}_\omega^{-1}$ is initially estimated by the sample covariance matrix of first-differenced data and then re-estimated by iterating the estimation of φ to convergence. Under the null hypothesis, $H_0: \rho = 0$,

$$\psi_0(N) \xrightarrow{d} \frac{1}{2} \frac{\sum_{i=1}^N (W_i(1)^2 - 1)}{(\sum_{i=1}^N \int_0^1 W_i(r)^2 dr)^{0.5}}$$

where $W_i(r)$ are independent standard Brownian motion processes, $i=1, \dots, N$; if N is large, $\psi_0(N)$ is approximately Gaussian. The null hypothesis is rejected when $\psi_0(N)$ less than a given critical value δ .

An interesting feature of the MHDF test is that it is invariant to any nonsingular transformation of x_t . Consequently, it is invariant to which country is chosen as benchmark. This feature is lost in case of heterogeneous model in which α is diagonal.

One can designate a parametric correction of the variance of the errors, through the addition of lagged differenced terms of x_t , to cope with serial correlation of the errors. The critical values of the test can be obtained from Harvey and Bates (2003); see also O'Connell (1998).

A generalization of the KPSS test can be applied to x_t to test whether the N metros have converged in the context of stability analysis. Then, the involved statistic is given by

$$\vartheta_0(N) = \text{Trace}(\hat{\Omega}^{-1}C), \quad (5)$$

where $C = \sum_{t=1}^T (\sum_{j=1}^t x_j) (\sum_{j=1}^t x_j)'$ and $\widehat{\Omega}^{-1}$ is a non-parametric estimation of the long run variance of x_t . Under the null hypothesis of zero mean stationarity, $\vartheta_0(n) \xrightarrow{d} \sum_{i=1}^N \int_0^1 W_i(r)^2 dr$, with d denoting weak convergence in distribution. Critical values are provided in Nyblom (1989) and Hobijn and Franses (2000). A non-rejection of the null hypothesis would suggest overall evidence of stability, in the sense that the n countries should have converged absolutely.

There may be confusion as to the role that unit root and stationarity tests play in detecting convergence. As described by Busetti *et al.* (2007), the two types of tests are in fact meant for different purposes and cannot be arbitrarily interchanged. Unit root tests are used for estimating whether series are in the process of converging, dependent on initial conditions. Stationarity tests however, are used for exploring whether series have converged. This implies that the difference between the series is stable. This is again confirmed by Harvey and Carvalho (2002).

It is therefore important to distinguish between convergence and stability. Convergence is analysed by testing the null hypothesis of unit root, whereas stability is tested by way of the null of stationarity. Thus the unit root tests come in handy to conclude whether the metros *are converging*, while the stationarity tests are used to conclude whether the metros *have converged*.

2.2 Panel stationarity test with structural changes: the Carrion-i-Silvestre, Del Barrio-Castro and López-Bazo [CBL] (2005) test

The reasons for taking into account structural breaks in the income per capita series are due to the potential shifts in the data due to shocks- such as the stock market crashes, and more recently the global crisis. It goes without saying the economic system is subject to capricious up and down-swings. Therefore, the income per capita series will be subjected to a number of structural changes. That is why we have taken account of Carrión-i-Silvestre *et al.* (2005) test in the analysis of convergence. In what follows, we briefly describe the CBL (2005) test, which, by design, has the ability to test the null hypothesis of panel stationarity while allowing multiple structural breaks. It will be described as follows:

$$x_{i,t} = c_i + \sum_{k=1}^{m_i} \theta_{i,k} DU_{i,k,t} + \beta_i t + \sum_{k=1}^{m_i} \gamma_{i,k} DT_{i,k,t}^* + \varepsilon_{i,t}, \dots, t = 1, \dots, T, \quad (6)$$

Where $x_{i,t}$ is the logarithm of the series of income per capita, $i=1, \dots, N$ represents the number of cross section units and $\varepsilon_{i,t}$ is the error term. The dummy variables $DU_{i,k,t}$ and $DT_{i,k,t}^*$ are defined as $DU_{i,k,t} = 1$ for $t > T_{b,k}^i$ and 0 otherwise, and $DT_{i,k,t}^* = t - T_{b,k}^i$ for $t > T_{b,k}^i$ and 0 otherwise; and $T_{b,k}^i$ denotes the k th date of the break for the i th individual, $k = \{1, \dots, m_i\}, m_i \geq 1$.

The model in equation (6) constitutes a generalization of that of Hadri (2000) and it includes individual effects, individual structural break effects (i.e., shift in the mean caused by the structural breaks known as temporal effects where $\beta_i \neq 0$), and temporal structural break effects (i.e., shift in the individual time trend where $\gamma_i \neq 0$). In addition, the specification given by equation (6) considers several structural breaks, which are located on different unidentified dates and where the number of structural breaks are allowed to vary between the members of the panel. The test statistic is constructed by running individual KPSS regressions for each member of the panel, and then taking the average of the N individual statistics. The general expression of the test statistic is

$$LM(\lambda) = N^{-1} \sum_{i=1}^N (\hat{\omega}_i^{-2} T^{-2} \sum_{t=1}^T S_{i,t}^2), \quad (7)$$

where $S_{i,t} = \sum_{j=1}^t \hat{\varepsilon}_{i,j}$ represents the partial sum process that is obtained using the estimated OLS residuals of equation (6), and $\hat{\omega}_i^2$ is the consistent estimate of the long-run variance of residual $\varepsilon_{i,t}$; this allows the disturbances to be heteroscedastic across the cross-sectional dimension.

In equation (7), λ is defined as the vector $\lambda_i = (\lambda_{i,1}, \dots, \lambda_{i,m_i})' = \left(\frac{T_{b,1}^i}{T}, \dots, \frac{T_{b,m_i}^i}{T} \right)'$.

The test statistic for the null hypothesis of a stationary panel with multiple shifts is

$$Z(\lambda) = \sqrt{N} (LM(\lambda) - \bar{\zeta}) / \bar{\zeta} \xrightarrow{d} N(0,1) \quad (8)$$

As in the case of the univariate KPSS test statistic, the null hypothesis of stationarity in the panel is rejected for large values of $Z(\lambda)$. $\bar{\zeta}$ and $\bar{\zeta}$ are the cross-sectional average of the individual mean and variance of $\delta_i(\lambda) = \hat{\omega}_i^{-2} T^{-2} \sum_{t=1}^T S_{i,t}^2$.

3. Data

We use annual US data, measuring real metro level Income per capita across the U.S. Data incorporating 384 metros from all 50 States is available from 1969 – 2011, obtained from the Bureau of Economic Analysis regional economic accounts.

We use U.S. data to study convergence, as it represents a unique and vast resource that covers 40 years, and it mimics many separate global ‘economies’; the states represent over 50 separate economies as the metro areas are dispersed over the states. This allows more in depth analysis and isolation of particular phenomena. Moreover, there is substantial heterogeneity among the U.S. metros, in terms of wealth, income, regulatory institutions, geographical location, and income per capita.

These separate economies are very open due to the fact that they lie in the same country. This allows for unrestricted movement of capital, labour and technology - high mobility of factors is a cornerstone of neo-classical models on which the idea of convergence is based. Fluctuations in exchange rates are all but eliminated, as the regions use the same currency.

The effects of inflation and differing consumer prices are also somewhat mitigated, as price variations in consumer goods across countries (i.e. within a country) also tend to be smaller than in a cross country (i.e. between countries) analysis. We make use of the U.S. regions as they act as a benchmark for what may be observed in an analysis that makes use of global data, and to which other studies of this nature may be compared.

All the U.S. metros used are available in the appendix if needed for reference.

4. Empirical Results

Before we proceed with the presentation of our results, we make a note of the specification of our KPSS unit root test. The literature establishes that the KPSS test without a constant has power against a stationary process with a non-zero mean, as well as against a non-stationary process (Busetti and Harvey, 2002). Thus we perform the KPSS test without a constant term, given its increased power when performed in this manner. In this way, we test if the series have converged individually or in groups, and if the involved convergence is absolute.

The Levin–Lin–Chu (2002) and Im–Pesaran–Shin (2003) tests have as the null hypothesis that all the panels contain a unit root. The Hadri (2000) Lagrange multiplier (LM) test has as the null hypothesis that all the panels are (trend) stationary. The KPSS has a null of stationarity, as do the CBL and Hadri LM tests.

With regard to multivariate tests, the cross-section mean was subtracted from each individual series. This can be beneficial in two ways: First, the cross-section mean series can be regarded as a benchmark, and then, the study of all individual series is guaranteed. Second, this subtraction can mitigate the effects of not taking into account the cross-sectional dependence. This assumption reflects reality, as the analysis of macroeconomic time series for different metros may be affected by similar events that could introduce dependency between individuals in the panel data set. We therefore follow Levin et al, (Levin, Lin and Chu [LLC]) (2002), who suggested removing the cross-section mean, which is equivalent to include temporal effects in the panel data. We applied the LLC test to the series to compare its results with those from the other multivariate homogeneous test, including, the MHDF test. Given that the MHDF test does not take account of heterogeneity, we decided to add the Im et al. (Im, Pesaran and Shin [IPS]) (2003) test that has been formulated by allowing for this heterogeneity.

Table 1: Summary of the results of the tests for unit roots.

Test	Statistic	p-value	Decision
Multivariate homogeneous Dickey-Fuller (MHDF)	-29.0945	$2.1069e^{-186}$	Reject H_0 of a unit root
Levin Lin Chu (LLC)	-3.6540	$1.2907e^{-0.004}$	Reject H_0 of a unit root
In, Pesaran and Shin (IPS)	-3.5929	$1.6351e^{-0.004}$	Reject H_0 of a unit root

From table 1 above, we can see that all the tests reject the null of a unit root, both under the homogeneity and heterogeneity assumptions, which indicates that the series are in the process of converging, as they do not have a permanent memory and are heading towards their respective steady states. This does not necessarily imply convergence; however, given the time frame it confirms that in the long run the income of the respective metros should all reach their steady states –we can say that the metros are converging. This is as predicted by contemporary macroeconomic models.

Next, we consider Multivariate tests for stability which, as described, are used to test if the series have converged.

Table 2: Summary of the results of the panel and multivariate test for stationarity.

Test	Statistic	p-value	Decision
MKPSS	46668	0.000	Reject H_0 of stationarity
Ng-BAI Panic test for stationarity	1611.134	0.144	Cannot Reject H_0 of stationarity
Hadri LM Test	15.794725	$1.6913e^{-0.056}$	Reject the H_0 of stationarity
CBL Test	77.181	0.000	Reject the H_0 of stationarity

As we see from table 2, the MKPSS, Hadri and CBL tests all reject the null hypothesis of stationarity. For comparison to the MKPSS test, we used the Ng-Bai (2004) PANIC test for stationarity hypothesis. A specific feature of PANIC is that it tests the data's unobserved components instead of the observed series. From a cursory glance, this procedure is based on the factor structure of the large dimensional panels to reveal the nature of non-stationarity in the data. Using the PANIC test, we failed to reject the null of stationarity.

Due to the fact that the MKPSS test does not take heterogeneity into account, we include the panel stationarity test of Hadri (2000), which allows for heterogeneity. With regards to convergence, this may be advantageous, as the homogeneity assumption restricts every metro to converge at the same rate. The Hadri test that includes structural breaks, as well as Hadri test with individual and temporal effects, both reject the null of stationarity.

Referring in particular to the CBL test, we see that the null hypothesis of stationarity with structural breaks is rejected. A little digression is absolutely essential here. From an econometric point of view, the conflicting results of stationarity and unit root tests may be an indicator of nonlinearity and structural changes. We are therefore justified in using the CBL test.

Based on the results from table 2, we reject the null of stationarity for the panel as a whole. This would indicate that rather than no convergence, there is actually a divergence of income per capita in the U.S. metros. This result is reasonable within the current investigation, as given the literature, the income per capita in the U.S. metros were typically close together, and have now tended to widen. This divergence terminology is supported by Buseti *et al.* (2007).

Overall, based on test results from table 1 and 2, our finds are that the unit root tests reject the null hypothesis of unit root, and the stationarity tests reject the null hypothesis of stationarity. We can thus conclude from the unit root tests that the series are in the process of converging. However, given the rejection of stationarity hypothesis in the stationarity tests, we can conclude that there is no evidence for overall stability of the income per capita among the U.S. metros, and this implies that the series have diverged.

Potential reasons for this divergence of income per capita in the U.S. metros are outlined by Ganong and Shoag (2012). They argue that migration of labour can account for all of the observed change in convergence. In their study, it is shown that the relationship between migration and housing prices has changed in the recent past. Even though housing prices have always been higher in richer areas, housing prices now capitalize a far greater proportion of the income differences across states. Due to the fact that housing prices are now a bigger divider between income groups, labour markets no longer clear through migration, but rather by skill-sorting. Thus, the divergence in income per capita may be attributed to a divergence in the skill-specific returns to productive places, a redirection of low-skilled migration, diminished human capital convergence, and continued convergence among places with unconstrained housing supply.

Consequently, the reason that convergence of income per capita has ceased, can be answered by a divergence in workers with tertiary education across places – where high-skilled workers are becoming relatively more concentrated. As argued by the authors, there is an increase in consumers' desire to live in places that are highly educated, as well as an increase in firms' desire for highly skilled labour. The fact that are willing to pay increasingly

large amounts to live in their place of choosing, drives up the price of housing in these areas.

From the firm side, the rise of the so-called information economy and a bias towards highly skilled technological change, causes an upsurge in the demand for skilled labour, due to their higher productivity levels. This means that firms in highly-skilled areas may pay higher wages, however, due to the fact that migration of labour has been prevented by the excessive housing prices, only a select few highly-skilled individuals can take advantage of the higher wages in these areas. The fact that housing prices constrain the movement of labour, means that workers from poorer regions are not able to move to regions where their remuneration may be higher, and this is due to the up-surge of housing prices in the areas that offer higher wages. Further, because low-workers are no longer able to move to well-educated regions, there is a slowdown of human capital convergence – which may be due to diminished learning by doing and skills-sharing, all caused by increased housing prices.

5. Conclusion

The confirmation of convergence is of utmost importance to policy makers and economists, since it is necessary to find out what impact certain policies might have on growth, as well as to test to see if model predictions hold in the real world – which would indicate the validity of certain macroeconomic models. Having recently undergone a major global crises which may have affected the distribution of income, we test the convergence hypothesis across the U.S metros for the time period 1969 – 2011.

Firstly, we make use of multivariate tests for existence of unit roots. Given that the series are likely to contain structural breaks, and that these breaks must be accounted for, we proceed with the analysis using the panel stationarity test accounting for structural changes as proposed by Carrion-i-Silvestre et al., (2005).

Overall, our results indicate that while the U.S metros are indeed converging, they have not converged but have indeed diverged. Potential reasons for this are vast, and to be sure a full study needs to be undertaken to determine probable causes. However, given the increase in housing prices in rich areas, migration of labour may be constrained, which limits the convergence of human capital and productive returns to specific skills. This may limit the “catch up” factor that drives convergence of income per capita.

Given the finding in this paper, future studies may test for convergence over a large sample of countries, both developed and potentially developing. A limitation of this study, which may be rectified in future work, is that a more in-depth study focusing on the reasons for the divergence found in the U.S. metros could be carried out.

Our findings have important implications for literature related to macroeconomic modelling, but also policy regarding land-ownership. Literature may need to take into account the role of the price of land, and how it affects labour, in modelling economic growth, while policy makers should take note of the fact that increases in house prices may limit the migration of labour, and ultimately affect productivity. Policy that encourages the continued migration of labour by way of ensuring realistic housing prices for the working class, may ensure future convergence.

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Appendix

a.) List of all Metro's.

1	hp10180	Abilene, TX (Metropolitan Statistical Area)
2	hp10420	Akron, OH (Metropolitan Statistical Area)
3	hp10500	Albany, GA (Metropolitan Statistical Area)
4	hp10580	Albany-Schenectady-Troy, NY (Metropolitan Statistical Area)
5	hp10740	Albuquerque, NM (Metropolitan Statistical Area)
6	hp10780	Alexandria, LA (Metropolitan Statistical Area)
7	hp10900	Allentown-Bethlehem-Easton, PA-NJ (Metropolitan Statistical Area)
8	hp11020	Altoona, PA (Metropolitan Statistical Area)
9	hp11100	Amarillo, TX (Metropolitan Statistical Area)
10	hp11180	Ames, IA (Metropolitan Statistical Area)
11	hp11260	Anchorage, AK (Metropolitan Statistical Area)
12	hp11300	Anderson, IN (Metropolitan Statistical Area)
13	hp11340	Anderson, SC (Metropolitan Statistical Area)
14	hp11460	Ann Arbor, MI (Metropolitan Statistical Area)
15	hp11500	Anniston-Oxford, AL (Metropolitan Statistical Area)
16	hp11540	Appleton, WI (Metropolitan Statistical Area)
17	hp11700	Asheville, NC (Metropolitan Statistical Area)
18	hp12020	Athens-Clarke County, GA (Metropolitan Statistical Area)
19	hp12060	Atlanta-Sandy Springs-Marietta, GA (Metropolitan Statistical Area)
20	hp12100	Atlantic City-Hammonton, NJ (Metropolitan Statistical Area)
21	hp12220	Auburn-Opelika, AL (Metropolitan Statistical Area)
22	hp12260	Augusta-Richmond County, GA-SC (Metropolitan Statistical Area)
23	hp12420	Austin-Round Rock-San Marcos, TX (Metropolitan Statistical Area)
24	hp12540	Bakersfield-Delano, CA (Metropolitan Statistical Area)
25	hp12580	Baltimore-Towson, MD (Metropolitan Statistical Area)
26	hp12620	Bangor, ME (Metropolitan Statistical Area)
27	hp12700	Barnstable Town, MA (Metropolitan Statistical Area)
28	hp12940	Baton Rouge, LA (Metropolitan Statistical Area)
29	hp12980	Battle Creek, MI (Metropolitan Statistical Area)
30	hp13020	Bay City, MI (Metropolitan Statistical Area)
31	hp13140	Beaumont-Port Arthur, TX (Metropolitan Statistical Area)
32	hp13380	Bellingham, WA (Metropolitan Statistical Area)
33	hp13460	Bend, OR (Metropolitan Statistical Area)
34	hp13644	Bethesda-Rockville-Frederick, MD (MSAD)
35	hp13740	Billings, MT (Metropolitan Statistical Area)
36	hp13780	Binghamton, NY (Metropolitan Statistical Area)
37	hp13820	Birmingham-Hoover, AL (Metropolitan Statistical Area)
38	hp13900	Bismarck, ND (Metropolitan Statistical Area)
39	hp13980	Blacksburg-Christiansburg-Radford, VA (Metropolitan Statistical Area)
40	hp14020	Bloomington, IN (Metropolitan Statistical Area)
41	hp14060	Bloomington-Normal, IL (Metropolitan Statistical Area)

42	hp14260	Boise City-Nampa, ID (Metropolitan Statistical Area)
43	hp14484	Boston-Cambridge-Quincy, MA-NH (Metropolitan Statistical Area)
44	hp14500	Boulder, CO (Metropolitan Statistical Area)
45	hp14540	Bowling Green, KY (Metropolitan Statistical Area)
46	hp14740	Bremerton-Silverdale, WA (Metropolitan Statistical Area)
47	hp14860	Bridgeport-Stamford-Norwalk, CT (Metropolitan Statistical Area)
48	hp15180	Brownsville-Harlingen, TX (Metropolitan Statistical Area)
49	hp15260	Brunswick, GA (Metropolitan Statistical Area)
50	hp15380	Buffalo-Niagara Falls, NY (Metropolitan Statistical Area)
51	hp15500	Burlington, NC (Metropolitan Statistical Area)
52	hp15540	Burlington-South Burlington, VT (Metropolitan Statistical Area)
53	hp15764	Cambridge-Newton-Framingham, MA (MSAD)
54	hp15804	Camden, NJ (MSAD)
55	hp15940	Canton-Massillon, OH (Metropolitan Statistical Area)
56	hp15980	Cape Coral-Fort Myers, FL (Metropolitan Statistical Area)
57	hp16020	Cape Girardeau-Jackson, MO-IL (Metropolitan Statistical Area)
58	hp16180	Carson City, NV (Metropolitan Statistical Area)
59	hp16220	Casper, WY (Metropolitan Statistical Area)
60	hp16300	Cedar Rapids, IA (Metropolitan Statistical Area)
61	hp16580	Champaign-Urbana, IL (Metropolitan Statistical Area)
62	hp16620	Charleston, WV (Metropolitan Statistical Area)
63	hp16700	Charleston-North Charleston-Summerville, SC (Metropolitan Statistical Area)
64	hp16740	Charlotte-Gastonia-Rock Hill, NC-SC (Metropolitan Statistical Area)
65	hp16820	Charlottesville, VA (Metropolitan Statistical Area)
66	hp16860	Chattanooga, TN-GA (Metropolitan Statistical Area)
67	hp16940	Cheyenne, WY (Metropolitan Statistical Area)
68	hp16974	Chicago-Joliet-Naperville, IL-IN-WI (Metropolitan Statistical Area)
69	hp17020	Chico, CA (Metropolitan Statistical Area)
70	hp17140	Cincinnati-Middletown, OH-KY-IN (Metropolitan Statistical Area)
71	hp17300	Clarksville, TN-KY (Metropolitan Statistical Area)
72	hp17420	Cleveland, TN (Metropolitan Statistical Area)
73	hp17460	Cleveland-Elyria-Mentor, OH (Metropolitan Statistical Area)
74	hp17660	Coeur d'Alene, ID (Metropolitan Statistical Area)
75	hp17780	College Station-Bryan, TX (Metropolitan Statistical Area)
76	hp17820	Colorado Springs, CO (Metropolitan Statistical Area)
77	hp17860	Columbia, MO (Metropolitan Statistical Area)
78	hp17900	Columbia, SC (Metropolitan Statistical Area)
79	hp17980	Columbus, GA-AL (Metropolitan Statistical Area)
80	hp18020	Columbus, IN (Metropolitan Statistical Area)
81	hp18140	Columbus, OH (Metropolitan Statistical Area)
82	hp18580	Corpus Christi, TX (Metropolitan Statistical Area)
83	hp18700	Corvallis, OR (Metropolitan Statistical Area)
84	hp18880	Crestview-Fort Walton Beach-Destin, FL (Metropolitan Statistical Area)
85	hp19060	Cumberland, MD-WV (Metropolitan Statistical Area)
86	hp19124	Dallas-Fort Worth-Arlington, TX (Metropolitan Statistical Area)

87	hp19140	Dalton, GA (Metropolitan Statistical Area)
88	hp19180	Danville, IL (Metropolitan Statistical Area)
89	hp19260	Danville, VA (Metropolitan Statistical Area)
90	hp19340	Davenport-Moline-Rock Island, IA-IL (Metropolitan Statistical Area)
91	hp19380	Dayton, OH (Metropolitan Statistical Area)
92	hp19460	Decatur, AL (Metropolitan Statistical Area)
93	hp19500	Decatur, IL (Metropolitan Statistical Area)
94	hp19660	Deltona-Daytona Beach-Ormond Beach, FL (Metropolitan Statistical Area)
95	hp19740	Denver-Aurora-Broomfield, CO (Metropolitan Statistical Area)
96	hp19780	Des Moines-West Des Moines, IA (Metropolitan Statistical Area)
97	hp19804	Detroit-Warren-Livonia, MI (Metropolitan Statistical Area)
98	hp20020	Dothan, AL (Metropolitan Statistical Area)
99	hp20100	Dover, DE (Metropolitan Statistical Area)
100	hp20220	Dubuque, IA (Metropolitan Statistical Area)
101	hp20260	Duluth, MN-WI (Metropolitan Statistical Area)
102	hp20500	Durham-Chapel Hill, NC (Metropolitan Statistical Area)
103	hp20740	Eau Claire, WI (Metropolitan Statistical Area)
104	hp20764	Edison-New Brunswick, NJ (MSAD)
105	hp20940	El Centro, CA (Metropolitan Statistical Area)
106	hp21060	Elizabethtown, KY (Metropolitan Statistical Area)
107	hp21140	Elkhart-Goshen, IN (Metropolitan Statistical Area)
108	hp21300	Elmira, NY (Metropolitan Statistical Area)
109	hp21340	El Paso, TX (Metropolitan Statistical Area)
110	hp21500	Erie, PA (Metropolitan Statistical Area)
111	hp21660	Eugene-Springfield, OR (Metropolitan Statistical Area)
112	hp21780	Evansville, IN-KY (Metropolitan Statistical Area)
113	hp21820	Fairbanks, AK (Metropolitan Statistical Area)
114	hp22020	Fargo, ND-MN (Metropolitan Statistical Area)
115	hp22140	Farmington, NM (Metropolitan Statistical Area)
116	hp22180	Fayetteville, NC (Metropolitan Statistical Area)
117	hp22220	Fayetteville-Springdale-Rogers, AR-MO (Metropolitan Statistical Area)
118	hp22380	Flagstaff, AZ (Metropolitan Statistical Area)
119	hp22420	Flint, MI (Metropolitan Statistical Area)
120	hp22500	Florence, SC (Metropolitan Statistical Area)
121	hp22520	Florence-Muscle Shoals, AL (Metropolitan Statistical Area)
122	hp22540	Fond du Lac, WI (Metropolitan Statistical Area)
123	hp22660	Fort Collins-Loveland, CO (Metropolitan Statistical Area)
124	hp22744	Fort Smith, AR-OK (Metropolitan Statistical Area)
125	hp22900	Fort Smith, AR-OK
126	hp23060	Fort Wayne, IN (Metropolitan Statistical Area)
127	hp23104	Fort Worth-Arlington, TX (MSAD)
128	hp23420	Fresno, CA (Metropolitan Statistical Area)
129	hp23460	Gadsden, AL (Metropolitan Statistical Area)
130	hp23540	Gainesville, FL (Metropolitan Statistical Area)
131	hp23580	Gainesville, GA (Metropolitan Statistical Area)

132	hp23844	Gary, IN (MSAD)
133	hp24020	Glens Falls, NY (Metropolitan Statistical Area)
134	hp24140	Goldsboro, NC (Metropolitan Statistical Area)
135	hp24220	Grand Forks, ND-MN (Metropolitan Statistical Area)
136	hp24300	Grand Junction, CO (Metropolitan Statistical Area)
137	hp24340	Grand Rapids-Wyoming, MI (Metropolitan Statistical Area)
138	hp24500	Great Falls, MT (Metropolitan Statistical Area)
139	hp24540	Greeley, CO (Metropolitan Statistical Area)
140	hp24580	Green Bay, WI (Metropolitan Statistical Area)
141	hp24660	Greensboro-High Point, NC (Metropolitan Statistical Area)
142	hp24780	Greenville, NC (Metropolitan Statistical Area)
143	hp24860	Greenville-Mauldin-Easley, SC (Metropolitan Statistical Area)
144	hp25060	Gulfport-Biloxi, MS (Metropolitan Statistical Area)
145	hp25180	Hagerstown-Martinsburg, MD-WV (Metropolitan Statistical Area)
146	hp25260	Hanford-Corcoran, CA (Metropolitan Statistical Area)
147	hp25420	Harrisburg-Carlisle, PA (Metropolitan Statistical Area)
148	hp25500	Harrisonburg, VA (Metropolitan Statistical Area)
149	hp25540	Hartford-West Hartford-East Hartford, CT (Metropolitan Statistical Area)
150	hp25620	Hattiesburg, MS (Metropolitan Statistical Area)
151	hp25860	Hickory-Lenoir-Morganton, NC (Metropolitan Statistical Area)
152	hp25980	Hinesville-Fort Stewart, GA (Metropolitan Statistical Area)
153	hp26100	Holland-Grand Haven, MI (Metropolitan Statistical Area)
154	hp26180	Honolulu, HI (Metropolitan Statistical Area)
155	hp26300	Hot Springs, AR (Metropolitan Statistical Area)
156	hp26380	Houma-Bayou Cane-Thibodaux, LA (Metropolitan Statistical Area)
157	hp26420	Houston-Sugar Land-Baytown, TX (Metropolitan Statistical Area)
158	hp26580	Huntington-Ashland, WV-KY-OH (Metropolitan Statistical Area)
159	hp26620	Huntsville, AL (Metropolitan Statistical Area)
160	hp26820	Idaho Falls, ID (Metropolitan Statistical Area)
161	hp26900	Indianapolis-Carmel, IN (Metropolitan Statistical Area)
162	hp26980	Iowa City, IA (Metropolitan Statistical Area)
163	hp27060	Ithaca, NY (Metropolitan Statistical Area)
164	hp27100	Jackson, MI (Metropolitan Statistical Area)
165	hp27140	Jackson, MS (Metropolitan Statistical Area)
166	hp27180	Jackson, TN (Metropolitan Statistical Area)
167	hp27260	Jacksonville, FL (Metropolitan Statistical Area)
168	hp27340	Jacksonville, NC (Metropolitan Statistical Area)
169	hp27500	Janesville, WI (Metropolitan Statistical Area)
170	hp27620	Jefferson City, MO (Metropolitan Statistical Area)
171	hp27740	Johnson City, TN (Metropolitan Statistical Area)
172	hp27780	Johnstown, PA (Metropolitan Statistical Area)
173	hp27860	Jonesboro, AR (Metropolitan Statistical Area)
174	hp27900	Joplin, MO (Metropolitan Statistical Area)
175	hp28020	Kalamazoo-Portage, MI (Metropolitan Statistical Area)
176	hp28100	Kankakee-Bradley, IL (Metropolitan Statistical Area)

177	hp28140	Kansas City, MO-KS (Metropolitan Statistical Area)
178	hp28420	Kennewick-Pasco-Richland, WA (Metropolitan Statistical Area)
179	hp28660	Killeen-Temple-Fort Hood, TX (Metropolitan Statistical Area)
180	hp28700	Kingsport-Bristol-Bristol, TN-VA (Metropolitan Statistical Area)
181	hp28740	Kingston, NY (Metropolitan Statistical Area)
182	hp28940	Knoxville, TN (Metropolitan Statistical Area)
183	hp29020	Kokomo, IN (Metropolitan Statistical Area)
184	hp29100	La Crosse, WI-MN (Metropolitan Statistical Area)
185	hp29140	Lafayette, IN (Metropolitan Statistical Area)
186	hp29180	Lafayette, LA (Metropolitan Statistical Area)
187	hp29340	Lake Charles, LA (Metropolitan Statistical Area)
188	hp29404	Lake County-Kenosha County, IL-WI (MSAD)
189	hp29420	Lake Havasu City-Kingman, AZ (Metropolitan Statistical Area)
190	hp29460	Lakeland-Winter Haven, FL (Metropolitan Statistical Area)
191	hp29540	Lancaster, PA (Metropolitan Statistical Area)
192	hp29620	Lansing-East Lansing, MI (Metropolitan Statistical Area)
193	hp29700	Laredo, TX (Metropolitan Statistical Area)
194	hp29740	Las Cruces, NM (Metropolitan Statistical Area)
195	hp29820	Las Vegas-Paradise, NV (Metropolitan Statistical Area)
196	hp29940	Lawrence, KS (Metropolitan Statistical Area)
197	hp30020	Lawton, OK (Metropolitan Statistical Area)
198	hp30140	Lebanon, PA (Metropolitan Statistical Area)
199	hp30300	Lewiston, ID-WA (Metropolitan Statistical Area)
200	hp30340	Lewiston-Auburn, ME (Metropolitan Statistical Area)
201	hp30460	Lexington-Fayette, KY (Metropolitan Statistical Area)
202	hp30620	Lima, OH (Metropolitan Statistical Area)
203	hp30700	Lincoln, NE (Metropolitan Statistical Area)
204	hp30780	Little Rock-North Little Rock-Conway, AR (Metropolitan Statistical Area)
205	hp30860	Logan, UT-ID (Metropolitan Statistical Area)
206	hp30980	Longview, TX (Metropolitan Statistical Area)
207	hp31020	Longview, WA (Metropolitan Statistical Area)
208	hp31084	Los Angeles-Long Beach-Santa Ana, CA (Metropolitan Statistical Area)
209	hp31140	Louisville-Jefferson County, KY-IN (Metropolitan Statistical Area)
210	hp31180	Lubbock, TX (Metropolitan Statistical Area)
211	hp31340	Lynchburg, VA (Metropolitan Statistical Area)
212	hp31420	Macon, GA (Metropolitan Statistical Area)
213	hp31460	Madera-Chowchilla, CA (Metropolitan Statistical Area)
214	hp31540	Madison, WI (Metropolitan Statistical Area)
215	hp31700	Manchester-Nashua, NH (Metropolitan Statistical Area)
216	hp31740	Manhattan, KS (Metropolitan Statistical Area)
217	hp31860	Mankato-North Mankato, MN (Metropolitan Statistical Area)
218	hp31900	Mansfield, OH (Metropolitan Statistical Area)
219	hp32580	McAllen-Edinburg-Mission, TX (Metropolitan Statistical Area)
220	hp32780	Medford, OR (Metropolitan Statistical Area)
221	hp32820	Memphis, TN-MS-AR (Metropolitan Statistical Area)

222	hp32900	Merced, CA (Metropolitan Statistical Area)
223	hp33124	Miami-Fort Lauderdale-Pompano Beach, FL (Metropolitan Statistical Area)
224	hp33140	Michigan City-La Porte, IN (Metropolitan Statistical Area)
225	hp33260	Midland, TX (Metropolitan Statistical Area)
226	hp33340	Milwaukee-Waukesha-West Allis, WI (Metropolitan Statistical Area)
227	hp33460	Minneapolis-St. Paul-Bloomington, MN-WI (Metropolitan Statistical Area)
228	hp33540	Missoula, MT (Metropolitan Statistical Area)
229	hp33660	Mobile, AL (Metropolitan Statistical Area)
230	hp33700	Modesto, CA (Metropolitan Statistical Area)
231	hp33740	Monroe, LA (Metropolitan Statistical Area)
232	hp33780	Monroe, MI (Metropolitan Statistical Area)
233	hp33860	Montgomery, AL (Metropolitan Statistical Area)
234	hp34060	Morgantown, WV (Metropolitan Statistical Area)
235	hp34100	Morristown, TN (Metropolitan Statistical Area)
236	hp34580	Mount Vernon-Anacortes, WA (Metropolitan Statistical Area)
237	hp34620	Muncie, IN (Metropolitan Statistical Area)
238	hp34740	Muskegon-Norton Shores, MI (Metropolitan Statistical Area)
239	hp34820	Myrtle Beach-North Myrtle Beach-Conway, SC (Metropolitan Statistical Area)
240	hp34900	Napa, CA (Metropolitan Statistical Area)
241	hp34940	Naples-Marco Island, FL (Metropolitan Statistical Area)
242	hp34980	Nashville-Davidson-Murfreesboro-Franklin, TN (Metropolitan Statistical Area)
243	hp35004	Nassau-Suffolk, NY (MSAD)
244	hp35084	Newark-Union, NJ-PA (MSAD)
245	hp35300	New Haven-Milford, CT (Metropolitan Statistical Area)
246	hp35380	New Orleans-Metairie-Kenner, LA (Metropolitan Statistical Area)
247	hp35644	New York-Northern New Jersey-Long Island, NY-NJ-PA (Metropolitan Statistical Area)
248	hp35660	Niles-Benton Harbor, MI (Metropolitan Statistical Area)
249	hp35840	North Port-Bradenton-Sarasota, FL (Metropolitan Statistical Area)
250	hp35980	Norwich-New London, CT (Metropolitan Statistical Area)
251	hp36084	Oakland-Fremont-Hayward, CA (MSAD)
252	hp36100	Ocala, FL (Metropolitan Statistical Area)
253	hp36140	Ocean City, NJ (Metropolitan Statistical Area)
254	hp36220	Odessa, TX (Metropolitan Statistical Area)
255	hp36260	Ogden-Clearfield, UT (Metropolitan Statistical Area)
256	hp36420	Oklahoma City, OK (Metropolitan Statistical Area)
257	hp36500	Olympia, WA (Metropolitan Statistical Area)
258	hp36540	Omaha-Council Bluffs, NE-IA (Metropolitan Statistical Area)
259	hp36740	Orlando-Kissimmee-Sanford, FL (Metropolitan Statistical Area)
260	hp36780	Oshkosh-Neenah, WI (Metropolitan Statistical Area)
261	hp36980	Owensboro, KY (Metropolitan Statistical Area)
262	hp37100	Oxnard-Thousand Oaks-Ventura, CA (Metropolitan Statistical Area)
263	hp37340	Palm Bay-Melbourne-Titusville, FL (Metropolitan Statistical Area)
264	hp37380	Palm Coast, FL (Metropolitan Statistical Area)
265	hp37460	Panama City-Lynn Haven-Panama City Beach, FL (Metropolitan Statistical Area)
266	hp37620	Parkersburg-Marietta-Vienna, WV-OH (Metropolitan Statistical Area)

267	hp37700	Pascagoula, MS (Metropolitan Statistical Area)
268	hp37764	Peabody, MA (MSAD)
269	hp37860	Pensacola-Ferry Pass-Brent, FL (Metropolitan Statistical Area)
270	hp37900	Peoria, IL (Metropolitan Statistical Area)
271	hp37964	Philadelphia-Camden-Wilmington, PA-NJ-DE-MD (Metropolitan Statistical Area)
272	hp38060	Phoenix-Mesa-Glendale, AZ (Metropolitan Statistical Area)
273	hp38220	Pine Bluff, AR (Metropolitan Statistical Area)
274	hp38300	Pittsburgh, PA (Metropolitan Statistical Area)
275	hp38340	Pittsfield, MA (Metropolitan Statistical Area)
276	hp38540	Pocatello, ID (Metropolitan Statistical Area)
277	hp38860	Portland-South Portland-Biddeford, ME (Metropolitan Statistical Area)
278	hp38900	Portland-Vancouver-Hillsboro, OR-WA (Metropolitan Statistical Area)
279	hp38940	Port St. Lucie, FL (Metropolitan Statistical Area)
280	hp39100	Poughkeepsie-Newburgh-Middletown, NY (Metropolitan Statistical Area)
281	hp39140	Prescott, AZ (Metropolitan Statistical Area)
282	hp39300	Providence-New Bedford-Fall River, RI-MA (Metropolitan Statistical Area)
283	hp39340	Provo-Orem, UT (Metropolitan Statistical Area)
284	hp39380	Pueblo, CO (Metropolitan Statistical Area)
285	hp39460	Punta Gorda, FL (Metropolitan Statistical Area)
286	hp39540	Racine, WI (Metropolitan Statistical Area)
287	hp39580	Raleigh-Cary, NC (Metropolitan Statistical Area)
288	hp39660	Rapid City, SD (Metropolitan Statistical Area)
289	hp39740	Reading, PA (Metropolitan Statistical Area)
290	hp39820	Redding, CA (Metropolitan Statistical Area)
291	hp39900	Reno-Sparks, NV (Metropolitan Statistical Area)
292	hp40060	Richmond, VA (Metropolitan Statistical Area)
293	hp40140	Riverside-San Bernardino-Ontario, CA (Metropolitan Statistical Area)
294	hp40220	Roanoke, VA (Metropolitan Statistical Area)
295	hp40340	Rochester, MN (Metropolitan Statistical Area)
296	hp40380	Rochester, NY (Metropolitan Statistical Area)
297	hp40420	Rockford, IL (Metropolitan Statistical Area)
298	hp40484	Rockingham County-Strafford County, NH (MSAD)
299	hp40580	Rocky Mount, NC (Metropolitan Statistical Area)
300	hp40660	Rome, GA (Metropolitan Statistical Area)
301	hp40900	Sacramento-Arden-Arcade-Roseville, CA (Metropolitan Statistical Area)
302	hp40980	Saginaw-Saginaw Township North, MI (Metropolitan Statistical Area)
303	hp41060	St. Cloud, MN (Metropolitan Statistical Area)
304	hp41100	St. George, UT (Metropolitan Statistical Area)
305	hp41140	St. Joseph, MO-KS (Metropolitan Statistical Area)
306	hp41180	St. Louis, MO-IL (Metropolitan Statistical Area)
307	hp41420	Salem, OR (Metropolitan Statistical Area)
308	hp41500	Salinas, CA (Metropolitan Statistical Area)
309	hp41540	Salisbury, MD (Metropolitan Statistical Area)
310	hp41620	Salt Lake City, UT (Metropolitan Statistical Area)
311	hp41660	San Angelo, TX (Metropolitan Statistical Area)

312	hp41700	San Antonio-New Braunfels, TX (Metropolitan Statistical Area)
313	hp41740	San Diego-Carlsbad-San Marcos, CA (Metropolitan Statistical Area)
314	hp41780	Sandusky, OH (Metropolitan Statistical Area)
315	hp41884	San Francisco-Oakland-Fremont, CA (Metropolitan Statistical Area)
316	hp41940	San Jose-Sunnyvale-Santa Clara, CA (Metropolitan Statistical Area)
317	hp42020	San Luis Obispo-Paso Robles, CA (Metropolitan Statistical Area)
318	hp42044	Santa Ana-Anaheim-Irvine, CA (MSAD)
319	hp42060	Santa Barbara-Santa Maria-Goleta, CA (Metropolitan Statistical Area)
320	hp42100	Santa Cruz-Watsonville, CA (Metropolitan Statistical Area)
321	hp42140	Santa Fe, NM (Metropolitan Statistical Area)
322	hp42220	Santa Rosa-Petaluma, CA (Metropolitan Statistical Area)
323	hp42340	Savannah, GA (Metropolitan Statistical Area)
324	hp42540	Scranton-Wilkes-Barre, PA (Metropolitan Statistical Area)
325	hp42644	Seattle-Tacoma-Bellevue, WA (Metropolitan Statistical Area)
326	hp42680	Sebastian-Vero Beach, FL (Metropolitan Statistical Area)
327	hp43100	Sheboygan, WI (Metropolitan Statistical Area)
328	hp43300	Sherman-Denison, TX (Metropolitan Statistical Area)
329	hp43340	Shreveport-Bossier City, LA (Metropolitan Statistical Area)
330	hp43580	Sioux City, IA-NE-SD (Metropolitan Statistical Area)
331	hp43620	Sioux Falls, SD (Metropolitan Statistical Area)
332	hp43780	South Bend-Mishawaka, IN-MI (Metropolitan Statistical Area)
333	hp43900	Spartanburg, SC (Metropolitan Statistical Area)
334	hp44060	Spokane, WA (Metropolitan Statistical Area)
335	hp44100	Springfield, IL (Metropolitan Statistical Area)
336	hp44140	Springfield, MA (Metropolitan Statistical Area)
337	hp44180	Springfield, MO (Metropolitan Statistical Area)
338	hp44220	Springfield, OH (Metropolitan Statistical Area)
339	hp44300	State College, PA (Metropolitan Statistical Area)
340	hp44600	Steubenville-Weirton, OH-WV (Metropolitan Statistical Area)
341	hp44700	Stockton, CA (Metropolitan Statistical Area)
342	hp44940	Sumter, SC (Metropolitan Statistical Area)
343	hp45060	Syracuse, NY (Metropolitan Statistical Area)
344	hp45104	Tacoma, WA (MSAD)
345	hp45220	Tallahassee, FL (Metropolitan Statistical Area)
346	hp45300	Tampa-St. Petersburg-Clearwater, FL (Metropolitan Statistical Area)
347	hp45460	Terre Haute, IN (Metropolitan Statistical Area)
348	hp45500	Texarkana, TX-Texarkana, AR (Metropolitan Statistical Area)
349	hp45780	Toledo, OH (Metropolitan Statistical Area)
350	hp45820	Topeka, KS (Metropolitan Statistical Area)
351	hp45940	Trenton-Ewing, NJ (Metropolitan Statistical Area)
352	hp46060	Tucson, AZ (Metropolitan Statistical Area)
353	hp46140	Tulsa, OK (Metropolitan Statistical Area)
354	hp46220	Tuscaloosa, AL (Metropolitan Statistical Area)
355	hp46340	Tyler, TX (Metropolitan Statistical Area)
356	hp46540	Utica-Rome, NY (Metropolitan Statistical Area)

357	hp46660	Valdosta, GA (Metropolitan Statistical Area)
358	hp46700	Vallejo-Fairfield, CA (Metropolitan Statistical Area)
359	hp47020	Victoria, TX (Metropolitan Statistical Area)
360	hp47220	Vineland-Millville-Bridgeton, NJ (Metropolitan Statistical Area)
361	hp47260	Virginia Beach-Norfolk-Newport News, VA-NC (Metropolitan Statistical Area)
362	hp47300	Visalia-Porterville, CA (Metropolitan Statistical Area)
363	hp47380	Waco, TX (Metropolitan Statistical Area)
364	hp47580	Warner Robins, GA (Metropolitan Statistical Area)
365	hp47644	Warren-Troy-Farmington Hills, MI (MSAD)
366	hp47894	Washington-Arlington-Alexandria, DC-VA-MD-WV (MSAD)
367	hp47940	Waterloo-Cedar Falls, IA (Metropolitan Statistical Area)
368	hp48140	Wausau, WI (Metropolitan Statistical Area)
369	hp48300	Wenatchee-East Wenatchee, WA (Metropolitan Statistical Area)
370	hp48424	West Palm Beach-Boca Raton-Boynton Beach, FL (MSAD)
371	hp48540	Wheeling, WV-OH (Metropolitan Statistical Area)
372	hp48620	Wichita, KS (Metropolitan Statistical Area)
373	hp48660	Wichita Falls, TX (Metropolitan Statistical Area)
374	hp48700	Williamsport, PA (Metropolitan Statistical Area)
375	hp48864	Wilmington, DE-MD-NJ (MSAD)
376	hp48900	Wilmington, NC (Metropolitan Statistical Area)
377	hp49020	Winchester, VA-WV (Metropolitan Statistical Area)
378	hp49180	Winston-Salem, NC (Metropolitan Statistical Area)
379	hp49340	Worcester, MA (Metropolitan Statistical Area)
380	hp49420	Yakima, WA (Metropolitan Statistical Area)
381	hp49620	York-Hanover, PA (Metropolitan Statistical Area)
382	hp49660	Youngstown-Warren-Boardman, OH-PA (Metropolitan Statistical Area)
383	hp49700	Yuba City, CA (Metropolitan Statistical Area)
384	hp49740	Yuma, AZ (Metropolitan Statistical Area)