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ARE HOUSING PRICE CYCLES ASYMMETRIC? EVIDENCE FROM THE US STATES AND METROPOLITAN AREAS

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Abstract. This paper investigates asymmetry in US housing price cycles at the state and metropolitan statistical area (MSA) level, using the Triples test (Randles, Flinger, Policello, & Wolfe, 1980) and the Entropy test of Racine and Maasoumi (2007). Several reasons may account for asymmetry in housing prices, including non-linearity in their determinants and in behavioural responses, in particular linked to equity constraints and loss aversion. However, few studies have formally tested the symmetry of housing price cycles. We find that housing prices are asymmetric in the vast majority of cases. Taking into account the results of the two tests, deepness asymmetry, which represents differences in the magnitude of upswings and downturns, is found in 39 out of the 51 states (including the District of Columbia) and 238 out of the 381 MSAs. Steepness asymmetry, which measures differences in the speed of price changes during upswings and downturns, is found in 40 states and 257 MSAs. These results imply that linear models are in most cases insufficient to capture housing price dynamics.

Keywords: asymmetry, house prices, US economy.

Introduction

Housing market developments have played a major role in the Great Recession, the largest contraction in US output in decades. The meltdown of the subprime mortgage market in 2007 was at the epicentre of the global financial crisis, which was followed by a deep recession and years of lacklustre ecomomic performance. More generally, the literature has abundantly documented the links between housing market slumps, financial and banking crises and protracted economic recessions (e.g. Detken & Smets, 2004; European Central Bank [ECB], 2005; Cecchetti, 2008; Claessens, Kose, & Terrones, 2008; Reinhart & Rogoff, 2009; International Monetary Fund [IMF], 2011; Jordá, Schularick, & Taylor, 2014). Hence, it is essential for economists and policymakers to better understand the properties of housing price cycles. Chronologies covering large samples of countries have been established. They show that housing prices generally exhibit long, ample and asymmetric cycles. Girouard, Kennedy, Van den Noord, and André (2006) find that the typical duration of a real housing price cycle in a sample of 18 OECD countries over the period 1970Q1–2005Q1 is around 10 years, roughly similar to that of the business cycle, with which it has been synchronised most of the time, with the notable exception of the early 2000s. The expansion lasts about 23 quarters, during which real housing prices increase by about 45% and the contraction lasts around 18 quarters, with prices falling by around 25%. Igan and Loungani (2012) find in a sample of 55 advanced and emerging economies over the period 1970–2010 that the typical expansion lasts 16 quarters with real housing prices increasing by 37%, while the average contraction lasts 11 quarters with real housing prices falling by 17%.

However, few studies have formally tested for asymmetry in aggregate housing prices. Against this background, this paper investigates asymmetry in housing price series for the 50 US states plus the District of Columbia and 381 metropolitan statistical areas (MSAs) using monthly Freddie Mac House Price Indices spanning the period 1975:1-2015:6. The choice of this dataset is motivated by

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the availability of a large set of high quality, methodologically consistent series, with a wide coverage of the United States. Developments in housing prices tend to vary widely across US states and MSAs. For example, over the past decade or so, the "Sand states" (Arizona, California, Florida, Nevada) experienced dramatic boom-bust cycles, while the housing cycle was muted in large parts of the Midwest. Hence the use of disaggregated data allows a more precise assessment of the extent of asymmetry in the housing price cycle than the use of broad aggregates, which may mask specific market evolutions.

The methodology used for investigating asymmetry in this paper draws on the literature on business cycle asymmetry (Sichel, 1993; Verbrugge, 1997; Razzak, 2001). More specifically, we use the Triples test (Randles et al., 1980), which beyond its traditional use in business cycle analysis, has been used, for example, to test asymmetry in electricity demand in G7 countries (Narayan & Popp, 2009) and in health expenditure in the United States (Zerihun, Cunado, & Gupta, 2016). The Triples test has been used by Cook (2006) to investigate asymmetry in UK housing prices. We complement the Triples test results by using the Entropy test of Racine and Maasoumi (2007). While in many cases both tests give similar results, the Entropy test detects more cases of asymmetry. However, some cases of asymmetry are detected by Triples test but not by the Entropy test, justifying the use of both tests. In addition, the Triples test distinguishes between positive and negative asymmetry, which is useful for the economic interpretation of the results.

We investigate both the deepness and steepness of cycles. Deepness measures the relative magnitude of peaks and troughs. Steepness measures the speed at which peaks and troughs are reached. A thorough technical description is provided in the methodological section. But let us provide at this stage a summary description of possible cases of asymmetry and give examples, anticipating on results described below (Figure 1). Positive deepness asymmetry implies that peaks are high, while downturns are relatively mild. Such a pattern can be observed in Connecticut. Negative deepness asymmetry is characterised by modest peaks but deep recessions, as illustrated by Oklahoma. Positive steepness asymmetry indicates rapid increases followed by slower declines in prices, as seen in Hawaii. Negative steepness asymmetry refers to rapid price falls following slower increases, a pattern observed in Georgia. To the best of our knowledge, this is the first paper which carries out an extensive analysis of asymmetry in US housing prices at the regional (states and MSAs) level. The remainder of the paper is organized as follows: Section 1 briefly reviews the literature. Section 2 presents the methodology. Section 3 describes the data. Section 4 discusses the empirical results. Last section concludes.

1. Brief literature review

The literature points to a number of factors that can explain the cyclicality of housing prices. First, housing prices are closely related to the business cycle (see André (2010), for evidence from a sample of OECD countries and Leamer

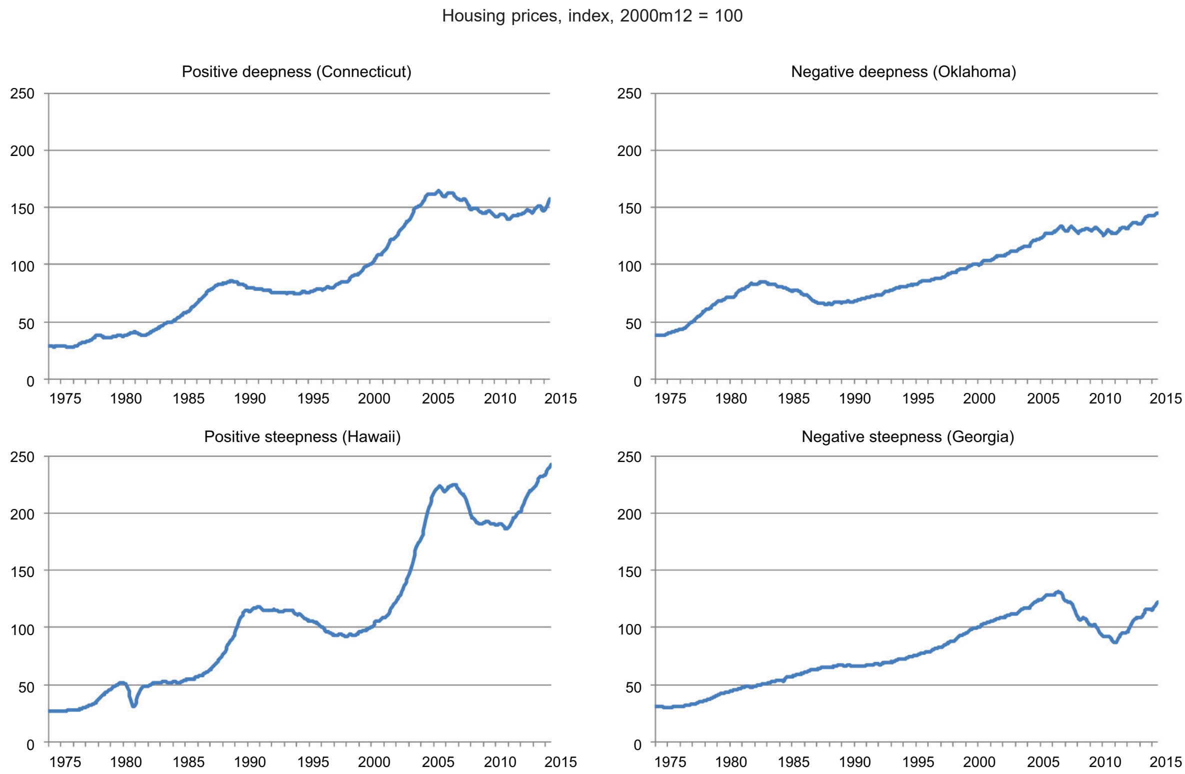

Figure 1. Types of asymmetry: illustrative examples (source: Freddy Mac)

(2007), for evidence from the United States). Second, the financial cycle is an additional source of housing price fluctuations. While there is no commonly agreed definition of the financial cycle, it can be described as "self-reinforcing interactions between perceptions of value and risk, attitudes towards risk and financing constraints, which translate into booms followed by busts" (Borio, 2012). The financial cycle also relates to the notion of pro-cyclicality of the financial system and the financial accelerator, where increases in credit and in the value of collateral reinforce each other (Kiyotaki & Moore, 1997; Bernanke, Gertler, & Gilchrist, 1998; Aoki, Proudman, & Vlieghe, 2002). Third, cyclicality can be induced by the combination of extrapolative expectations and slow supply responses, which can generate hog-type cycles (André, 2015). Getting construction permits and building homes takes time and there is evidence that the rate of appreciation of housing prices over the preceding four years is a good proxy for the expected rate of housing price increase in several countries (Muellbauer, 2012). Fourth, momentum traders, who believe it is a good time to buy a dwelling because housing prices will rise further, can significantly amplify the housing price cycle (Shiller, 2007; Piazzesi & Schneider, 2009).

While the cyclicality of housing prices is well documented in the literature, little attention has been paid so far to the statistical properties of housing price cycles. In particular, few studies have formally tested the symmetry of housing price cycles, despite the existence of theoretical reasons for potential asymmetry and the implications for modelling and forecasting. Before reviewing the existing empirical studies on asymmetry and non-linearity in housing prices, a brief discussion of the potential causes of asymmetry is in order. Asymmetry in housing cycles may result from asymmetry in the determinants of housing prices and/or from non-linearity in the relationships between these determinants and housing prices. Determinants of housing cycles may behave in an asymmetric way. The main determinants of housing prices, besides generally relatively slow-moving variables like demographics and the dwelling stock, are household income and mortgage interest rates. Zerihun et al. (2016) find asymmetric behaviour of real per capita personal disposable income in only 7 US states. This is consistent with the general finding of little evidence of asymmetry in aggregate US GDP or GNP (Sichel, 1993; Verbrugge, 1997; Razzak, 2001). Mortgage interest rates seem to behave in a more asymmetric way. This may result from two causes. First, monetary policy reaction functions to inflation and output may be asymmetric. However, empirical support for this hypothesis in the United States is mixed. Dolado, María-Dolores, and Naveira (2005) find that under certain conditions, the optimal monetary policy is non-linear, with stronger reactions when inflation or output is above target than when they are below target. Nonetheless, they find no asymmetry in the interest rate-setting behaviour of the US Federal Reserve (henceforth, Fed) over the period 1984–2001. Other studies show that the Fed's reaction function has changed over time. Favero and Rovelli (2003), in a study covering the period 1961–1998, find that the policy preferences of the Fed have changed drastically after 1979. Cukierman and Muscatelli (2008) find evidence of non-linearity in US interest-rate reaction functions, with substantial variations over sub-periods within the sample 1960–2005. Second, several studies on the United States and other countries show the presence of asymmetry in the pass-through from policy rates to bank lending rates. Payne and Waters (2008) find asymmetric pass-through from the federal funds rate to the prime rate over the period 1987–2005. Asymmetric pass-through between policy rates and bank mortgage or other lending rates has also been documented in other countries, including Australia (Lim, 2001; Valadkhani & Anwar, 2012), Ireland (Goggin, Holton, Kelly, Lydonm, & McQuinn, 2012) and Switzerland (Cecchin, 2011).

Even in the absence of asymmetry in their determinants, housing prices may display asymmetry as a result of non-linearity in the relationship between housing prices and their determinants. The magnitude and speed of diffusion of economic shocks to housing prices varies across regions because of structural differences in housing markets (Meen, 1999). Ripple effect are often observed in housing markets, as price increases in prime locations induce buyers to move to more affordable areas. In particular, several studies document ripple effects in the United States (Pollakowski & Ray, 1997; Vansteenkiste, 2007; Canarella, Miller, & Pollard, 2012; Gupta & Miller, 2012a, 2012b). In a series of papers, Cook shows that taking asymmetry into account is essential in the analysis of ripple effects and housing price convergence. Using asymmetric unit root tests, he demonstrates that UK housing price adjustments are asymmetric and that taking this feature into account allows identifying widespread housing price convergence across regions (Cook, 2003). He shows that allowing for asymmetry helps detect long-run relationships in UK regional housing prices (Cook, 2005). Analysing cyclical sub-samples, he finds that UK regional housing price convergence is strongest during downturns (Cook, 2012). Cook and Watson (2016) examine the diffusion of changes in housing prices across UK regions over cyclical sub-samples. They find evidence of a ripple effect, especially strong from London to contiguous regions. They also uncover that comovement is strongest during upturns than downturns. Chiang and Tsai (2016), allowing for asymmetry, find ripple effects in US regional housing markets, originating from Los Angeles, New York and Miami. Comovement is again found to be stronger during upswings than downswings. Wu, Lu, Chen, and Chu (2017) also find that comovement between US regional housing prices is time-dependent, with in particular a fall in correlations in 2006, which is consistent with the previous findings of weaker comovement during downturns than upturns.

The behavioural literature shows that asymmetry in housing prices may result from equity constraints and loss aversion. Stein (1995) highlights the impact of required downpayments for the purchase of homes on potential sellers. In depressed markets, liquidity constrained households are reluctant to sell if the downpayment requirement makes them unable to purchase a new home. This may increase the volatility of housing prices relative to standard efficient market settings and account for the positive correlation between housing prices and transactions. Moreover, Stein's model contributes to explaining differences in housing price cycles across states or cities, among which the proportion of households with high loan-to-value ratios differs, affecting downpayment capacities. Loss aversion is another potential explanation for low transaction volumes following price falls. Tversky and Kahneman (1991) show in experimental settings that individuals tend to show loss aversion. Empirical studies support the hypothesis of loss aversion in housing markets. Genesove and Mayer (2001) find evidence of loss aversion in the Boston condominium market in the 1990s. More specifically, they find that condominium owners facing nominal losses set higher asking prices, achieve higher selling prices and exhibit a much lower sale hazard than other sellers. Engelhardt (2003) finds that nominal loss aversion significantly affects household mobility in the United States over the period 1985–1996. Conversely, he finds little evidence that low equity resulting from lower housing prices constrains mobility. Anenberg (2011) finds strong evidence that, in the San Francisco Bay Area real estate market over the period 1988–2005, owners facing nominal losses and those with high loan-to-value ratios sell on average for higher prices than other sellers.

Non-linearity can also be induced by expectations of housing prices, which can generate bubbles. As noted above, expectations tend to be extrapolative. In other words, the lagged appreciation of housing prices acts as a "bubble builder". But at some point the deviation of housing prices from fundamentals acts as a "bubble burster" (Abraham & Hendershott, 1996; Muellbauer & Murphy, 2008). Such dynamics are bound to generate asymmetric cycles, especially as events triggering the bursting of a bubble are largely random. Furthermore, Bolt, Demertzis, Diks, Hommes, and Van der Leij (2014) find evidence of heterogeneity in housing price expectations with temporary switching between fundamental-reverting and trend-following beliefs in eight countries, including the United States, over the period 1970–2013. They show that a housing market model with heterogenous expectations and endogenous switching between optimistic and pessimistic expectations generates non-linear aggregate price fluctuations with booms and busts triggered by stochastic shocks and strongly amplified by self-fulfilling expectations.

Other potential sources of non-linearity in housing price behaviour have been identified in the literature. For example, Chowdhuri and Maclennan (2014) point to the asymmetric effect of monetary policy on UK housing prices over the period 1980–2012, which they relate to variations in the degree of asymmetric information depending on the state of the economy. Tsai (2013) also finds an asymmetric impact of monetary policy (proxied by money supply) on UK housing prices from 1986 to 2011 and relates it to downward price rigidity. Antonakakis, Gupta, and André (2015) show that housing market returns are affected in a non-linear way by economic policy uncertainty.

The empirical literature focussing on linearity tests and relative performances of linear and non-linear models also finds some support for non-linearity in US housing prices. Kim and Bhattacharya (2009) find non-linearity over the period 1969–2004 in US aggregate housing prices and in three of the four Census regions, the exception being the Midwest. Miles (2008) estimates a generalized autoregressive (GAR) model over the period 1979–2005 in five US states – California, Florida, Massachusetts, Ohio and Texas – and performs out-of-sample forecasts of housing prices at a two, five and ten year horizon. He finds that the GAR model significantly improves forecasting performances in states with volatile housing markets, such as California, while they bring little improvement in relatively stable markets, such as Ohio. Balcilar, Gupta, and Miller (2015) find evidence of non-linearity in US aggregate housing prices and the four Census regions over the period 1968–2000. However, they find that linear and non-linear models perform similarly in out-of-sample forecasting at short horizons.

Altogether, there are many reasons which could account for asymmetry in housing price cycles. Nevertheless, the literature investigating asymmetry in aggregate housing price series is quite limited. In particular, few studies have formally tested for asymmetry in aggregate housing prices. Cook (2006) investigates asymmetric behavior in the UK housing market, using national and regional data spanning the period 1973–2004. He performs the Triples test (Randles et al., 1980), which is also used in the present paper. Cook finds extensive asymmetry in UK housing prices, with cyclical peaks typically of greater magnitude than corresponding troughs. Li (2015) finds asymmetry in serial correlation and mean reversion in Californian metropolitan housing prices, specifically downward price rigidity and greater mean reversion during downturns. Canepa and Chini (2016) estimate a generalised smooth transition model on Irish, Spanish, UK and US housing prices to show evidence of dynamic asymmetries in cycles, with expansions at exponential rates and contractions at logarithmic rates, resulting in longer contractions than expansions.

2. Methodology: the Triples and Entropy tests

The Triples test was initially developed by Randles et al. (1980). Testing deepness asymmetry requires decomposing the series into trend and cyclical components. In order to do so, the Hodrick-Prescott filter can be used (see for example, Razzak, 2001; Narayan, 2009; Zerihun et al., 2016, amongst others). Steepness is tested using first differenced data.

Formally, the Triples test can be described as follows: let $x_i, \ldots, x_N$ denote a random sample drawn from $F(x - \theta)$ where $F(\cdot)$ is a cumulative distribution function for a continuous population with $F(0)=\frac{1}{2}$ and θ is the median of the *x* population.

Let,

$$f^*\left(x_i,x_j,x_k\right)=\begin{bmatrix} sign\left(x_i+x_j-2x_k\right)+sign\left(x_i+x_k-2x_j\right)+ \\ sign\left(x_j+x_k-2x_i\right)\end{bmatrix}^3, \quad (1)$$

where: $sign(u)=-1{,}0$ or 1 when u is equal, greater, or smaller than 0.

x_i,x_j,x_k forms a right triple if $f^*\left(x_i,x_j,x_k\right)=\frac{1}{3}$. Note that $f^*\left(x_i,x_j,x_k\right)$ can only assume the values $1/3,0,1/3$. A left triple is defined as any $\left(x_i,x_j,x_k\right)$ for which $f^*\left(x_i,x_j,x_k\right)=\frac{-1}{3}$. When $f^*\left(x_i,x_j,x_k\right)=0$, the triple is neither right nor left skewed. This last event, however, has probability zero when sampling from a continuous population. The proposed test statistics is then the U statistics given by:

$$\hat{\eta}=\binom{N}{3}^{-1}\sum_{i<j<k} f^*\left(x_i,x_j,x_k\right). \quad (2)$$

So that

$$\hat{\eta}=\frac{\left[\left(number\ of\ right\ triples\right)-\left(number\ of\ left\ triples\right)\right]}{\left[3\binom{N}{3}\right]}. \quad (3)$$

It follows from Hoeffding (1948) that this is a U statistics estimate

$$E\left(\hat{\eta}\right)=\eta=Pr\left\{X_1+X_2-2X_3>0\right\}-Pr\left\{X_1+X_2-2X_3<0\right\}, \quad (4)$$

with

$$var\left(\hat{\eta}\right)=\binom{N}{3}^{-1}\sum_{c=1}^{3}\binom{3}{c}\binom{N\ \ -3}{3\ \ -c}\zeta_c, \quad (5)$$

where:

$$\zeta_c=var\left[f_c^*\left(x_1,\ldots,x_c\right)\right], \quad (6)$$

and

$$f_c^*\left(x_1,\ldots,x_c\right)=E\left[f^*\left(x_1,\ldots,x_c,\ x_{c+1},\ldots,x_3\right)\right]. \quad (7)$$

Letting $\sigma_A^2=9\zeta_1$ and since $\sigma_N^2=\sigma_A^2+\sigma(1)$, Randles et al. (1980) use the Slutsky theorem to show that $N^{1/2}=\left(\hat{\eta}-\eta\right)/\sigma_A$ also has a standard normal limiting distribution. The appropriate hypotheses to be tested now need to be discussed. First, note that if the underlying distribution is symmetric, $X_1+X_2-2X_3$ has the same distribution as $-X_1-X_2+2X_3$ and therefore, $\eta=0$. Hence $\hat{\eta}$ can be used as a statistic for testing,

$$H_0:\hat{\eta}=0 \text{ versus } H_1:\hat{\eta}\neq 0. \quad (8)$$

This is a two-sided test, but it can be used as a one-sided test. This test is used to test the hypothesis that the distribution is symmetric around the unknown median θ against a broad class of asymmetric alternatives. The Triples test can be interpreted according to the hypothesis tested in equation (8). Rejecting the null hypothesis implies asymmetry. Failure to reject the null hypothesis implies symmetry.

The simple nature of $f^*(\cdot)$ makes ζ_1,ζ_2 and ζ_3 expressible in terms of probabilities, and thus it is possible to use U statistics to estimate these quantities consistently as follows:

$$\zeta_1=var\left[f_1^*\left(x_1\right)\right] \text{ with } f_1^*\left(x_1\right)=E\left[f_1^*(\cdot)\right]; \quad (9)$$

$$\zeta_1=N^{-1}\sum_{i=1}^{N}\left(f_1^*\left(x_i\right)-\hat{\eta}\right)^2, \quad (10)$$

where:

$$f_1^*\left(x_i\right)=\binom{N-1}{2}\sum_{\substack{j<k\\ j\neq i\neq k}}\Sigma f_1^*\left(x_i,x_j,x_k\right). \quad (11)$$

Similarly,

$$\zeta_2=\frac{1}{\binom{N}{2}}\sum_{j<k}\Sigma\left(f_2^*\left(x_i,x_k\right)-\hat{\eta}\right)^2, \quad (12)$$

where:

$$f_2^*\left(x_j,x_k\right)=\frac{1}{N-2}\sum_{\substack{i=1\\ j\neq i\neq k\\ i\neq k}}\Sigma f^*\left(x_i,x_j,x_k\right), \quad (13)$$

and

$$\zeta_3=\frac{1}{9}-\hat{\eta}^2. \quad (14)$$

Replacing each with ζ_i and $\hat{\zeta}_i$ in the expressions σ_N and σ_A gives the estimators $\hat{\sigma}_N$ and $\hat{\sigma}_A$. Both estimators are consistent because each $\hat{\zeta}_i$ is written as a linear combination of U statistics.

To test the hypothesis in (8), the Triples test is defined on the basis of $T_1=n^{1/2}\hat{\eta}/\hat{\sigma}_N$ and an associated test based on $T_2=n^{1/2}\hat{\eta}/\hat{\sigma}_A$ so that they reject H_0 as $\left|T_i\right|>Z_{(\alpha/2)}$, $i=1{,}2$ and $Z_{(\alpha/2)}$ is as the upper percentile of the standard normal distribution. Note that these tests are asymptotically distribution free provided only that the underlying distribution is not degenerate.

The entropy test of asymmetry described in Racine and Maasoumi (2008) is based on the normalization of the Bhattacharya – Hellinger statistic measure of dependence S_p given by:

$$S_p=\frac{1}{2}\int_{-\infty}^{+\infty}\left(f_1^{1/2}-f_2^{1/2}\right)^2 \mathrm{dy}, \quad (15)$$

where: $f_1=f(\mathrm{y})$ is the marginal density of a continuous stationary random variable Y_i, and $f_2=f(\hat{\mathrm{y}})$ that of $\widehat{Y_i}$; $\widehat{Y_i}$ being a rotation of Y_i about its mean i.e. $\widehat{Y_i}=-Y_i+2E\left(Y_i\right)$. The vector Y_i is parametrically asymmetric about the mean if $f(\mathrm{y})\equiv f(\hat{\mathrm{y}})$ which corresponds to the following test of asymmetry:

$$H_0: f(\mathrm{y})=f(\hat{\mathrm{y}}) \text{ for all y.}$$

To obtain an entropy version of this asymmetry test; Racine and Maasoumi (2007, 2008) make use of the standard Parzen kernel estimators (see Parzen, 1962) of the statistic S_p with a specific number of bootstrap resampling based on Efron (1982)'s methodology.[1]

3. Data

The measure of housing prices used in this study is the monthly Freddie Mac house price index (FMHPI) covering the period 1975:01-2015:06. The FMHPI is a repeat-sales index covering transactions on one-family detached and townhome properties serving as collateral on loans purchased by Freddy Mac or Fannie Mae. The repeat-sales methodology is widely used to measure housing price changes, particularly in the United States. The most prominent examples are the Federal Housing Finance Agency (FHFA), Standard & Poor's (S&P) Case-Shiller and CoreLogic house price indices. By measuring the evolution of the value of the same property between two transactions, the repeat-sales methodology allows to measure price changes holding constant property type and location. A limitation of the procedure is that significant renovation or deterioration of the property may affect price changes. However, in the case of the FMHPI, this problem is mitigated by the exclusion of outliers. The FMHPI includes appraisal values related to refinancing transactions in addition to home sales/purchases, with the restriction that at least one transaction in a pair must be a purchase. Appraisal values may be less accurate than purchase prices. However, the inclusion of refinancing transactions more than quadruples the sample size to over 25 million pairs between 1975 and 2010. Increasing the sample particularly increases the quality of estimates at a disaggregated level. Furthermore, the calculation of the FMHPI accounts for potential systematic deviations between appraisal values and purchase prices.[2]

The main advantage of the FMHPI in the context of this study is that it provides monthly data at the MSA level. A limitation to bear in mind is that the FMHPI only covers transactions associated with conforming loans purchased by Freddy Mac or Fannie Mae. This excludes subprime loans and loans with an amount in excess of the ceiling for conforming loans. Conforming loans account for the vast majority of mortgages. However, in some periods non-conforming loans make a significant share of mortgage originations. For example, at its peak in the middle of the first decade of the new century, subprime mortgages accounted for about 20% of mortgage originations. While it is unlikely to dramatically affect the shape of the housing price cycle, the exclusion of some transactions may dampen somewhat the volatility of prices and the amplitude of the cycle over some periods. Conversely, the use of weights based on end of previous year estimated property values in the FMHPI is bound to amplify cycles compared with measures using weights based on numbers of housing units, such as the FHFA index.

Series have been adjusted for seasonality using the standard US Census Bureau X13 ARIMA-SEATS Seasonal Adjustment Program. Series have not been adjusted for inflation, because asymmetry in the behaviour of housing prices is likely to result, at least in part, from nominal rigidities, as suggested by the discussion of loss aversion and equity constraints above. Table 1 provides a summary description of the data. The average housing price monthly growth rate over the sample period is 0.39% (4.76% annualized) for the United States. Prices are volatile, with a standard deviation of 0.48% and an average absolute deviation from trend of 0.36%. Differences between states and across MSAs in average growth rates and volatility are fairly large.

Table 1. Descriptive statistics

	Average growth rate	Standard deviation	Average absolute deviation from trend
USA			
	0.3884	0.4764	0.3555
States			
Min	0.2305	0.4388	0.3395
Max	0.5907	1.4410	0.8500
Q1	0.2960	0.5580	0.4286
Median	0.3370	0.6644	0.5043
Q3	0.3825	0.8117	0.6134
MSAs			
Min	0.1037	0.4022	0.3074
Max	0.6250	1.4786	0.9414
Q1	0.2650	0.5751	0.4369
Median	0.3050	0.6708	0.5123
Q3	0.3548	0.8308	0.6150

Note: Q1 and Q3 correspond to the first and third quartile of the distribution, respectively. The trend is computed using the Hodrick-Prescott filter, with $\lambda = 14{,}400$.

4. Results

The Triples test finds deepness asymmetry in 8 states, amounting to about 16% of the total (51, including the District of Columbia), and steepness asymmetry in 22 states, or more than 40% of the total (Table 2).[3] Results at the MSA level are consistent with those at the state level. Evidence of deepness asymmetry is found in about

[1] The R codes for the implementation of this test are provided in the *np package* of the R software freely available at: http://www.r-project.org.

[2] For more details on the FMHPI, see http://www.freddiemac.com/finance/fmhpi.

[3] The significance threshold used throughout this paper is 10%, unless otherwise specified.

8% of MSAs (29 out of 381) and steepness asymmetry in about 40% (154). Positive deepness asymmetry is found in 5 states and 11 MSAs. Negative deepness asymmetry is found in 3 states and 18 MSAs. Steepness asymmetry is more common, with positive cases in 12 states and 55 MSAs and negative cases in 10 states and 100 MSAs. States with asymmetric cycles generally contain a number of MSAs where asymmetry of the same type is found. For example, Massachusetts has 3 MSAs with positive steepness asymmetry, California has 7 MSAs with negative steepness and Michigan has 9. This confirms that asymmetry is not the result of an aggregation artifact.

The varying forms of asymmetry across states and MSAs suggest that different underlying economic factors are at play in different places. The Triples test allows distinguishing positive from negative forms of asymmetry, which provides further insights into the economic interpretation of asymmetry. Positive deepness asymmetry, corresponding to high peaks followed by mild downturns, is mainly found in small states of the North-East of the country (Connecticut, Delaware, Maine and Vermont). In these states, the relative scarcity of land may put a floor on housing prices. The only MSA within these states exhibiting deepness asymmetry is Portland-South Portland (Maine). Positive deepness asymmetry is also found in South Dakota (and its MSA of Sioux Falls), but the amplitude of the cycle there is low (Figure 2). Positive steepness asymmetry is found in 12 states. Half of them are in the densely populated North East, while the others are scattered all over the country, including Hawaii. Evidence of positive steepness asymmetry at the state level is associated with the presence of at least one MSA exhibiting the same property, except in Vermont, where nevertheless one MSA (Burlington-South Burlington) comes close to the 10% confidence threshold.

Table 2. Housing price asymmetry in US states according to the Triples test. Statistically significant at the 10% confidence level

Deepness		Steepness	
Positive	Negative	Positive	Negative
Connecticut	Alaska	Connecticut	California
Delaware	Oklahoma	Hawaii	Georgia
Maine	Wisconsin	Idaho	Illinois
South Dakota		Massachusetts	Louisiana
Vermont		North Dakota	Michigan
		Nebraska	New Hampshire
		New Jersey	Ohio
		New Mexico	Oregon
		New York	Virginia
		Rhode Island	Wisconsin
		Utah	
		Vermont	

Note: Triples test z-statistics and p-values are reported in Table A1.

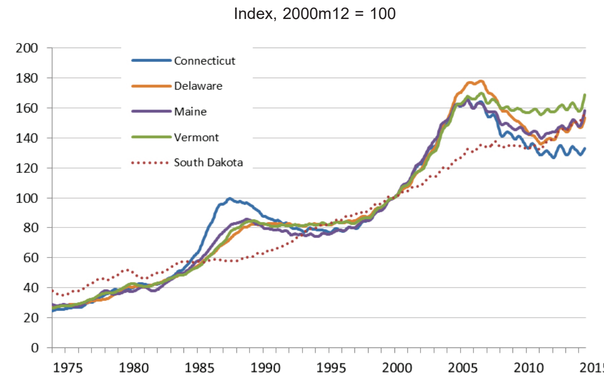

Figure 2. Housing price cycles displaying positive deepness asymmetry (source: Freddy Mac)

Steep downturns are found in several states of the Midwest, where the decline in traditional industries has severely hit the economy. Michigan, Ohio and Wisconsin show negative steepness asymmetry at the 5% confidence level and Illinois at the 10% level. In these states, negative steepness asymmetry also appears at the MSA level. Housing prices in Wisconsin, in addition to negative steepness asymmetry, show negative deepness asymmetry. These features are also observed in many of its MSAs. While Midwest states did not experience very sharp increases in housing prices, they suffered steep falls following the latest economic recession (Figure 3).

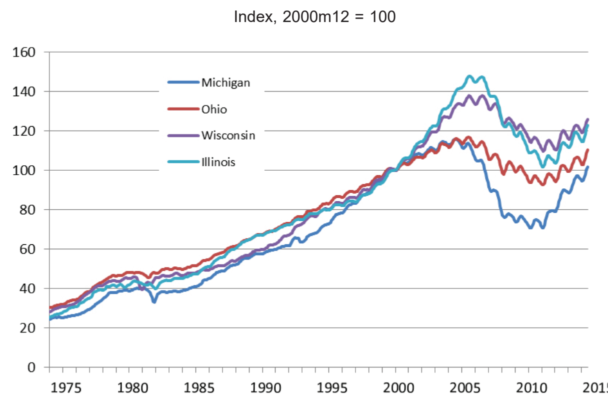

Figure 3. Asymmetric housing price cycles in the Midwest (source: Freddy Mac)

Developments in other states where asymmetry is found seem more idiosyncratic. Negative deepness asymmetry in Alaska and Oklahoma is related to a marked downturn in the late 1980s. Deepness asymmetry is observed in Oklahoma city, but not in MSAs in Alaska. States characterised by positive steepness asymmetry include Hawaii, which has experienced a number of steep increases in housing prices over the sample period, Idaho, which had a housing price spike in the mid-2000s, North Dakota, where the recent oil and gas boom boosted housing prices. Positive steepness asymmetry is also present in Nebraska and New Mexico, but with relatively low amplitude cycles. The latest economic downturn, during which prices declined rapidly, drives negative steepness asymmetry in Georgia and Virginia, as well as Oregon. Sharp housing price falls between mid-2006 and mid-2012 largely account for negative steepness asymmetry in California. Furthermore, the expansion of subprime lending during the early 2000s, followed by an abrupt reduction in mortgage credit after the global financial crisis may account for quick falls in housing prices, at least in some parts of the state. The type of steepness asymmetry found in these states is also present in at least one of its MSAs.

The Entropy test does not allow distinguishing between positive and negative forms of asymmetry, which restrains its economic interpretation. However, it detects much more cases of asymmetry than the Triples test (Table 3). Deepness asymmetry is found in 35 states (nearly 70% of the total) and 226 MSAs (nearly 60% of the total). Steepness asymmetry is found in 35 states (nearly 70% of the total) and 228 MSAs (nearly 60% of the total). As the literature suggests that the Entropy test is more powerful than the Triples test (Racine & Maasoumi, 2007, 2008), it is possible to conclude that asymmetry in housing prices is the norm. Furthermore, as assuming symmetry when the series display asymmetric behaviour can lead to biased econometric estimates and forecasts, and erroneous economic conclusions, asymmetry should systematically be envisaged when modelling housing prices.

The Entropy test results differ from those of the Triples test for some of the "Sand states" (Arizona, California, Florida, Nevada), which are particularly interesting because they contributed most to the US housing price boom which preceded the Great Recession. Prices skyrocketed in the mid-2000s, but collapsed rapidly after the

Table 3. Summary of asymmetry tests results

	States	
Deepness	Triples test	8
	Entropy test	35 (For the states, there are 43 cases in all of which 4 cases are overlapping)
	MSAs	
	Triples test	29
	Entropy test	226 (For the MSAs, there are 255 cases in all of which 17 cases are overlapping)
	States	
Steepness	Triples test	22
	Entropy test	35 (For the states, there are 57 cases in all of which 17 cases are overlapping)
	MSAs	
	Triples test	155
	Entropy test	228 (For the MSAs, there are 382 cases in all of which 126 cases are overlapping)

Note: The significance threshold is 10%. Triples test values are reported in Tables A1 and A2. The list of states and MSAs displaying asymmetry is reported in Tables A3 and A4.

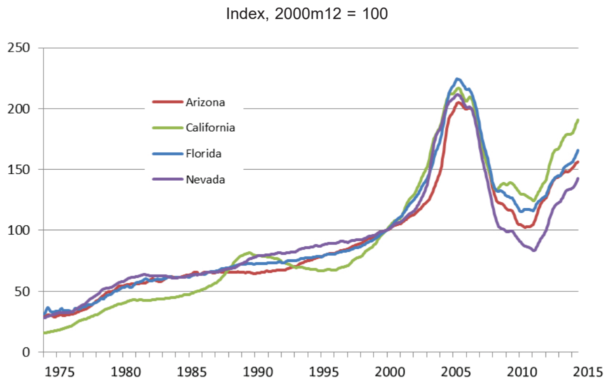

Figure 4. Housing price cycles in the "Sand states" (source: Freddy Mac)

subprime crisis, as over-valuation became obvious, oversupply proved massive and credit dried up (Figure 4). The Triples test found negative steepness asymmetry in California, a result confirmed by the Entropy test, which however also finds deepness in that state. The Entropy test identifies both deepness and steepness asymmetry in Arizona and Nevada. No evidence of asymmetry is found in Florida, which conforms to the Triples test results. However, asymmetry is present in the MSA which includes Miami and a number of other MSAs in Florida, as it is present in the largest MSAs of other "Sand states". A precise characterisation of cyclical patterns is difficult in these states, in part because, except in California, the large boom-bust cycle of the 2000s was preceded by only fairly mild cycles. The rebound in housing prices over the past few years, suggests that cyclicality is here to stay. More observations will be necessary to delineate a cyclical shape, but asymmetry cannot be ruled out.

To sum up, housing cycle asymmetry is found in the majority of US states and MSAs. However, it takes different shapes in different areas, suggesting underlying causes differ. While the most intuitive case of downward rigidity of housing prices, especially related to loss aversion, is widespread, cases where housing price falls are of greater magnitude than increases are also found, predominantly in areas hit by adverse economic shocks. The Triples test results for steepness asymmetry suggest that in many cases housing price adjustments towards troughs are faster than towards peak, indicating that deviations from equilibrium are often corrected in an abrupt way.

Conclusions

This paper has investigated asymmetry in US housing price cycles at the state and MSA level, using the Triples test (Randles et al., 1980) and the Entropy test of Racine and Maasoumi (2007). Several reasons may account for asymmetry in housing prices, including non-linearity in their determinants and in behavioural responses, in particular linked to equity constraints and loss aversion. However, few studies have formally tested the symmetry of housing price cycles. Both the Triples and the Entropy test point to widespread asymmetry in US housing prices, even though the Entropy test detects more cases than the Triples test. In a majority of cases, asymmetry identified by the Triples test is also detected by the Entropy test, but there are some exceptions. Altogether, taking into account the results of both tests, deepness asymmetry is found in 39 of the 51 states (including the District of Columbia) and 238 of the 381 MSAs. Steepness asymmetry is found in 40 states and 257 MSAs. These results imply that potential asymmetry needs to be taken into account when analysing housing price dynamics. In particular, linear models may not provide an adequate description of the data and may display low forecasting performances. The relatively high occurrence of negative steepness asymmetry suggests that linear models may underestimate the likelihood that deviations from equilibrium are corrected in an abrupt way. Potential asymmetry also has consequences for the analysis of comovement and convergence in housing prices, as differences in adjustments over different cycle phases may blur price diffusion patterns.

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Appendix

Table A1. Triples test for US States and national aggregate

State	Steepness		Deepness	
	z-stat	p-value	z-stat	p-value
AK	−0.8508	0.3949	−2.324	0.0201
AL	−1.5146	0.1299	−0.2401	0.8102
AR	−0.5332	0.5939	0.3783	0.7052
AZ	−0.2782	0.7809	−0.6999	0.4840
CA	−2.6196	0.0088	0.4495	0.6531
CO	−0.7044	0.4812	0.2317	0.8167
CT	2.7676	0.0056	1.8418	0.0655
DC	−0.5718	0.5675	−0.1086	0.9135
DE	−0.0567	0.9548	2.3182	0.0204
FL	−0.6871	0.4920	−0.6239	0.5327
GA	−2.1248	0.0336	0.5909	0.5546
HI	3.2437	0.0012	0.5634	0.5732
IA	−1.1276	0.2595	−0.7957	0.4262
ID	1.9794	0.0478	0.4378	0.6616
IL	−1.8067	0.0708	−0.0647	0.9484
IN	−0.2153	0.8295	−0.2893	0.7723
KS	0.8798	0.3790	0.4643	0.6424
KY	0.5731	0.5666	−0.1011	0.9195
LA	−1.7245	0.0846	0.1183	0.9058
MA	2.0681	0.0386	−0.5046	0.6134
MD	−1.4905	0.1361	0.5852	0.5584
ME	0.4874	0.6260	2.6178	0.0088
MI	−2.0880	0.0368	−0.1057	0.9158
MN	−0.4528	0.6507	−0.9858	0.3242
MO	−0.3046	0.7606	0.1400	0.8886
MS	0.7288	0.4661	0.8022	0.4224

State	Steepness		Deepness	
	z-stat	p-value	z-stat	p-value
MT	−0.8562	0.3919	1.2398	0.2151
NC	−1.4510	0.1468	0.3974	0.6911
ND	2.5718	0.0101	−0.8392	0.4013
NE	2.1131	0.0346	0.9043	0.3658
NH	−2.5398	0.0111	1.0857	0.2776
NJ	2.1968	0.0280	1.4534	0.1461
NM	2.7444	0.0061	1.0244	0.3056
NV	−0.0594	0.9526	−0.7370	0.4611
NY	2.5578	0.0105	1.4764	0.1398
OH	−2.0161	0.0438	−0.7845	0.4328
OK	−0.6695	0.5031	−2.1182	0.0342
OR	−2.4876	0.0129	−0.5604	0.5752
PA	0.2946	0.7683	−0.3782	0.7053
RI	4.5012	0.0000	0.2126	0.8316
SC	−0.5004	0.6168	0.5650	0.5721
SD	−0.6591	0.5098	2.8492	0.0044
TN	0.7492	0.4537	−0.7916	0.4286
TX	1.2588	0.2081	−0.5374	0.5910
UT	1.7710	0.0766	−0.6483	0.5168
VA	−2.0075	0.0447	0.1069	0.9149
VT	1.9373	0.0527	1.9037	0.0570
WA	1.0119	0.3116	−0.3026	0.7622
WI	−3.2034	0.0014	−2.3822	0.0172
WV	−0.5672	0.5706	0.6601	0.5092
WY	−0.0235	0.9813	0.9006	0.3678
USA	−5.6131	0.0000	1.3669	0.1716

Table A2. Triples test for the US MSAs

City	Steepness		Deepness	
	z-stat	p-value	z-stat	p-value
Abilene, TX	1.2890	0.1974	1.5156	0.1296
Akron, OH	–2.5614	0.0104	–0.8398	0.401
Albany, GA	–0.7988	0.4244	–0.6314	0.5278
Albany, OR	–1.4575	0.1450	–2.3535	0.0186
Albany-Schenectady-Troy, NY	3.2441	0.0012	2.3811	0.0173
Albuquerque, NM	3.7007	0.0000	0.1219	0.9029
Alexandria, LA	–1.1567	0.2474	–1.0259	0.3049
Allentown-Bethlehem-Easton, PA-NJ	1.3431	0.1792	–0.2412	0.8094
Altoona, PA	0.6472	0.5175	–0.4726	0.6365
Amarillo, TX	0.4210	0.6738	1.1206	0.2625
Ames, IA	–1.1291	0.2588	–0.4359	0.6629
Anchorage, AK	–1.0886	0.2763	0.8846	0.3764
Ann Arbor, MI	–1.9511	0.0510	–0.6505	0.5154
Anniston-Oxford-Jacksonville, AL	–1.7226	0.0850	–0.6238	0.5327
Appleton, WI	–1.4231	0.1547	–1.119	0.2631
Asheville, NC	–2.4495	0.0143	–0.5914	0.5543
Athens-Clarke County, GA	–0.5927	0.5534	–0.4169	0.6767
Atlanta-Sandy Springs-Roswell, GA	–2.2066	0.0273	–0.3228	0.7468
Atlantic City-Hammonton, NJ	4.1726	0.0000	0.3518	0.725
Auburn-Opelika, AL	–3.7128	0.0000	–0.8329	0.4049
Augusta-Richmond County, GA-SC	–0.8786	0.3796	–0.5257	0.5991
Austin-Round Rock, TX	–2.2274	0.0259	0.2873	0.7739
Bakersfield, CA	0.9382	0.3482	–1.0017	0.3165
Baltimore-Columbia-Towson, MD	–1.5014	0.1332	0.482	0.6298
Bangor, ME	–1.1548	0.2482	0.7289	0.4661
Barnstable Town, MA	2.4491	0.0143	–0.4557	0.6486
Baton Rouge, LA	0.2864	0.7745	–0.6356	0.5251
Battle Creek, MI	–2.2348	0.0254	–0.9152	0.3601
Bay City, MI	–3.0674	0.0022	–1.0504	0.2935
Beaumont-Port Arthur, TX	0.8055	0.4205	1.2745	0.2025
Beckley, WV	–1.1712	0.2415	–1.0393	0.2987
Bellingham, WA	2.1329	0.0329	0.0623	0.9503
Bend-Redmond, OR	–2.8275	0.0047	–0.8307	0.4061
Billings, MT	–0.0691	0.9449	–0.0965	0.9231
Binghamton, NY	4.4235	0.0000	0.8953	0.3706
Birmingham-Hoover, AL	–1.8415	0.0655	–0.5932	0.5531
Bismarck, ND	2.3743	0.0176	–0.0806	0.9357
Blacksburg-Christiansburg-Radford, VA	–2.9398	0.0033	–0.3021	0.7626
Bloomington, IL	0.2921	0.7702	–0.8915	0.3727
Bloomington, IN	–1.4789	0.1392	–0.8645	0.3873
Bloomsburg-Berwick, PA	–0.3368	0.7362	–0.4656	0.6415
Boise City, ID	1.5448	0.1224	–0.2625	0.7929
Boston-Cambridge-Newton, MA-NH	2.2991	0.0215	–0.3012	0.7632
Boulder, CO	0.5591	0.5761	–0.4863	0.6268
Bowling Green, KY	3.0437	0.0023	–0.2497	0.8028
Bremerton-Silverdale, WA	0.2133	0.8311	–0.4685	0.6394
Bridgeport-Stamford-Norwalk, CT	2.9784	0.0029	0.1279	0.8982

Continued of Table A2

City	Steepness		Deepness	
	z-stat	p-value	z-stat	p-value
Brownsville-Harlingen, TX	1.5040	0.1326	1.4092	0.1588
Brunswick, GA	–4.6152	0.0000	–0.2459	0.8058
Buffalo-Cheektowaga-Niagara Falls, NY	2.2406	0.0251	0.761	0.4467
Burlington, NC	0.0119	0.9905	–0.9272	0.3538
Burlington-South Burlington, VT	1.6186	0.1055	0.3197	0.7492
California-Lexington Park, MD	–0.7249	0.4685	0.3734	0.7088
Canton-Massillon, OH	–2.6604	0.0078	–0.6978	0.4853
Cape Coral-Fort Myers, FL	–1.5029	0.1329	–0.9021	0.367
Cape Girardeau, MO-IL	0.1567	0.8755	1.2485	0.2118
Carbondale-Marion, IL	0.1882	0.8507	–0.7205	0.4712
Carson City, NV	0.2372	0.8125	0.0074	0.9941
Casper, WY	–4.2402	0.0000	0.718	0.4727
Cedar Rapids, IA	–1.6173	0.1058	–0.8998	0.3682
Chambersburg-Waynesboro, PA	3.2757	0.0011	–0.3285	0.7425
Champaign-Urbana, IL	0.8933	0.3717	–0.8392	0.4014
Charleston, WV	0.1296	0.8969	–17.318	0.0000
Charleston-North Charleston, SC	1.0474	0.2949	17.8223	0.0000
Charlotte-Concord-Gastonia, NC-SC	–0.6203	0.5351	–0.5652	0.5719
Charlottesville, VA	–2.9269	0.0034	–0.0461	0.9632
Chattanooga, TN-GA	–0.8222	0.4109	–0.4323	0.6655
Cheyenne, WY	4.0057	0.0000	0.6206	0.5349
Chicago-Naperville-Elgin, IL-IN-WI	–2.0425	0.0411	–0.7842	0.4329
Chico, CA	0.8393	0.4013	–0.3246	0.7455
Cincinnati, OH-KY-IN	–1.8428	0.0654	–0.6951	0.487
Clarksville, TN-KY	–1.3383	0.1808	–0.1882	0.8507
Cleveland, TN	–1.7166	0.0861	–0.0538	0.9571
Cleveland-Elyria, OH	–2.5110	0.0120	–0.9182	0.3585
Coeur d'Alene, ID	3.4297	0.0000	–0.3042	0.761
College Station-Bryan, TX	2.3414	0.0192	0.977	0.3286
Colorado Springs, CO	–0.5301	0.5961	–0.6656	0.5057
Columbia, MO	0.3589	0.7196	0.8311	0.4059
Columbia, SC	–0.7857	0.4320	–3.0106	0.0026
Columbus, GA-AL	–3.3148	0.0000	–0.5494	0.5827
Columbus, IN	1.0991	0.2717	–1.2747	0.2024
Columbus, OH	–1.3557	0.1752	–0.7015	0.483
Corpus Christi, TX	2.0408	0.0413	1.1082	0.2678
Corvallis, OR	–1.9499	0.0512	–0.6563	0.5117
Crestview-Fort Walton Beach-Destin, FL	2.5588	0.0105	–0.5455	0.5854
Cumberland, MD-WV	0.3201	0.7489	0.0256	0.9796
Dallas-Fort Worth-Arlington, TX	1.9362	0.0528	0.8359	0.4032
Dalton, GA	–2.5019	0.0124	–0.5279	0.5976
Danville, IL	–1.5007	0.1334	–1.182	0.2372
Daphne-Fairhope-Foley, AL	–3.0270	0.0025	–0.8939	0.3714
Davenport-Moline-Rock Island, IA-IL	–1.6811	0.0927	–0.8375	0.4023
Dayton, OH	–1.2170	0.2236	–0.9248	0.3551
Decatur, AL	–1.2910	0.1967	–0.899	0.3687
Decatur, IL	–1.6874	0.0915	–0.8393	0.4013
Deltona-Daytona Beach-Ormond Beach, FL	–1.0902	0.2756	–0.5565	0.5779

Continued of Table A2

City	Steepness		Deepness	
	z-stat	p-value	z-stat	p-value
Denver-Aurora-Lakewood, CO	−0.2714	0.7861	−0.4042	0.6861
Des Moines-West Des Moines, IA	−0.8200	0.4122	−0.926	0.3545
Detroit-Warren-Dearborn, MI	−1.8742	0.0609	−1.1349	0.2564
Dothan, AL	−1.6074	0.1080	−0.7266	0.4675
Dover, DE	−0.3946	0.6931	−0.4981	0.6184
Dubuque, IA	−0.2975	0.7661	−0.7324	0.4639
Duluth, MN-WI	−2.4460	0.0144	−0.2217	0.8245
Durham-Chapel Hill, NC	−0.2554	0.7984	−0.4999	0.6172
East Stroudsburg, PA	−1.5398	0.1236	−0.4901	0.6241
Eau Claire, WI	−2.0505	0.0403	−1.0604	0.289
El Centro, CA	0.6703	0.5027	−0.9432	0.3456
Elizabethtown-Fort Knox, KY	0.1295	0.8969	−0.09	0.9283
Elkhart-Goshen, IN	0.2682	0.7885	−1.5831	0.1134
Elmira, NY	4.2836	0.0000	0.5394	0.6137
El Paso, TX	3.2448	0.0012	1.5157	0.1296
Erie, PA	0.2658	0.7904	−0.1103	0.9122
Eugene, OR	−1.2428	0.2140	−0.6481	0.5169
Evansville, IN-KY	2.2311	0.0257	−1.2215	0.2219
Fairbanks, AK	−0.5035	0.6146	0.6474	0.5174
Fargo, ND-MN	0.7030	0.4820	−0.4834	0.6288
Farmington, NM	0.0472	0.9623	−0.1476	0.8827
Fayetteville, NC	−1.4854	0.1374	−0.7609	0.4467
Fayetteville-Springdale-Rogers, AR-MO	−2.9924	0.0028	0.7318	0.4643
Flagstaff, AZ	−1.2046	0.2283	−0.0715	0.943
Flint, MI	−2.2081	0.0272	−1.1617	0.2454
Florence, SC	−1.3083	0.1908	−0.7788	0.4361
Florence-Muscle Shoals, AL	−1.0336	0.3013	−0.9749	0.3296
Fond du Lac, WI	−2.1743	0.0297	−1.2976	0.1944
Fort Collins, CO	1.2954	0.1952	−0.1047	0.9166
Fort Smith, AR-OK	0.4966	0.6195	0.802	0.4226
Fort Wayne, IN	1.5434	0.1227	−1.8129	0.0698
Fresno, CA	0.3301	0.7413	−0.5689	0.5695
Gadsden, AL	−2.8761	0.0040	−0.6568	0.5113
Gainesville, FL	−0.7843	0.4329	−0.5735	0.5663
Gainesville, GA	−2.5167	0.0118	−0.4064	0.6844
Gettysburg, PA	−1.3756	0.1690	−0.2084	0.8349
Glens Falls, NY	3.4026	0.0000	0.6296	0.5289
Goldsboro, NC	−1.1105	0.2668	−0.7363	0.4615
Grand Forks, ND-MN	1.1604	0.2459	−0.1559	0.8761
Grand Island, NE	−0.9832	0.3255	−0.2423	0.8086
Grand Junction, CO	−7.5320	0.0000	−0.2398	0.8105
Grand Rapids-Wyoming, MI	−2.2748	0.0229	−0.8448	0.3982
Grants Pass, OR	−2.1783	0.0294	−0.6196	0.5355
Great Falls, MT	0.8684	0.3852	−0.05	0.9602
Greeley, CO	−2.0541	0.0400	−0.5892	0.5557
Green Bay, WI	−1.8469	0.0648	−1.1323	0.2575
Greensboro-High Point, NC	−0.6724	0.5013	−0.6551	0.5124
Greenville, NC	0.1285	0.8978	−0.6824	0.495

Continued of Table A2

City	Steepness		Deepness	
	z-stat	p-value	z-stat	p-value
Greenville-Anderson-Mauldin, SC	0.6178	0.5367	−1.1819	0.2372
Gulfport-Biloxi-Pascagoula, MS	0.4504	0.6524	0.8552	0.3924
Hagerstown-Martinsburg, MD-WV	−1.9731	0.0485	−0.0608	0.9515
Hammond, LA	1.2951	0.1953	−0.6601	0.5092
Hanford-Corcoran, CA	0.5648	0.5722	−0.534	0.5934
Harrisburg-Carlisle, PA	0.5293	0.5966	−0.3673	0.7134
Harrisonburg, VA	−2.3165	0.0205	−0.0761	0.9393
Hartford-West Hartford-East Hartford, CT	3.0651	0.0022	0.0518	0.9587
Hattiesburg, MS	0.7520	0.4520	1.3185	0.1873
Hickory-Lenoir-Morganton, NC	−7.0856	0.0000	−0.9168	0.3593
Hilton Head Island-Bluffton-Beaufort, SC	−1.7112	0.0870	−0.5722	0.5672
Hinesville, GA	−0.6396	0.5225	−0.4374	0.6618
Homosassa Springs, FL	−0.6011	0.5478	−0.6009	0.5479
Hot Springs, AR	−0.5956	0.5514	0.392	0.6951
Houma-Thibodaux, LA	−3.3606	0.0000	−0.499	0.6178
Houston-The Woodlands-Sugar Land, TX	−0.2473	0.8047	1.312	0.1895
Huntington-Ashland, WV-KY-OH	−1.2525	0.2104	−1.1271	0.2597
Huntsville, AL	0.4413	0.6590	−0.4558	0.6485
Idaho Falls, ID	1.4437	0.1488	−0.5011	0.6163
Indianapolis-Carmel-Anderson, IN	−0.2365	0.8130	−1.2727	0.2031
Iowa City, IA	−0.1837	0.8542	−0.6843	0.4938
Ithaca, NY	3.0805	0.0021	0.6148	0.5387
Jackson, MI	−2.0977	0.0359	−1.3559	0.1751
Jackson, MS	1.1868	0.2353	1.1366	0.2557
Jackson, TN	−1.2641	0.2062	−0.4879	0.6256
Jacksonville, FL	−1.7965	0.0724	−0.571	0.568
Jacksonville, NC	−1.2612	0.2072	−0.6265	0.531
Janesville-Beloit, WI	−1.5658	0.1174	−1.1945	0.2323
Jefferson City, MO	1.0814	0.2795	1.1459	0.2518
Johnson City, TN	−0.3817	0.7027	−13.2276	0.0000
Johnstown, PA	−1.3387	0.1807	−0.4828	0.6292
Jonesboro, AR	−0.3187	0.7500	0.7954	0.4264
Joplin, MO	1.4797	0.1390	1.2609	0.2073
Kahului-Wailuku-Lahaina, HI	−1.5182	0.1290	0.585	0.5585
Kalamazoo-Portage, MI	−2.4739	0.0134	−0.8663	0.3863
Kankakee, IL	−3.0154	0.0026	−0.5768	0.5641
Kansas City, MO-KS	1.3491	0.1773	0.4059	0.6848
Kennewick-Richland, WA	0.2442	0.8070	−0.9365	0.349
Killeen-Temple, TX	0.9766	0.3288	1.1131	0.2657
Kingsport-Bristol-Bristol, TN-VA	−0.2071	0.8359	−0.1184	0.9058
Kingston, NY	3.4189	0.0000	0.485	0.6277
Knoxville, TN	−0.3176	0.7508	−0.0607	0.9516
Kokomo, IN	−1.0197	0.3078	−1.3589	0.1742
La Crosse-Onalaska, WI-MN	−0.6560	0.5118	−0.8399	0.401
Lafayette, LA	−3.4763	0.0000	−0.9748	0.3297
Lafayette-West Lafayette, IN	−1.1377	0.2552	−1.3099	0.1902
Lake Charles, LA	1.5833	0.1134	−0.6961	0.4863
Lake Havasu City-Kingman, AZ	−1.6144	0.1064	−0.0131	0.9895

Continued of Table A2

City	Steepness		Deepness	
	z-stat	p-value	z-stat	p-value
Lakeland-Winter Haven, FL	−0.6075	0.5435	−0.9134	0.361
Lancaster, PA	0.8249	0.4095	−0.3814	0.7029
Lansing-East Lansing, MI	−2.5830	0.0098	−1.0101	0.3124
Laredo, TX	1.8237	0.0682	1.1891	0.2344
Las Cruces, NM	3.0230	0.0025	0.0098	0.9922
Las Vegas-Henderson-Paradise, NV	−0.0988	0.9213	−0.5442	0.5863
Lawrence, KS	−1.9444	0.0518	−0.1201	0.9044
Lawton, OK	−0.8534	0.3934	−0.7161	0.4739
Lebanon, PA	0.5160	0.6058	−0.5519	0.581
Lewiston, ID-WA	1.0508	0.2934	−0.3073	0.7586
Lewiston-Auburn, ME	−0.1895	0.8497	0.3709	0.7107
Lexington-Fayette, KY	1.4907	0.1360	−0.4051	0.6854
Lima, OH	−0.7093	0.4781	−0.9463	0.344
Lincoln, NE	1.6853	0.0919	−0.2056	0.8371
Little Rock-North Little Rock-Conway, AR	0.9074	0.3642	0.4917	0.623
Logan, UT-ID	2.6831	0.0073	−0.8683	0.3852
Longview, TX	1.6317	0.1027	0.9466	0.3438
Longview, WA	−2.0291	0.0424	−0.8453	0.3979
Los Angeles-Long Beach-Anaheim, CA	−2.1515	0.0314	−0.457	0.6477
Louisville/Jefferson County, KY-IN	−1.0602	0.2890	−0.0033	0.9974
Lubbock, TX	1.9006	0.0574	1.1767	0.2393
Lynchburg, VA	−2.9756	0.0029	−0.0488	0.9611
Macon, GA	−2.8035	0.0051	0.531	0.5954
Madera, CA	0.0698	0.9443	−1.0345	0.3009
Madison, WI	−2.8550	0.0043	−12.5336	0.0000
Manchester-Nashua, NH	−3.1215	0.0018	0.9223	0.3564
Manhattan, KS	−0.3452	0.7299	0.2713	0.7862
Mankato-North Mankato, MN	−1.5458	0.1222	−0.228	0.8197
Mansfield, OH	−2.8127	0.0049	−1.2605	0.2075
McAllen-Edinburg-Mission, TX	1.9691	0.0489	2.943	0.0033
Medford, OR	−2.7651	0.0057	−0.2118	0.8323
Memphis, TN-MS-AR	0.0242	0.9807	−1.7773	0.0755
Merced, CA	−1.6203	0.1052	−0.0751	0.9401
Miami-Fort Lauderdale-West Palm Beach, FL	−0.2261	0.8211	−0.3073	0.7587
Michigan City-La Porte, IN	−2.9505	0.0032	0.037	0.9705
Midland, MI	−2.2293	0.0258	0.7794	0.4358
Midland, TX	3.5009	0.0000	0.7451	0.4562
Milwaukee-Waukesha-West Allis, WI	−3.2061	0.0013	−1.8414	0.0656
Minneapolis-St. Paul-Bloomington, MN-WI	−0.1704	0.8647	−1.2229	0.2214
Missoula, MT	−0.8504	0.3951	0.6516	0.5146
Mobile, AL	−0.1694	0.8655	−1.4418	0.1494
Modesto, CA	−1.6700	0.0949	0.7255	0.4681
Monroe, LA	−1.9474	0.0515	−0.9105	0.3625
Monroe, MI	−2.9983	0.0027	−0.1558	0.8762
Montgomery, AL	−0.7348	0.4625	−0.4402	0.6598
Morgantown, WV	−0.7826	0.4339	−0.616	0.5379
Morristown, TN	2.1225	0.0338	−0.0771	0.9386
Mount Vernon-Anacortes, WA	0.6364	0.5245	−0.1966	0.8442

Continued of Table A2

City	Steepness		Deepness	
	z-stat	p-value	z-stat	p-value
Muncie, IN	−1.4845	0.1377	0.7834	0.4334
Muskegon, MI	−0.5395	0.5895	−1.1858	0.2357
Myrtle Beach-Conway-North Myrtle Beach, SC-NC	−1.6350	0.1020	−0.6146	0.5388
Napa, CA	−3.1707	0.0015	0.6256	0.5316
Naples-Immokalee-Marco Island, FL	−1.5614	0.1184	0.4507	0.6522
Nashville-Davidson--Murfreesboro--Franklin, TN	1.8126	0.0699	−0.5172	0.605
New Bern, NC	0.0340	0.9729	0.5542	0.5794
New Haven-Milford, CT	3.2944	0.0000	1.2502	0.2112
New Orleans-Metairie, LA	−1.8806	0.0600	0.8241	0.4099
New York-Newark-Jersey City, NY-NJ-PA	1.7778	0.0754	1.4242	0.1544
Niles-Benton Harbor, MI	−4.4644	0.0000	−1.1903	0.2339
North Port-Sarasota-Bradenton, FL	−1.3786	0.1680	−0.7338	0.4631
Norwich-New London, CT	1.1581	0.2468	1.235	0.2168
Ocala, FL	−1.1613	0.2455	−1.1393	0.2546
Ocean City, NJ	3.4801	0.0000	0.5718	0.5675
Odessa, TX	2.9948	0.0027	−0.244	0.8073
Ogden-Clearfield, UT	2.5976	0.0094	−0.4751	0.6347
Oklahoma City, OK	−0.3859	0.6995	−2.3283	0.0199
Olympia-Tumwater, WA	−0.4959	0.6199	−0.849	0.3959
Omaha-Council Bluffs, NE-IA	1.4906	0.1361	1.2641	0.2062
Orlando-Kissimmee-Sanford, FL	−0.6837	0.4941	−0.75	0.4533
Oshkosh-Neenah, WI	−1.8624	0.0625	−2.6952	0.007
Owensboro, KY	3.1576	0.0016	−0.9863	0.324
Oxnard-Thousand Oaks-Ventura, CA	−1.3234	0.1857	0.244	0.8072
Palm Bay-Melbourne-Titusville, FL	0.4551	0.6490	−0.4473	0.6546
Panama City, FL	0.8927	0.3720	−1.2568	0.2088
Parkersburg-Vienna, WV	1.2751	0.2023	0.1956	0.845
Pensacola-Ferry Pass-Brent, FL	0.3194	0.7494	−0.7851	0.4324
Peoria, IL	−3.1193	0.0018	0.382	0.7024
Philadelphia-Camden-Wilmington, PA-NJ-DE-MD	0.3257	0.7446	1.1753	0.2399
Phoenix-Mesa-Scottsdale, AZ	−0.2853	0.7755	−0.5289	0.5968
Pine Bluff, AR	0.1782	0.8586	0.5673	0.5705
Pittsburgh, PA	2.1313	0.0331	−0.0178	0.9858
Pittsfield, MA	0.1134	0.9097	0.1868	0.8518
Pocatello, ID	2.9084	0.0036	2.3302	0.0198
Portland-South Portland, ME	1.1019	0.2705	1.8053	0.071
Portland-Vancouver-Hillsboro, OR-WA	−1.5692	0.1166	−9.417	0.0000
Port St. Lucie, FL	−0.8140	0.4156	−3.3176	0.00091
Prescott, AZ	−1.5408	0.1234	−0.4198	0.6747
Providence-Warwick, RI-MA	3.3497	0.0000	0.2097	0.8339
Provo-Orem, UT	1.1206	0.2625	−0.516	0.6059
Pueblo, CO	−1.3275	0.1843	1.826	0.0679
Punta Gorda, FL	−1.4468	0.1480	−0.5772	0.5638
Racine, WI	−4.8334	0.0000	−2.5737	0.0101
Raleigh, NC	0.7664	0.4434	1.7244	0.0846
Rapid City, SD	−1.6480	0.0994	1.5149	0.1298
Reading, PA	0.8831	0.3772	1.2578	0.2085
Redding, CA	0.2234	0.8232	0.3855	0.6998

Continued of Table A2

City	Steepness		Deepness	
	z-stat	p-value	z-stat	p-value
Reno, NV	0.6179	0.5366	−1.0087	0.3131
Richmond, VA	−2.2430	0.0249	−0.4821	0.6297
Riverside-San Bernardino-Ontario, CA	−2.1903	0.0285	0.1558	0.8762
Roanoke, VA	−2.6974	0.0070	−1.0178	0.3088
Rochester, MN	0.0341	0.9728	−1.0936	0.2741
Rochester, NY	2.2456	0.0247	0.483	0.6291
Rockford, IL	−2.9319	0.0034	−1.0246	0.3055
Rocky Mount, NC	−1.9876	0.0469	0.0384	0.9694
Rome, GA	−4.2333	0.0000	−1.0725	0.2835
Sacramento--Roseville--Arden-Arcade, CA	−1.9009	0.0573	0.0721	0.9425
Saginaw, MI	−3.4549	0.0000	0.1849	0.8533
St. Cloud, MN	−2.0475	0.0406	−0.9904	0.322
St. George, UT	0.8761	0.3810	−0.8325	0.4051
St. Joseph, MO-KS	−1.3829	0.1667	0.9999	0.3173
St. Louis, MO-IL	−0.0598	0.9523	−0.1818	0.8558
Salem, OR	−1.6606	0.0968	−0.1712	0.864
Salinas, CA	−2.1342	0.0328	0.5255	0.5993
Salisbury, MD-DE	−1.0777	0.2812	−0.0122	0.9902
Salt Lake City, UT	1.4956	0.1348	−0.7795	0.4357
San Angelo, TX	3.3209	0.0000	1.7813	0.0749
San Antonio-New Braunfels, TX	0.6797	0.4967	1.1786	0.2386
San Diego-Carlsbad, CA	−0.3997	0.6894	0.4538	0.65
San Francisco-Oakland-Hayward, CA	−1.4264	0.1538	1.2091	0.2266
San Jose-Sunnyvale-Santa Clara, CA	0.7877	0.4309	1.2065	0.2276
San Luis Obispo-Paso Robles-Arroyo Grande, CA	0.2991	0.7649	0.1056	0.9159
Santa Cruz-Watsonville, CA	−1.1327	0.2574	1.2331	0.2175
Santa Fe, NM	−1.6625	0.0964	0.8796	0.3791
Santa Maria-Santa Barbara, CA	−3.5579	0.0000	0.8846	0.3764
Santa Rosa, CA	−1.5300	0.1260	0.8824	0.3776
Savannah, GA	−1.5575	0.1194	−0.0806	0.9357
Scranton--Wilkes-Barre--Hazleton, PA	0.2968	0.7666	−0.6117	0.5407
Seattle-Tacoma-Bellevue, WA	1.5734	0.1156	0.0748	0.9404
Sebastian-Vero Beach, FL	−1.4301	0.1527	−0.0744	0.9407
Sebring, FL	−2.1397	0.0324	−0.9948	0.3198
Sheboygan, WI	−2.2942	0.0218	−0.6168	0.5374
Sherman-Denison, TX	0.7832	0.4335	1.0199	0.3078
Shreveport-Bossier City, LA	−2.3445	0.0191	−0.362	0.7173
Sierra Vista-Douglas, AZ	−0.5881	0.5565	0.7594	0.4476
Sioux City, IA-NE-SD	−0.2095	0.8340	0.0375	0.9701
Sioux Falls, SD	0.8184	0.4131	3.1021	0.0019
South Bend-Mishawaka, IN-MI	0.1460	0.8839	−0.8211	0.4116
Spartanburg, SC	−1.2086	0.2268	−2.4079	0.016
Spokane-Spokane Valley, WA	0.3720	0.7099	−0.5793	0.5624
Springfield, IL	0.2871	0.7740	−0.8575	0.3911
Springfield, MA	1.6648	0.0959	0.5656	0.5717
Springfield, MO	0.0861	0.9314	0.6391	0.5228
Springfield, OH	−2.9955	0.0027	−0.4705	0.638
State College, PA	0.6749	0.4998	0.0483	0.9615

End of Table A2

City	Steepness		Deepness	
	z-stat	p-value	z-stat	p-value
Staunton-Waynesboro, VA	−2.4212	0.0155	−0.4225	0.6727
Stockton-Lodi, CA	−3.0645	0.0022	0.4679	0.6398
Sumter, SC	−1.2001	0.2301	0.5857	0.5581
Syracuse, NY	2.2885	0.0221	−0.9081	0.3638
Tallahassee, FL	0.2053	0.8373	0.6177	0.5368
Tampa-St. Petersburg-Clearwater, FL	−0.6092	0.5424	−0.8141	0.4156
Terre Haute, IN	−1.4046	0.1601	−0.0914	0.9272
Texarkana, TX-AR	2.6747	0.0075	−0.5331	0.594
The Villages, FL	1.0998	0.2714	0.9834	0.3254
Toledo, OH	−3.0712	0.0021	−0.5016	0.6159
Topeka, KS	0.1388	0.8896	−1.8577	0.0632
Trenton, NJ	3.1214	0.0018	1.4119	0.158
Tucson, AZ	−0.0795	0.9366	−0.607	0.5438
Tulsa, OK	0.2273	0.8202	−1.04	0.2983
Tuscaloosa, AL	−0.5260	0.5989	0.5619	0.5742
Tyler, TX	1.9065	0.0566	−0.2412	0.8094
Urban Honolulu, HI	3.7424	0.0000	0.399	0.6899
Utica-Rome, NY	2.7676	0.0056	0.5466	0.5847
Valdosta, GA	−2.5480	0.0108	1.0674	0.2858
Vallejo-Fairfield, CA	−3.3090	0.0000	0.2763	0.7823
Victoria, TX	0.1693	0.8656	1.5051	0.1323
Vineland-Bridgeton, NJ	0.0789	0.9371	−0.0568	0.9547
Virginia Beach-Norfolk-Newport News, VA-NC	−0.0416	0.9668	−0.6537	0.5133
Visalia-Porterville, CA	0.7977	0.4250	−0.727	0.4672
Waco, TX	1.4500	0.1471	−0.8627	0.3883
Walla Walla, WA	−0.5672	0.5706	0.8084	0.4189
Warner Robins, GA	−2.0141	0.0440	−0.6527	0.514
Washington-Arlington-Alexandria, DC-VA-MD-WV	−1.0991	0.2717	0.3888	0.6974
Waterloo-Cedar Falls, IA	−1.7512	0.0799	−1.6639	0.0961
Watertown-Fort Drum, NY	5.5675	0.0000	1.8065	0.0708
Wausau, WI	−2.5290	0.0114	−2.1883	0.0286
Weirton-Steubenville, WV-OH	−2.3368	0.0194	−0.5583	0.5766
Wenatchee, WA	0.9975	0.3185	−1.993	0.0463
Wheeling, WV-OH	−0.5432	0.5870	0.2609	0.7942
Wichita, KS	2.1059	0.0352	2.4434	0.0145
Wichita Falls, TX	1.6916	0.0907	0.1799	0.8572
Williamsport, PA	0.5138	0.6074	−0.5566	0.5778
Wilmington, NC	0.1330	0.8942	−0.6426	0.5205
Winchester, VA-WV	−1.8620	0.0626	−0.7308	0.4649
Winston-Salem, NC	−1.4835	0.1379	−0.3948	0.693
Worcester, MA-CT	0.8631	0.3881	0	0.9711
Yakima, WA	0.0241	0.9808	0.7176	0.473
York-Hanover, PA	0.2699	0.7873	0.4219	0.6731
Youngstown-Warren-Boardman, OH-PA	−2.0057	0.0449	−0.5766	0.5642
Yuba City, CA	−0.4579	0.6470	−0.6603	0.5091
Yuma, AZ	−0.5136	0.6075	−0.667	0.5048

Table A3. Cases of deepness asymmetry according to the Triples and Entropy tests

States	
Triples test	Alaska, **Connecticut**, Delaware, Maine, **Oklahoma**, **South Dakota**, Vermont, **Wisconsin**
Entropy test	Alabama, Arkansas, Arizona, California, Colorado, **Connecticut,** Georgia, Hawaii, Idaho, Indiana, Kentucky, Louisiana, Massachusetts, Minnesota, Missouri, Mississippi, North Carolina, North Dakota, Nebraska, New Hampshire, New Jersey, New Mexico, Nevada, Ohio, **Oklahoma**, Oregon, Rhode Island, **South Dakota**, Tennessee, Texas, Utah, Virginia, Washington, **Wisconsin**, USA
MSAs	
Triples test	Albany, OR; **Albany-Schenectady-Troy, NY**; Charleston, WV; **Charleston-North Charleston, SC**; Columbia, SC; **Fort Wayne, IN**; Johnson City, TN; **Madison, WI**; **McAllen-Edinburg-Mission, TX**; Memphis, TN-MS-AR; **Milwaukee-Waukesha-West Allis, WI**; **Oklahoma City, OK**; Oshkosh-Neenah, WI; **Pocatello, ID**; Portland-South Portland, ME; Portland-Vancouver-Hillsboro, OR-WA; Port St. Lucie, FL; Pueblo, CO; **Racine, WI; Raleigh, NC**; **San Angelo, TX**; **Sioux Falls, SD**; Spartanburg, SC; Topeka, KS; **Waterloo-Cedar Falls, IA**; **Watertown-Fort Drum, NY**; **Wausau, WI; Wenatchee, WA**; **Wichita, KS**
Entropy test	Akron, OH; Albany, GA; **Albany-Schenectady-Troy, NY**; Albuquerque, NM; Alexandria, LA; Anchorage, AK; Ann Arbor, MI; Anniston-Oxford-Jacksonville, AL; Asheville, NC; Athens-Clarke County, GA; Atlanta-Sandy Springs-Roswell, GA; Atlantic City-Hammonton, NJ; Auburn-Opelika, AL; Augusta-Richmond County, GA-SC; Bakersfield, CA; Bangor, ME; Barnstable Town, MA; Battle Creek, MI; Bay City, MI; Bellingham, WA; Bend-Redmond, OR; Binghamton, NY; Birmingham-Hoover, AL; Bismarck, ND; Blacksburg-Christiansburg-Radford, VA; Bloomington, IN; Boise City, ID; Boston-Cambridge-Newton, MA-NH; Bowling Green, KY; Bremerton-Silverdale, WA; Bridgeport-Stamford-Norwalk, CT; Brunswick, GA; Canton-Massillon, OH; Cape Coral-Fort Myers, FL; Cape Girardeau, MO-IL; Carson City, NV; Casper, WY; Cedar Rapids, IA; Chambersburg-Waynesboro, PA; Champaign-Urbana, IL; **Charleston-North Charleston, SC**; Charlotte-Concord-Gastonia, NC-SC; Charlottesville, VA; Chattanooga, TN-GA; Cheyenne, WY; Chico, CA; Cincinnati, OH-KY-IN; Clarksville, TN-KY; Cleveland, TN; Cleveland-Elyria, OH; Coeur d'Alene, ID; Colorado Springs, CO; Columbus, GA-AL; Columbus, IN; Crestview-Fort Walton Beach-Destin, FL; Cumberland, MD-WV; Dallas-Fort Worth-Arlington, TX; Dalton, GA; Daphne-Fairhope-Foley, AL; Duluth, MN-WI; Eau Claire, WI; El Centro, CA; Elizabethtown-Fort Knox, KY; Elmira, NY; El Paso, TX; Evansville, IN-KY; Fargo, ND-MN; Fayetteville, NC; Fayetteville-Springdale-Rogers, AR-MO; Flint, MI; Florence-Muscle Shoals, AL; Fond du Lac, WI; **Fort Wayne, IN**; Fresno, CA; Gadsden, AL; Gainesville, GA; Glens Falls, NY; Grand Forks, ND-MN; Grand Junction, CO; Grants Pass, OR; Greeley, CO; Gulfport-Biloxi-Pascagoula, MS; Hammond, LA; Hanford-Corcoran, CA; Harrisonburg, VA; Hartford-West Hartford-East Hartford, CT; Hattiesburg, MS; Hickory-Lenoir-Morganton, NC; Hilton Head Island-Bluffton-Beaufort, SC; Hinesville, GA; Houma-Thibodaux, LA; Huntington-Ashland, WV-KY-OH; Ithaca, NY; Jackson, MI; Jackson, MS; Jefferson City, MO; Kahului-Wailuku-Lahaina, HI; Kalamazoo-Portage, MI; Kankakee, IL; Kansas City, MO-KS; Kennewick-Richland, WA; Kingsport-Bristol-Bristol, TN-VA; Kingston, NY; La Crosse-Onalaska, WI-MN; Lafayette, LA; Lake Havasu City-Kingman, AZ; Lansing-East Lansing, MI; Las Cruces, NM; Las Vegas-Henderson-Paradise, NV; Lawrence, KS; Lexington-Fayette, KY; Lima, OH; Lincoln, NE; Little Rock-North Little Rock-Conway, AR; Logan, UT-ID; Longview, WA; Los Angeles-Long Beach-Anaheim, CA; Louisville/Jefferson County, KY-IN; Lubbock, TX; Lynchburg, VA; Macon, GA; Madera, CA; **Madison, WI**; Manchester-Nashua, NH; Mansfield, OH; **McAllen-Edinburg-Mission, TX**; Medford, OR; Merced, CA; Miami-Fort Lauderdale-West Palm Beach, FL; Michigan City-La Porte, IN; Midland, MI; Midland, TX; **Milwaukee-Waukesha-West Allis, WI**; Minneapolis-St. Paul-Bloomington, MN-WI; Missoula, MT; Modesto, CA; Monroe, LA; Monroe, MI; Morristown, TN; Mount Vernon-Anacortes, WA; Myrtle Beach-Conway-North Myrtle Beach, SC-NC; Napa, CA; Naples-Immokalee-Marco Island, FL; Nashville-Davidson--Murfreesboro--Franklin, TN; New Haven-Milford, CT; New Orleans-Metairie, LA; New York-Newark-Jersey City, NY-NJ-PA; Niles-Benton Harbor, MI; Ocala, FL; Ocean City, NJ; Odessa, TX; Ogden-Clearfield, UT; **Oklahoma City, OK**; Omaha-Council Bluffs, NE-IA; Owensboro, KY; Oxnard-Thousand Oaks-Ventura, CA; Palm Bay-Melbourne-Titusville, FL; Peoria, IL; Phoenix-Mesa-Scottsdale, AZ; **Pocatello, ID**; Port St. Lucie, FL; Prescott, AZ; Providence-Warwick, RI-MA; Provo-Orem, UT; Pueblo, CO; Punta Gorda, FL; **Racine, WI; Raleigh, NC**; Rapid City, SD; Redding, CA; Reno, NV; Richmond, VA; Riverside-San Bernardino-Ontario, CA; Roanoke, VA; Rochester, NY; Rockford, IL; Rome, GA; Sacramento--Roseville--Arden-Arcade, CA; Saginaw, MI; St. Cloud, MN; St. George, UT; St. Joseph, MO-KS; St. Louis, MO-IL; Salinas, CA; Salt Lake City, UT; **San Angelo, TX**; San Antonio-New Braunfels, TX; San Diego-Carlsbad, CA; San Francisco-Oakland-Hayward, CA; San Jose-Sunnyvale-Santa Clara, CA; Santa Cruz-Watsonville, CA; Santa Maria-Santa Barbara, CA; Santa Rosa, CA; Savannah, GA; Seattle-Tacoma-Bellevue, WA; Sebastian-Vero Beach, FL; Shreveport-Bossier City, LA; **Sioux Falls, SD**; Spokane-Spokane Valley, WA; Springfield, MO; Springfield, OH; State College, PA; Staunton-Waynesboro, VA; Stockton-Lodi, CA; Syracuse, NY; Terre Haute, IN; Texarkana, TX-AR; Toledo, OH; Trenton, NJ; Tulsa, OK; Tuscaloosa, AL; Urban Honolulu, HI; Utica-Rome, NY; Valdosta, GA; Vallejo-Fairfield, CA; Virginia Beach-Norfolk-Newport News, VA-NC; Visalia-Porterville, CA; Walla Walla, WA; Warner Robins, GA; **Waterloo-Cedar Falls, IA**; **Watertown-Fort Drum, NY**; **Wausau, WI; Wenatchee, WA**; **Wichita, KS**; Wichita Falls, TX; Winchester, VA-WV; Youngstown-Warren-Boardman, OH-PA; Yuba City, CA

Note: The significance threshold is 10%.

Table A4. Cases of steepness asymmetry according to the Triples and Entropy tests

States	
Triples test	**Connecticut**, **California**, **Hawaii**, **Georgia**, **Idaho**, Illinois, **Massachusetts**, **Louisiana**, **North Dakota**, Nebraska, **New Jersey**, **New Mexico**, **New York**, **Rhode Island**, Utah, Vermont, Michigan, **New Hampshire**, **Ohio**, **Oregon**, **Virginia**, **Wisconsin**
Entropy test	Alabama, Arkansas, Arizona, **California**, **Connecticut**, **Georgia**, **Hawaii**, **Idaho**, Indiana, Kentucky, **Louisiana**, **Massachusetts**, Minnesota, Missouri, Mississippi, North Carolina, **North Dakota**, Nebraska, **New Hampshire**, **New Jersey**, **New Mexico**, Nevada, **New York**, **Ohio**, Oklahoma, **Oregon**, **Rhode Island**, South Dakota, Tennessee, Texas, Utah, **Virginia**, Washington, **Wisconsin**, USA
MSAs	
Triples test	**Akron, OH**; **Albany-Schenectady-Troy, NY**; **Albuquerque, NM**; **Ann Arbor, MI**; **Anniston-Oxford-Jacksonville, AL**; **Asheville, NC**; **Atlanta-Sandy Springs-Roswell, GA**; **Atlantic City-Hammonton, NJ**; **Auburn-Opelika, AL**; Austin-Round Rock, TX; **Barnstable Town, MA**; **Battle Creek, MI; Bay City, MI**; **Bellingham, WA**; **Bend-Redmond, OR**; **Binghamton, NY**; **Birmingham-Hoover, AL**; **Bismarck, ND**; **Blacksburg-Christiansburg-Radford, VA**; **Boston-Cambridge-Newton, MA-NH**; **Bowling Green, KY**; **Bridgeport-Stamford-Norwalk, CT**; **Brunswick, GA**; Buffalo-Cheektowaga-Niagara Falls, NY; **Canton-Massillon, OH**; **Casper, WY**; **Chambersburg-Waynesboro, PA**; Charlottesville, VA; **Cheyenne, WY**; Chicago-Naperville-Elgin, IL-IN-WI; **Cincinnati, OH-KY-IN**; **Cleveland, TN**; **Cleveland-Elyria, OH**; **Coeur d'Alene, ID**; **College Station-Bryan, TX**; **Columbus, GA-AL**; Corpus Christi, TX; Corvallis, OR; **Crestview-Fort Walton Beach-Destin, FL**; **Dallas-Fort Worth-Arlington, TX**; **Dalton, GA**; **Daphne-Fairhope-Foley, AL**; Davenport-Moline-Rock Island, IA-IL; Decatur, IL; Detroit-Warren-Dearborn, MI; **Duluth, MN-WI**; **Eau Claire, WI**; **Elmira, NY**; **El Paso, TX**; **Evansville, IN-KY**; **Fayetteville-Springdale-Rogers, AR-MO**; **Flint, MI**; **Fond du Lac, WI**; **Gadsden, AL**; **Gainesville, GA**; **Glens Falls, NY**; **Grand Junction, CO**; Grand Rapids-Wyoming, MI; **Grants Pass, OR**; **Greeley, CO**; Green Bay, WI; Hagerstown-Martinsburg, MD-WV; **Harrisonburg, VA**; **Hartford-West Hartford-East Hartford, CT**; **Hickory-Lenoir-Morganton, NC**; **Hilton Head Island-Bluffton-Beaufort, SC**; **Houma-Thibodaux, LA**; **Ithaca, NY**; **Jackson, MI**; Jacksonville, FL; **Kalamazoo-Portage, MI**; **Kankakee, IL**; **Kingston, NY**; **Lafayette, LA**; **Lansing-East Lansing, MI**; Laredo, TX; **Las Cruces, NM**; **Lawrence, KS**; **Lincoln, NE**; **Logan, UT-ID**; **Longview, WA**; **Los Angeles-Long Beach-Anaheim, CA**; **Lubbock, TX**; **Lynchburg, VA**; **Macon, GA**; **Madison, WI**; **Manchester-Nashua, NH**; **Mansfield, OH**; **McAllen-Edinburg-Mission, TX**; **Medford, OR**; **Michigan City-La Porte, IN**; **Midland, MI**; **Midland, TX**; **Milwaukee-Waukesha-West Allis, WI**; **Modesto, CA**; **Monroe, LA**; **Monroe, MI**; **Morristown, TN**; **Napa, CA**; **Nashville-Davidson--Murfreesboro--Franklin, TN**; **New Haven-Milford, CT**; **New Orleans-Metairie, LA**; **New York-Newark-Jersey City, NY-NJ-PA**; **Niles-Benton Harbor, MI**; **Ocean City, NJ**; **Odessa, TX**; **Ogden-Clearfield, UT**; Oshkosh-Neenah, WI; **Owensboro, KY**; **Peoria, IL**; Pittsburgh, PA; **Pocatello, ID**; **Providence-Warwick, RI-MA**; **Racine, WI**; **Rapid City, SD**; **Richmond, VA**; **Riverside-San Bernardino-Ontario, CA**; **Roanoke, VA**; Rochester, NY; Rockford, IL; Rocky Mount, NC; **Rome, GA**; **Sacramento-Roseville-Arden-Arcade, CA**; **Saginaw, MI**; **St. Cloud, MN**; Salem, OR; Salinas, CA; **San Angelo, TX**; Santa Fe, NM; **Santa Maria-Santa Barbara, CA**; Sebring, FL; Sheboygan, WI; **Shreveport-Bossier City, LA**; Springfield, MA; **Springfield, OH**; Staunton-Waynesboro, VA; **Stockton-Lodi, CA**; **Syracuse, NY**; **Texarkana, TX-AR**; **Toledo, OH**; **Trenton, NJ**; Tyler, TX; **Urban Honolulu, HI**; **Utica-Rome, NY**; **Valdosta, GA**; **Vallejo-Fairfield, CA**; **Warner Robins, GA**; **Waterloo-Cedar Falls, IA**; **Watertown-Fort Drum, NY**; **Wausau, WI**; Weirton-Steubenville, WV-OH; **Wichita, KS**; **Wichita Falls, TX**; **Winchester, VA-WV**; **Youngstown-Warren-Boardman, OH-PA**
Entropy test	**Akron, OH**; **Albany-Schenectady-Troy, NY**; **Albuquerque, NM**; Alexandria, LA; Anchorage, AK; **Ann Arbor, MI**; **Anniston-Oxford-Jacksonville, AL**; **Asheville, NC**; Athens-Clarke County, GA; **Atlanta-Sandy Springs-Roswell, GA**; **Atlantic City-Hammonton, NJ**; **Auburn-Opelika, AL**; Augusta-Richmond County, GA-SC; Bakersfield, CA; Bangor, ME; **Barnstable Town, MA**; **Battle Creek, MI; Bay City, MI**; **Bellingham, WA**; **Bend-Redmond, OR**; **Binghamton, NY**; **Birmingham-Hoover, AL**; **Bismarck, ND**; **Blacksburg-Christiansburg-Radford, VA**; Bloomington, IN; Boise City, ID; **Boston-Cambridge-Newton, MA-NH**; **Bowling Green, KY**; Bremerton-Silverdale, WA; **Bridgeport-Stamford-Norwalk, CT**; **Brunswick, GA**; **Canton-Massillon, OH**; Cape Coral-Fort Myers, FL; Cape Girardeau, MO-IL; Carson City, NV; **Casper, WY**; Cedar Rapids, IA; **Chambersburg-Waynesboro, PA**; Champaign-Urbana, IL; Charleston-North Charleston, SC; Charlotte-Concord-Gastonia, NC-SC; Charlottesville, VA; Chattanooga, TN-GA; **Cheyenne, WY**; Chico, CA; **Cincinnati, OH-KY-IN**; Clarksville, TN-KY; **Cleveland, TN**; **Cleveland-Elyria, OH**; **Coeur d'Alene, ID**; **College Station-Bryan, TX**; Colorado Springs, CO; **Columbus, GA-AL**; **Columbus, IN**; **Crestview-Fort Walton Beach-Destin, FL**; Cumberland, MD-WV; **Dallas-Fort Worth-Arlington, TX**; **Dalton, GA**; **Daphne-Fairhope-Foley, AL**; **Duluth, MN-WI**; **Eau Claire, WI**; El Centro, CA; Elizabethtown-Fort Knox, KY; **Elmira, NY**; **El Paso, TX**; **Evansville, IN-KY**; Fargo, ND-MN; Fayetteville, NC; **Fayetteville-Springdale-Rogers, AR-MO**; **Flint, MI**; Florence-Muscle Shoals, AL; **Fond du Lac, WI**; Fort Wayne, IN; Fresno, CA; **Gadsden, AL**; **Gainesville, GA**; **Glens Falls, NY**; Grand Forks, ND-MN; **Grand Junction, CO**; **Grants Pass, OR**; **Greeley, CO**; Gulfport-Biloxi-Pascagoula, MS; Hammond, LA; Hanford-Corcoran, CA; **Harrisonburg, VA**; **Hartford-West Hartford-East Hartford, CT**; Hattiesburg, MS; **Hickory-Lenoir-Morganton, NC**; **Hilton Head Island-Bluffton-Beaufort, SC**; Hinesville, GA; **Houma-Thibodaux, LA**; Huntington-Ashland, WV-KY-OH; **Ithaca, NY**; **Jackson, MI**; Jackson, MS; Jefferson City, MO; Kahului-Wailuku-Lahaina, HI; **Kalamazoo-Portage, MI**; **Kankakee, IL**; Kansas City, MO-KS; Kennewick-Richland, WA; Kingsport-Bristol-Bristol, TN-VA; **Kingston, NY**; La Crosse-Onalaska, WI-MN; **Lafayette, LA**; Lake Havasu City-Kingman, AZ; **Lansing-East Lansing, MI**; **Las Cruces, NM**; Las Vegas-Henderson-Paradise, NV;

End of Table A4

States	
Entropy test	**Lawrence, KS**; Lexington-Fayette, KY; Lima, OH; **Lincoln, NE**; Little Rock-North Little Rock-Conway, AR; **Logan, UT-ID**; **Longview, WA**; **Los Angeles-Long Beach-Anaheim, CA**; Louisville/Jefferson County, KY-IN; **Lubbock, TX**; **Lynchburg, VA**; **Macon, GA**; Madera, CA; **Madison, WI**; **Manchester-Nashua, NH**; **Mansfield, OH**; **McAllen-Edinburg-Mission, TX**; **Medford, OR**; Merced, CA; Miami-Fort Lauderdale-West Palm Beach, FL; **Michigan City-La Porte, IN**; **Midland, MI; Midland, TX**; **Milwaukee-Waukesha-West Allis, WI**; Minneapolis-St. Paul-Bloomington, MN-WI; Missoula, MT; **Modesto, CA**; **Monroe, LA**; **Monroe, MI**; **Morristown, TN**; Mount Vernon-Anacortes, WA; Myrtle Beach-Conway-North Myrtle Beach, SC-NC; **Napa, CA**; Naples-Immokalee-Marco Island, FL; **Nashville-Davidson--Murfreesboro--Franklin, TN**; **New Haven-Milford, CT**; **New Orleans-Metairie, LA**; **New York-Newark-Jersey City, NY-NJ-PA**; **Niles-Benton Harbor, MI**; Ocala, FL; **Ocean City, NJ**; **Odessa, TX**; **Ogden-Clearfield, UT**; Oklahoma City, OK; Omaha-Council Bluffs, NE-IA; **Owensboro, KY**; Oxnard-Thousand Oaks-Ventura, CA; Palm Bay-Melbourne-Titusville, FL; **Peoria, IL**; Phoenix-Mesa-Scottsdale, AZ; **Pocatello, ID**; Port St. Lucie, FL; Prescott, AZ; **Providence-Warwick, RI-MA**; Provo-Orem, UT; Pueblo, CO; Punta Gorda, FL; **Racine, WI**; Raleigh, NC; **Rapid City, SD**; Redding, CA; Reno, NV; **Richmond, VA**; **Riverside-San Bernardino-Ontario, CA**; **Roanoke, VA**; Rochester, MN; Rockford, IL; **Rome, GA**; **Sacramento--Roseville--Arden-Arcade, CA**; **Saginaw, MI**; **St. Cloud, MN**; St. George, UT; St. Joseph, MO-KS; St. Louis, MO-IL; Salinas, CA; Salt Lake City, UT; **San Angelo, TX**; San Antonio-New Braunfels, TX; San Diego-Carlsbad, CA; San Francisco-Oakland-Hayward, CA; San Jose-Sunnyvale-Santa Clara, CA; Santa Cruz-Watsonville, CA; **Santa Maria-Santa Barbara, CA**; Santa Rosa, CA; Savannah, GA; Seattle-Tacoma-Bellevue, WA; Sebastian-Vero Beach, FL; **Shreveport-Bossier City, LA**; Sioux Falls, SD; Spokane-Spokane Valley, WA; Springfield, MO; **Springfield, OH**; State College, PA; **Stockton-Lodi, CA**; **Syracuse, NY**; Terre Haute, IN; **Texarkana, TX-AR**; **Toledo, OH**; **Trenton, NJ**; Tulsa, OK; Tuscaloosa, AL; **Urban Honolulu, HI**; **Utica-Rome, NY**; **Valdosta, GA**; **Vallejo-Fairfield, CA**; Virginia Beach-Norfolk-Newport News, VA-NC; Visalia-Porterville, CA; Walla Walla, WA; **Warner Robins, GA**; **Waterloo-Cedar Falls, IA**; **Watertown-Fort Drum, NY**; **Wausau, WI**; Wenatchee, WA; **Wichita, KS**; **Wichita Falls, TX**; **Winchester, VA-WV**; Winston-Salem, NC; **Youngstown-Warren-Boardman, OH-PA**; Yuba City, CA

Note: The significance threshold is 10%.