Is the health care price inflation in US urban areas stationary?

Evidence from panel unit root tests

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Abstract

Purpose – This study aims to investigate, for the first time in the literature, the stochastic properties of the US aggregate health-care price inflation rate series, using the data on health-care inflation rates for a panel of 17 major US urban areas for the period 1966-2006.

Design/methodology/approach – This goal is undertaken by applying the first- and second-generation panel unit root tests and the panel stationary test developed recently by Carrion-i-Silvestre *et al.* (2005) that allows for endogenously determined multiple structural breaks and is flexible enough to control for the presence of cross-sectional dependence.

Findings – The empirical findings indicate that after controlling for the presence of cross-sectional dependence, finite sample bias, and asymptotic normality, the US aggregate health-care price inflation rate series can be characterized as a non-stationary process and not as a regime-wise stationary innovation process.

Research limitations/implications – The research findings apply to understanding of health-care sector price escalation in US urban areas. These findings have timely implications for the understanding of the data structure and, therefore, constructs of economic models of urban health-care price inflation rates. The results confirming the presence of a unit root indicating a high degree of inflationary persistence in the health sector suggests need for further studies on health-care inflation rate persistence using the alternative measures of persistence. This study's conclusions do not apply to non-urban areas.

Practical implications – The mean and variance of US urban health-care inflation rate are not constant. Therefore, insurers and policy rate setters need good understanding of the interplay of the various factors driving the explosive health-care insurance rates over the large US metropolitan landscape. The study findings have implications for health-care insurance premium rate setting, health-care inflation econometric modeling and forecasting.

JEL classification – C32, E31, I1

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Social implications – Payers (private and public employers) of health-care insurance rates in US urban areas should evaluate the value of benefits received in relation to the skyrocketing rise of health-care insurance premiums.

Originality/value – This is the first empirical research focusing on the shape of urban health-care inflation rates in the USA.

Keywords Cross-sectional dependence, Health-care price inflation rate, Multiple structural breaks, Panel unit root tests

Paper type Research paper

1. Introduction

Applied economists are increasingly interested in studying the relationship between inflation and other economic variables (Thanh, 2015; Nguyen, 2015). This requires stationarity of the time-series data of the variables, in levels or when differenced, to avoid spurious regression parameter estimates. More specifically, for decades, economists have been testing whether the inflation rate series are stationary at the regional or national level in developed countries and in varying panels of the Organization for Economic Cooperation and Development (OECD) countries (Rose, 1988; Johansen, 1992; Culver and Papell, 1997; Ericsson *et al.*, 1998; Crowder and Wohar, 1999; Lee and, 2001; Rapach, 2002; Holmes, 2002; Charmeza *et al.*, 2005; Basher and Westerlund, 2006; Lee and Chang, 2007; Romero-Ávila and Usabiaga, 2009a, 2009b). However, empirical evidence on the stochastic properties of the inflation rate series is mixed. For example, while Lee and Chang (2007) and Culver and Papell (1997) claim that inflation rates in the OECD countries are stationary, integrated of the order of zero, I (0), Rodrizuez (2004) and Arize (2005) report that inflation rates in the Latin American and many developing countries are non-stationary, respectively, and therefore, they are integrated of the order one, I (1).

Whether the inflation rate is stationary or not has policy implications. If, for instance, the inflationary rate series is non-stationary and therefore has a unit root, then statistical inference in econometric modeling using such a variable will be spurious. Also, monetary policy actions in the presence of non-stationary inflation rate will result in permanent shocks to the system and therefore the inflation rate will not be mean reverting. Moreover, findings on stochastic properties of the inflation rate have theoretical implications for the validity of the Phillips curve phenomenon, the relevance of the Keynesian theory, and inter-temporal allocation decisions concerning saving and investment. The presence of a unit root in the inflation rate series and the attendant problem of persistence are of significance for policy effectiveness, inflation rate forecasting and the underlying theoretical models – see Levin and Piger (2004), O'Reilly and Whelan (2004) and Corvoisier and Mojon (2005). Therefore, fiscal and monetary policy authorities should be aware of the degree of persistence of inflation rate and, therefore, the differences in speed of its adjustment when designing effective inflationary containment policies. For example, if the aggregate inflation rate is non-stationary, I $\sim$ (1), and hence highly persistent, monetary policy actions aimed at containing the inflation rate will be futile and result in a permanent effect.

Consequently, economists, economic analysts and policy decision makers currently seek an understanding and evaluation of the time-series properties of inflation rates based on data at various aggregation levels. This is particularly important in the case of health-care price inflation rate (hereafter, health-care inflation rate) in urban areas. More specifically, the emerging evidence from health-care markets from implementing the 2010 US Affordable Care Act (ACA) reveals wide variances in the health-care coverage insurance rates, costs and prices across the major urban areas, even for preventive primary care visits[1]. More recently (Joszt, 2015), the Healthcare Cost Institute (HCI) created the Healthy Marketplace Index, a series of metrics measuring the economic performance (e.g. pricing) in health-care markets across the USA. The HCI's price index larger (smaller) than 1.0 indicates health-care markets with higher (less) than average prices[2]. This suggests that when designing health-care policies, it is critical to provide the insurers and policy makers with reliable guidance as to whether health-care price increases are stationary, using panel unit root tests that have more statistical power and relatively less size distortions. Implicit in the presence and persistence of a unit root in health-care inflation rates at the panel level are the roles of some major determinants of the adjustment speed of health-care prices (e.g. transportation cost variations, information asymmetries, market power variations in the relevant local market, medical technology adoption and diffusion rates, and the prevalence of different health-care-related institutional factors) play in various US urban areas. These important influences affect the degree of persistence of health-care inflation rate at both the aggregate and urban areas levels and hence on the degree of integration of the health-care inflation rate variable leading to the tendency for aggregation bias in unit root testing.

As discussed above, while there exists in the literature a number of econometric studies on the stochastic properties of the overall inflation rate and persistence in the USA, the UK and the OECD countries, and many econometric studies exploring the degree of integration of the health-care expenditure variable in these countries, no attempts are yet undertaken to explore the stochastic properties of the health-care inflation rates despite widespread global concerns for the rising health-care prices – see Gerdtham and Jonsson (2000), Murthy and Okunade (2000)[3] and Newhouse (1977). Moreover, Murthy and Okunade (2016), Okunade and Murthy (2002) and Bodenheimer (2005), among others, had alluded to the role and nature of technological change in the rise of US health-care costs and thus the price inflation. So as to fill this void, for the first time in the health economics literature, our current study, by utilizing the annual aggregate health-care inflation rate and the panel data of health-care inflation rate data from 17 major US urban areas for the period 1966-2006, applies a battery of the univariate, first- and second-generation panel unit root tests, the panel Lagrange multiplier (LM) unit root test that allows for two structural breaks recently developed by Im *et al.* (2005) and the recent panel unit root test of Carrion-i-Silvestre *et al.* (2005) that allows for endogenously determined multiple structural breaks experienced by individual members of the panel and is flexible enough to control for the presence of cross-sectional dependence (CD).

The goal of this paper is, therefore, to empirically study, by employing recent panel unit root techniques, whether the US health-care inflation rate series is stationary, using panel data from major urban areas in the US. Section 2 of this work covers the data, study methodology and the panel unit root testing methods. Section 3 discusses the empirical findings, and Section 4 concludes.

2. Data, methodology and panel unit root tests

Data on the aggregate US medical care consumer price index (CPI) inflation rate and the US urban area medical care CPI inflation rates for 17 large urban areas for the period 1966-2006 are obtained from Bureau of Labor Statistics – BLS (2007) (http://data.bls.gov/PDQ/outside.jsp?survey=cu). The BLS computes annual health-care inflation rates using the 1982-1984 = 100 as the base period. Details of the urban areas included in the analysis are given in the appendix. Data summary statistics in Table I show greater variations in the health-care price rise for some urban areas (e.g. Houston-Galveston; Kansas City) than others (e.g. Boston; Philadelphia-Wilmington). The mean annual rate of health-care price rise, greatest in Cincinnati-Hamilton, Boston-Brockton and Philadelphia-Wilmington areas, may arise

Table I. Average annual health-care inflation rates 1966-2006: US aggregate and major urban areas (1982-1984 = 100)

Urban area (abbreviated label)	Health-care inflation rate Mean	Maximum	Minimum	SD
Atlanta – GA	6.493	13.015	−1.231	3.241
Boston – Brockton	7.165	12.097	3.209	2.554
Chicago	6.564	12.869	2.326	2.827
Cincinnati – Hamilton	6.811	11.977	14.878	3.227
Dallas – Fort Worth	6.357	14.878	0.311	3.227
Detroit – Ann Arbor	6.635	15.068	0.187	2.767
Houston – Galveston	6.594	13.984	1.316	3.498
Kansas City, MO – KS	6.381	14.178	−1.037	3.481
Los Angeles – Riverside	6.668	14.756	1.354	3.295
Milwaukee – Racine	6.434	12.409	1.499	2.884
New York – North New Jersey	6.581	12.719	2.902	2.606
Philadelphia – Wilmington	7.069	13.594	2.312	2.569
Pittsburgh – Pennsylvania	6.592	12.611	1.508	3.054
Portland – Salem	6.557	12.747	2.528	2.838
Saint Louis – MO	6.459	14.181	1.907	2.859
San Francisco – Oakland	6.450	14.940	2.018	3.000
Seattle – Tacoma	6.303	12.462	1.955	2.909

from their greater incomes, demographics, more generous insurance coverage and greater use intensity of frontier medical treatment technologies and testing procedures (innovations).

With regard to the methodology for investigating the stochastic properties of the US health-care inflation rate series at the aggregate level, this paper applies the univariate, panel unit root tests and panel unit root tests that allow for structural breaks. The univariate unit root tests that are applied in this paper are the augmented Dickey–Fuller (ADF) tests, the Phillips–Perron tests and the Kwiatkowski *et al.* (1992) tests. While the ADF, Phillips and Perron (1988) and the Kwiatkowski, Phillips, Schmidt and Shin (KPSS) tests define the null hypothesis of the presence of a unit root (non-stationarity), the KPSS maintains the null of stationarity.

The Phillips–Perron unit root test is an alternative non-parametric test correcting for serial correlation in the series (Baltagi, 2005; Breitung and Pesaran, 2005; Murthy, 2007). As the univariate unit root tests lack power, at the outset we use some well-known first- and second-generation panel unit root tests to enhance power and minimize size distortions. The first-generation panel unit root tests that are applied in this paper are the Levin–Lin–Chu (LLC; Levin *et al.*, 2002), Im–Pesaran–Shin (IPS; Im *et al.*, 2003), Breitung (2000) and, finally, the Hadri (2000) tests. A brief theoretical description of these tests is presented as follows: Let the data generating process of the series *y*, in its difference form, be:

$$\Delta y_{it} = \alpha y_{it-1} + \sum_{j=1}^{p_i} \beta i_j \Delta y_{it-j} + X'\delta + \varepsilon_{it} \quad (1)$$

where $i = 1, 2, 3, \ldots, N$ representing cross-sections and $t = 1, 2, 3, \ldots, T$ denoting time period observations. X_{it} are the exogenous variables such as individual effects and linear trends, $\alpha = (\rho - 1)$, and ρ_i are the autoregressive coefficients. The LLC, Breitung and Hadri tests assume that the autoregressive coefficients in (1) are identical across the panel (common unit root process), whereas in the IPS test, they are free to vary. In the LLC test, the null hypothesis is the presence of a unit root for all i, and the alternative hypothesis requires that the individual process is stationary for all i, and in the IPS test, while the null hypothesis is the same, the alternative is stated to include a non-zero fraction of the individual process as stationary. Im *et al.* (2003) derive a panel unit root test statistic, t_{IPS}, called the IPS statistic, expressed as:

$$t_{IPS} = \frac{\sqrt{N}\left(\bar{t} - \frac{1}{N}\sum_{i=1}^{N} E\left[t_{iT}|\rho_i = 0\right]\right)}{\sqrt{\frac{1}{N}\sum_{i=1}^{N} Var\left[t_{iT}|\rho_i = 0\right]}} \tag{2}$$

In equation (2), based on the simple Lindberg–Levy theorem, especially when the number of observations is extremely large, the test statistic is asymptotically distributed as N (0.1). Im *et al.* (2003) provide tabulated values of the mean and variance for standardizing the test statistic – see Im *et al.* (2003). On the other hand, the Maddala and Wu (1999) test, which is a Fisher (1932) type test that combines the p-values, π_{i} of each of the N individual cross-sections' ADF regressions. The Maddala and Wu (MW) panel unit root test statistic is defined as follows:

$$MW\lambda = -2\sum_{i=1}^{N} \ell n \pi_i \tag{3}$$

The MW λ statistic is distributed as a χ^2 with $2N$ degrees of freedom. Similarly, the Phillips–Perron Fisher-type panel unit root test combines the p-values, π_{i} of the individual cross-sections' Phillips–Perron regressions.

The panel unit root tests discussed above assume that the cross-sectional units (members) are independent. But in the urban area health-care markets, cross-sectional correlation does arise because of such factors as the spillover effects, integration of markets, omitted observed factors, health-care cost-consolidation, economies of scope in hospital operating costs, residual interdependence and diffusion of medical care technology.

Therefore, econometric modeling in a panel context does require accounting for the CD phenomenon. Moreover, some econometricians have demonstrated that panel unit roots that ignore CD suffer from severe size distortions in letting the empirical size higher than the nominal level, at times raising the test's nominal level of 5 to 50 per cent, and leading to the frequent rejection of the true null hypothesis – see Banerjee *et al.* (2005), Gengenback *et al.* (2005), Strauss and Yigit (2003) and O'Connel (1998). In the econometrics literature, there are two approaches that are available to handle the cross-sectional problem in the context of panel unit root tests. These are, in the literature, referred to as the second-generation panel unit root tests. The first approach is to impose almost no restrictions on the covariance matrix of the residuals – see O'Connel (1998), Maddala and Wu (1999) and Chang (2002, 2004). The second approach, prior to an efficient designing of panel unit root tests, is to model and estimate the CD using a low dimensional common factor model. This latter approach is led by Pesaran (2004, 2007), Bai and Ng (2002, 2004), Moon and Perron (2004) and Phillips and Sul (2003).

This paper conducts the cross-section dependence test of Pesaran (CD) that can be employed to detect if there is any cross-sectional correlation and hence an indication of the degree of CD in the health-care inflation series among the members of the panel of US urban areas. If this phenomenon is confirmed statistically, we will handle the CD among US urban areas' health-care inflation rate series by applying the Moon and Perron (2004) panel unit root test and the Pesaran's (2007) cross-sectional augmented Im Pesaran and Shin (CIPS) test, derived from the cross-sectionally augmented Dickey–Fuller (CADF) test. To allow for residual serial correlation, the CADF test can be modified to incorporate the cross-section average of lagged levels and first differences of the individual panel member series to obtain the cross-sectionally augmented Dickey–Fuller test statistic (CADF) for each cross-sectional member of the panel. Pesaran constructs a modified version of the IPS t-bar test called CIPS test, based on the average of the observed individual cross-section CADF statistics. In Pesaran's (2007, p. 283) notations, the CIPS statistic can be derived as follows:

$$\Delta y_{it} = \alpha_i + \beta_i y_{i,t-1} + \gamma_i \bar{y}_{t-1} + \sum_{j=0}^{\Phi} \delta_{ij} \Delta \bar{y}_{t-j} + \sum_{j=1}^{\Phi} \theta_{ij} \Delta y_{i,t-j} + e_{it} \tag{4}$$

$$CIPS = \left(\frac{1}{N}\right) \sum_{i=1}^{N} CADF_i \tag{5}$$

where it is defined that $\bar{y}_{t-1} = \left(\frac{1}{N}\right)\sum_{i-1}^{N} y_{i,t-1}$, and $\Delta\bar{y}_t = \left(\frac{1}{N}\right)\sum_{i=1}^{N} \Delta y_{it}$. In equation (4), the critical values of t (N, T) are used for unit root testing in assessing the statistical significance of the actual t-statistic of the estimate of β_i. The CIPS test takes into account both CD and residual serial correlation. Pesaran (2007) reports the critical values, based on N, T, for various deterministic terms used in equation (4). Moreover, Pesaran (2007) demonstrates that in the presence of a low degree of cross-section dependence, the power and size distortions the CIPS (N, T), and its truncated version, the CIPS* panel unit root test perform very well even in small samples.

While Pesaran's (2007) CIPS panel unit root test considers one common factor in the error structure of the specified data-generating model, Moon and Perron (2004) consider multiple common factors to test the null of non-stationarity. Unlike the Pesaran's CIPS test, the Moon and Perron (2004) test is often employed to detect the presence of a unit root in the panel when CD arises because of multiple common factors. Moon and Perron (2004) have developed two modified test t-statistics, $t \times a$ and $t \times b$, based on the pooled estimation of the first-order serial correlation coefficient of the data series – see for details, Moon and Perron (2004). They show that both the test statistics are distributed as N (0, 1) under the null, and these statistics diverge under the stationary alternative hypothesis.

As indicated above, the outcome of both the univariate and panel unit root tests are subject to severe bias when structural breaks in the series are neglected – see Perron (1989) and Levin and Piger (2004). Often, ignoring structural break in the time-series might result in false evidence of a unit root. Therefore, this paper conducts the panel LM unit root test with heterogeneous structural breaks proposed recently by Im *et al.* (2005) to statistically find out whether the urban area panel health inflation rate series are stationary with two structural breaks. This test, besides being a very powerful test that combines both panel data and structural breaks and free of nuisance parameter problems, jointly estimates the heterogeneous optimal number and location of breaks for each cross-sectional member determined endogenously (also, see Lee and Strazicich, 2003). A distinguishing statistical feature of this test is that, unlike the Zivot and Andrews (1992) and the Lumsdaine and Papell (1997) univariate structural break tests, it allows for two structural breaks under both the null and alternative hypothesis. Im *et al.* (2005) compute the univariate *LM* unit root test statistic, given by the actual *t*-statistic, for each individual cross-section first and then compute the panel *LM* test statistic by standardizing the panel average *LM* statistic, $LM_{\overline{NT}}$. The statistic Γ_{LM} is standardized by the mean and variance simulated by Im *et al.* (2005) is computed as follows:

$$\Gamma_{LM} = \frac{\sqrt{N}\left[\overline{LM}_{NT} - E(L_T)\right]}{\sqrt{v(L_T)}} \tag{6}$$

Im *et al.* (2005) derive the asymptotic properties of the panel Γ_{LM} and demonstrate that it is normally distributed under the null as $N(0, 1)$. The univariate two-break minimum LM unit root tests proposed by Lee and Strazicich (2003) endogenously determine the location of each break point and the optimal value of the lag length, *k*, is decided by using the general-to-specific method suggested by Perron and Ng (1996) and Perron (1989). For details of the procedure, see Im *et al.* (2005).

To seek additional robust evidence to discern whether the panel of health-care inflation rates of the 17 US urban areas included in the study is individually and jointly as a panel stationary with multiple structural breaks, we conduct the most recent panel stationary test developed by Carrion-i-Silvestre *et al.* (2005) [hereafter, the CBL test]. In their epoch-making *Econometrics Journal* paper, Carrion-i-Silvestre *et al.* (2005) posit the following data-generating model and in describing their specification, we follow their notations to retain the letter and spirit of their proposition:

$$y_{i,t} = \alpha_i + \sum_{k=1}^{m_i} \theta_{i,k} DU_{i,k,t} + \beta_i t + \sum_{k=1}^{m_i} \gamma_{i,k} DT^{*}_{i,k,t} + \varepsilon_{i,t} \tag{7}$$

In model (7), $DU_{i,k,t}$ and $DT^*_{i\ k,t}$ are dummy variables with $DU_{i,k,t} = 1$ for $t > T^i{}_b$, *k* and 0 elsewhere and $DT^*_{i\ k,t} = t - T^i{}_b$, *k* and 0 elsewhere. $T^i{}_b$, *k* is the *k*th date of structural break for the ith member of the panel with $k = 1, \ldots, m_i$, $m_i \geq 1$. The model (7) can be used to allow structural breaks in both the mean and the time trend. The error terms associated with model (7) are assumed to be independent across cross-sections. As suggested by Silvestre *et al.*, allowing a maximum of five breaks, the number and location of the structural breaks are estimated by using the sequential procedure proposed by Bai and Perron (1998). See for details of the model estimation, Carrion-i-Silvestre *et al.* (2005). Depending on the trending nature of regressors used in the model, the investigator can select one among the three criteria, the Bai and Perron (2001) criteria, the Bayesian Information Criterion and the modified Schwartz information Li, Wu and Zidek (LWZ) of Liu *et al.* (1997), to determine the optimal number of structural breaks for individual members of the panel. The CBL panel stationary test, besides having better power and size properties than other structural break tests, has many econometrically desirable features in allowing each panel member to have a different number of breaks located at different dates.

As this test is a panel test based on Hadri's univariate KPSS test, model (7) is estimated using the Ordinary Least Squares (OLS) method. The OLS residuals are used to derive the individual KPSS statistics for each cross-section and then compute the average of these KPSS statistics, LM (λ), which in turn is transformed into the standardized test statistic, Z (λ). Here, λ is a vector of relative positions of the break points. The standardized panel data statistic, Z (λ), which, under the null hypothesis of variance stationarity and assumption of cross-sectional independence, is normally distributed as N (0, 1) and it can be expressed as:

$$Z(\lambda) = \frac{\sqrt{N}\left(LM(\lambda) - \bar{\xi}\right)}{\bar{\zeta}} \tag{8}$$

In (8), ξ-bar and ς-bar are the average of the individual mean and variance of η_I (λ i).

3. Empirical results and discussion

The univariate unit root test results for the aggregate US health-care inflation rate are reported in Table II. While the results of the ADF tests, ADF_{GLS} and Phillips–Perron tests, with the null hypothesis of the presence of a unit root, clearly indicate that the aggregate US health-care inflation rate series in levels are integrated of the order 1, I ~ (1), and therefore non-stationary, the series in their first differences are found to be integrated of order 0, I ~ (0), and hence is stationary. The results of KPSS unit root test with the null of stationarity show that the series are non-stationary in levels and in first differences, indicating that the aggregate US health-care inflation rate is persistent. Any shocks to these series are permanent and hence they do not return to their mean.

While it is tempting to conclude that the aggregate health inflation rate series is non-stationary, it is imperative that the series be tested for the presence of any structural breaks. As indicated before, Perron (1989) has demonstrated that ignoring the presence of structural breaks in a time-series and proceeding to conduct unit root testing would bias and statistical inference the results by mistaking the structural break for the presence of a unit root and – see for details, Perron (1989) and Zivot and Andrews (1992). In such an event, if the ADF unit root test is applied, the test lacks power and results in falsely accepting the presence of a unit root in the series. Therefore, this paper seeks to empirically determine whether the aggregate health-care inflation rate series has experienced any structural breaks in intercepts, trends or both by conducting the Zivot and Andrews (1992) endogenously estimated structural change unit root tests and the results are presented in Table III.

From the results shown in Table III, it is clear that at the 1 per cent level, the null of unit root cannot be rejected for all specified models with different deterministic terms. Therefore, the conclusion that the aggregate health-care inflation rate is non-stationary is still reinforced. To detect robust statistical evidence of the presence of a unit root in a time-series, an investigation of the stochastic properties of health-care inflation rate series should be conducted using data at a much disaggregated level.

Moreover, in recent years, the complementary approach of furnishing more information is encouraged by using panel data on the series to have effective statistical inference.

Table II. Univariate unit root test results: aggregate US health-care inflation rate, 1966-2006[a]

Series	ADF	ADF_{GLS}	Phillips–Perron	KPSS	Decision
Level	−2.723 (0.233)	−2.301 (0.026)	−2.565 (0.298)	0.162* [0.146]	I (1)
First differences	−5.423*(0.000)	−4.876* (0.000)	9.157* (0.000)	0.228* [0.146]	I (0)

Notes: [a]With a constant and a linear trend. Lags are based on the SIC criterion. p-values are in parentheses, and for the KPSS tests, 5% critical value in brackets; *Significant at the 5% level

Therefore, in this paper, several first-generation panel unit root tests are conducted and the results are reported in Table IV. Specifically, the Levin *et al.* (2002), Im *et al.* (2003), Maddala and Wu (1999) Fisher-type test, the Phillips and Perron (1988) Fisher-type test and, finally, the Hadri (2000) panel unit root tests are performed. For details on these tests, see Baltagi (2005), Breitung and Pesaran (2005), Hurlin (2007) and Murthy (2007). All these tests assume cross-section independence. While the LLC, MW, IPS and Phillips–Perron Fisher-type tests state the null hypothesis that all the individual series in the panel have a unit root, the IPS test specifically allows under its alternative hypothesis that some of the individual series in the panel to contain a unit root. Of these panel unit root tests, the LLC test makes the most restrictive assumption of allowing the autoregressive coefficient under the alternative hypothesis to be the same across the cross-sections. The Hadri panel unit root, as in the case of univariate KPSS unit root test, besides requiring the autoregressive parameter to be common to all the panel members, maintains the null hypothesis that all individual series of the panel do not have a unit root with the alternative of non-stationarity of all individual series. The LLC test also assumes a process with a common unit root process unlike the IPS, MW and Phillips–Perron's Fisher-type tests. The IPS and the MW tests are less restrictive in allowing the autoregressive parameter to vary freely among the members. The Breitung (2000) test corrects for the loss of power in the presence of individual specific trends in the IPS and LLC tests.

The panel unit root tests in Table IV clearly show that the results of a majority of the tests, IPS, MW and the Phillips–Perron Fisher-type tests, reject the null of the presence of a

Table III. Results of the Andrews–Zivot unit root tests for structural break: aggregate US health-care inflation rate, 1966-2006

Break	Observed minimum *t*-statistic	1% critical value
Breaks in intercept only	−5.067	−5.34
Breaks in trend only	−3.757	−5.34
Breaks in both intercept and trend	−5.081	−5.57

Table IV. Results of first-generation panel unit root tests

Test	Test-statistic *Levels*	*First differences*
Null hypothesis: unit root		
Levin–Lin–Chu (LLC) test	−8.210* (0.000)	−22.949* (0.000)
Breitung test (BT)	−5.329* (0.000)	−11.241* (0.000)
Im–Pesaran–Shin (IPS) test	−5.453* (0.000)	−21.713* (0.000)
ADF-Fisher x^2 (MW) test	84.901* (0.000)	384.494* (0.000)
Phillips–Perron–Fisher x^2 (PPF)	74.314* (0.000)	2,148.260* (0.000)
Null hypothesis: no unit root		
Common unit process	8.271*	21.041*
Hadri test (HT)	(0.000)	(0.000)

Notes: *Indicates statistical significance at the 1% level. For levels, deterministic terms included are individual effects and linear trends. Lags are based on the Schwartz information criteria (SIC) criterion. In Hadri's test, Heteroscedasticity-consistent Z-statistics are reported unit root for the panel and hence urban series are stationary in levels. This finding challenges the evidence provided by unit root tests at the aggregate level. On the other hand, the outcome of the Hadri's tests rejects the null. The conflicting results between these two sets of tests could be attributed to the lack of power of the Hadri's test and the assumption of cross-section dependence among the individual members in the panel. It has been statistically shown that not considering and controlling for CD among cross-sectional members would lead to severe size distortions of the tests and decreased efficiency of estimation – see, O'Connel (1998). CD is very common and pervasive in panel owing to the presence of spillover effects, co-movements, common shocks, financial and economic integration, herd behavior, technological change and interdependence of consumers' preferences. All these sources of CD are often present in health-care markets at the urban area level. Therefore, a robust testing of stochastic properties of health-care inflation rate does warrant the application of panel unit root tests, which are designed to handle the phenomenon of CD.

In Table V, test results are presented for Pesaran's, CADF tests. The results of Pesaran's CIPS tests and Moon and Perron tests, which are the second-generation panel unit root tests, are presented in Table VI. Also, the CD test's findings are shown in Table VI. The CD test is a diagnostic test proposed by Pesaran (2004) applied to statistically confirm whether any degree of CD is present in the panel data. In this test, the observed test statistic, normally distributed under the null of independence of cross-sectional units, is derived as:

$$CD = \left[TN(N-1)/2\right]^{-1/2}\hat{\hat{\rho}} \tag{9}$$

where, in equation (9), $\hat{\hat{\rho}}$ is the simple average of the pair-wise cross-section correlation coefficients. As shown in Table VI, the observed test statistic for the CD test exceeds the 5 per cent critical value, and therefore, the null hypothesis of no cross-sectional correlation is

Table V. Pesaran's CADF unit root test results for the panel data[a]

	$CADF_i$ *Levels*		$CADF_i$ *First differences*	
Urban area	*k = 1*	*k = 2*	*k = 1*	*k = 2*
Atlanta – GA	−2.332	−2.898**	−3.540*	−3.187*
Boston – Brockton	−3.149**	−2.441**	−5.869*	−5.233*
Chicago –	−5.427*	−3.782*	−6.190*	−6.190*
Cincinnati – Hamilton	−3.404**	−2.864**	−5.728*	−4.287*
Dallas – Fort Worth	−4.250*	−3.367**	−6.190*	−5.416*
Detroit – Ann Arbor	−3.153**	−3.018**	−5.460*	−4.283*
Houston – Galveston	−4.582*	−4.544*	−5.648*	−4.646*
Kansas City, MO – KS	−4.301*	−4.161*	−4.490*	−3.777*
Los Angeles – Riverside	−6.569*	−3.688*	−6.190*	−5.258*
Milwaukee – Racine	−3.160**	−2.543**	−6.154*	−4.771*
New York – N. New Jersey	−3.336**	−2.549**	−5.697*	−4.282*
Philadelphia – Wilmington	−3.862*	−4.102*	−5.446*	−5.233*
Pittsburgh – Pennsylvania	−3.515*	−2.949*	−5.971*	−3.795*
Portland – Salem	−4.832*	−3.724*	−6.190*	−6.190*
St. Louis – MO	−3.541*	−3.236**	−5.610*	−6.142*
San Francisco – Oakland	−3.035**	−2.441	−6.138*	−5.173*
Seattle – Tacoma	−3.126**	−2.942**	−5.040*	−4.522*

Notes: *k* = lags; * and **significant at the 5% and 10% levels, respectively; [a]With a deterministic trend rejected, and therefore, there is a strong statistical evidence of CD in the data sample. The outcome of the CD test is robust to the lag length ranging from 0 to 3. The observed values of the CADF and CIPS statistics exceed, in absolute values, the critical values at the 5 per cent level confirming that the health-care inflation rate series at the urban level are stationary. The results of the Moon and Perron panel tests, as indicated by the observed values of the t_{*-a} and t_{*-b} statistics, reject strongly the null hypothesis of non-stationarity at the 1 per cent level. These results show further evidence that the panel unit root tests results should not be taken conclusively as the health-care inflation rate series in the USA because of the observed CD among the members of the panel consisting of 17 US urban areas. In the present case, as the CIPS and CIPS* values are identical, only CIPS information is reported in Table VI.

Results of the panel *LM* unit root tests with structural breaks in both level and trend, Model C in Im *et al.* (2005), are reported in Table VII. It is clear from the results for all

Table VI. Second-generation panel unit root tests and the CD test results

Health care price inflation rate	Pesaran's (2007) CIPS*	Moon and Perron (2004) test** t^*_{-a}	t^*_{-b}	CD test-statistic**
A. Levels	−3.250**	−23.423*	−7.951*	28.82* (k = 2)
B. First differences	−4.956*	114.505*	−33.982*	25.38* (k = 2)

Notes: *and **indicate statistical significance at the 1% level and 5% level, respectively. k = lags. The observed common factor is equal to 1

Table VII. Im *et al.*'s panel LM unit root test results with two structural breaks: Model C**

Urban area	Univariate LM unit root test statistics	Lags	Break points
Atlanta – GA	−6.338*	2	1976, 2001
Boston – Brockton	−7.032*	8	1993, 2000
Chicago	−7.693*	7	1982, 1999
Cincinnati	−6.144*	8	1979, 1999
Dallas – Fort Worth	−6.345*	2	1990, 1998
Detroit – Ann Arbor	−7.294*	8	1979, 1999
Houston – Galveston	−6.486*	1	1986, 1998
Kansas City, MO – KS	−6.069*	8	1982, 1990
Los Angeles – Riverside	−8.071*	8	1984, 1991
Milwaukee – Racine	−5.986*	5	1979, 1998
New York – N. New Jersey	−6.367*	1	1977, 1990
Philadelphia – Wilmington	−7.245*	8	1984, 1998
Pittsburgh – Pennsylvania	−6.121*	5	1976, 1994
Portland – Salem	−6.102*	6	1981, 2002
St. Louis – MO	−5.319*	6	1982, 1990
San Francisco – Oakland	−6.025*	8	1984, 1992
Seattle – Tacoma	−8.506*	7	1978, 1998
Panel LM Statistic −6.576*	7		

Notes: The 5% critical value for the LM unit root with two breaks is −5.286. The 5% critical value for the panel unit root test with two breaks is −1.645; *denotes significance at the 5% level; **procedure allows for structural breaks both in level and trend the urban area health-care inflation rates that the null hypothesis of the presence of a unit root with structural change is rejected at the 5 per cent level, indicating that these series are stationary and each urban area has experienced two breaks. Furthermore, the panel *LM* unit root tests allowing for structural breaks reject the null hypothesis at the 5 per cent level. Thus, the results largely show health-care inflation rates as stationary with broken trends, and hence, they are mean reverting and any shocks they receive would have temporary effects. Results show that unlike the aggregate health-care inflation rate series, the urban area series do converge. The majority of the break points are found to be in the1970s and 1990s, which could be associated with the impact on health-care inflation rates owing to the global oil crisis, era of stagflation in the USA in the middle 1970s and the reduction of the inflation rate in the1990s brought by anti-inflationary monetary policy of Paul Volker in the USA and some of the institutional organizational and technological changes that took place in the area of health-care in the 1990s and early 2000s.

While the results shown in Table VII provide some insights on the structural breaks experienced by various urban areas and the panel as a whole, the Im *et al.* panel unit root tests assume that there is no CD. Additionally, these tests state the null hypothesis as non-stationary, whereas the Carrion-i-Silvestre *et al.* (2005) maintains that the null is stationarity and usually, the null hypothesis will be rejected only when there is strong evidence against it. Therefore, for robustness of results, we proceed to apply the CBL panel stationary test in the following section.

In Table VIII, the results of the Carrion-i-Silvestre *et al.* (2005) panel variance stationarity test allowing for endogenously determined multiple structural breaks (shifts in the mean owing to structural breaks) are presented. The model estimated includes the deterministic terms of constant and change in the level when there are breaks. The LWZ criterion is used for determining the optimal number of breaks. In this test, the null hypothesis is that the series are regime-wise stationary for all the panel members against the alternative of non-stationarity for some of the members. As asymptotic critical values are used in the KPSS tests, we have to control for the finite-sample bias as we have used a relatively small sample, we have computed finite-sample 10 and 5 per cent critical values for the individual KPSS tests with multiple structural breaks by conducting Monte Carlo simulations of using 20,000 draws and the resulting information is reported in Table VIII. The observed individual KPSS statistics with the estimated multiple breakpoints, presented in Panel A, show that the null hypothesis of stationarity with multiple-level shifts cannot be rejected at the 5 per cent level for all the urban areas with the exceptions of New York and Northern New Jersey and San Francisco and Oakland urban areas.

As earlier discussed in this paper, the presence of CD arising from both global and local spillovers, common shocks and other common factors would result in bias and size distortions. To detect presence of CD in the data used in this paper, the widely used Pesaran's (2004) CD test results are presented in Table VI (see for details, Pesaran, 2004). As a solution to mitigate the impact of the CD, we have reported, in Table VIII, the bootstrapped critical values, allowing for the presence of CD. There is no formal procedure to test the presence of CD on the results of the CBL tests.

It is clear that all of the urban areas experienced at least one structural break with positive shifts in their mean and most urban areas witnessed multiple breaks. This observed empirical finding in terms of varied number and position of structural breaks for different panel members might be indicative of a high degree of heterogeneity, which renders our results richer. Of the total 37 structural breaks

Table VIII. Carrion-i-Silvestre *et al.* Panel stationarity tests results

Urban area	Individual KPSS test	m_i	$T^i_{b,1}$	$T^i_{b,2}$	$T^i_{b,3}$	Finite sample KPSS critical values 10%	5%
Panel A: Individual panel member information							
Atlanta – Georgia	0.081	1	1994+			0.195	0.252
Boston – Brockton	0.044	2	1974+	1992+		0.108	0.129
Chicago	0.043	3	1973+	1983+	1993+	0.073	0.084
Cincinnati – Hamilton	0.076	1	1994+			0.197	0.253
Dallas – Ft. Worth	0.114	1	1992+			0.181	0.230
Detroit – Ann Arbor	0.098	1	1992+			0.175	0.222
Houston – Galveston	0.043	3	1974+	1983+	1992+	0.075	0.087
Kansas City – Missouri	0.060	3	1983+	1993+	1999+	0.073	0.084
Los Angeles – Riverside	0.069	3	1973+	1982+	1993+	0.073	0.085
Milwaukee – Racine	0.057	3	1973+	1981+	1995+	0.076	0.089
New York – N. New Jersey	0.127*	2	1973+	1992+		0.114	0.136
Philadelphia – Wilmington	0.091	1	1993+			0.185	0.235
Pittsburgh – Pennsylvania	0.064	3	1972+	1982+	1992+	0.076	0.090
Portland – Salem	0.134	2	1973+	1982+		0.143	0.183
St. Louis – Missouri	0.129	2	1973+	1983+		0.133	0.170
San Francisco – Oakland	0.121**	3	1973+	1982+	1993+	0.074	0.086
Seattle – Tacoma	0.058	3	1973+	1982+	1992+	0.075	0.088

Panel B: Panel test statistics		
$Z(\hat{\lambda})$	Homogeneous variance	2.093 (0.018)
$Z(\hat{\lambda})$	Heterogeneous variance	1.716 (0.043)

Panel C: Bootstrap distribution (allowing for cross-section dependence)				
Critical values	90%	95%	97.5%	99%
Homogeneous	0.318	0.650	0.949	1.301
Heterogeneous	0.220	0.500	0.753	1.050

Notes: * and **see, Kwiatkowski *et al.* (1992) significant at the 10% and 5% levels, respectively; The sign $^+$denotes an upward shift in the mean. *p*-values reported within parentheses.

experienced by all of the urban areas, we find two clusters of breaks circa 1973 (when the USA spent $162.6bn on health care) and 1982, the former associated with the energy crisis and the latter associated with Paul Volker's regime of restrictive monetary policy, that might have impacted health-care production and distribution. The 1973 cluster of breaks coincides with the Health Maintenance Organizations Act of 1973 following US President Nixon's passage and implementation of the 1971 Economic Stabilization Program (after price controls had been ineffective) to contain double-digit inflation in the economy. The 1982 cluster of breaks coincides with rapid changes in medical technology, slow health sector productivity growth and the new method for reimbursing hospitals took effect. The US Bureau of Labor Statistics (2014) also expanded the composition of the producer price index (PPI) Hospital Index in 1993 and the PPI Physician Index in 1994 and computed them monthly. This accounts for another cluster of breaks experienced by some of the major urban areas in the early 1990s.

Further in Table VIII, the observed panel test statistics, shown in Panel B, assuming CD along with the assumptions of homogeneous and heterogeneous variances used in computing the long run variance of the test statistic, rejects the null hypothesis at the 5 per cent level and leads to the conclusion that the series is non-stationary. Finally, controlling for general forms of CD and finite sample bias, the 1, 2.5, 5 and 10 per cent bootstrapped critical values of the panel statistic are generated, and reported in Table VIII, using 20,000 replications following the procedure recommended by Maddala and Wu (1999). The resulting critical values, using both the homogeneous and heterogeneous assumptions, are shown in Panel C of Table VIII. As it can be readily observed that owing to the size distribution caused by the presence of CD among the panel members, the bootstrapped standard normal distribution shifts to the right. Now, the computed long-run variance is greater than the bootstrapped 10, 5 or 1 per cent critical values, indicating that the null hypothesis is again rejected. Thus, from the CBL test results, we again have some robust empirical evidence that the urban area health-care inflation rates are non-stationary with individual panel members experiencing multiple structural breaks. Therefore, we find these series are not mean-reverting.

4. Conclusion

This paper, for the first time in the literature, using a battery of univariate, panel unit root tests, the Im *et al.*'s LM panel unit tests that permit two structural breaks and the recently developed Carrion-i-Silvestre *et al.* panel stationarity tests that allow for multiple structural break points, empirically confirms the existence of a unit root in the US health-care inflation rate series during the period 1966-2006. While the null of unit root cannot be rejected for the aggregate series, for the disaggregated series, they are rejected under the assumption that the panel members are independent. Stationarity of the disaggregated series implies that it is mean reverting. This suggests that related macroeconomic shocks (such as changes in fiscal or monetary policies) or health policy changes (e.g. reimbursement and financing of covered procedures) have transitory effects on health-care inflation rates.

Maximum number of breaks, mi, allowed is health-care sector prices are usually driven by quality improvements, and as a result the prices should be quality adjusted. Cutler *et al.* (1998) argue that increases in health-care prices could arise from quality improvements, meaning that the price per quality may remain more stable. This implies that while quality-adjusted prices could be stationary, quality itself could be non-stationary to also make the unadjusted price series non-stationary. However, health-care quality is multi-dimensional and adjusting for quality in a time-series and panel data context is challenging. This is an acknowledged limitation of our current study[4].

The presence of CD renders panel unit root tests severely size-distorted and hence generates spurious statistical inference. Therefore, to control for the presence of CD, in the presence of multiple structural breaks for individual panel members, the bootstrapped critical values are generated to test the unit root hypothesis panel test statistics applying the Carrion-i-Silvestre *et al.* panel stationarity test. The results show that the time-series of the US health-care inflation rates exhibit unit root behavior. Finally, our study findings have implications for health-care insurance premium rate setting, health-care inflation econometric modeling and forecasting. The results confirming the presence of a unit root indicating a high degree of inflationary persistence in the health sector signal the need for further studies on health-care inflation rate persistence using alternative measures of persistence.

Notes

1. Current calls for transparencies in health care prices, premiums and costs as the ACA unfolds are yielding some results. Joszt (2014), for example, presented data based on analysis from Castlight Health to rank urban areas based on their health care costs for primary care visits, MRIs and CT scans. The top ten cities (average price per visit, median income) are: San Diego, CA ($145, $63,990); Atlanta, GA ($147, $46,146); Chicago, IL ($165, $47,408); Seattle, WA ($189, $63,470); Boston, MA ($193, $53,136); Charlotte, NC ($199; $52,196); Minneapolis, MN ($209, $48,881); Portland, OR ($216, $51,238); Sacramento, CA ($219, $50,661); and San Francisco ($251, $73,802).
2. High-price areas in 2014 are: Boulder, CO; El Paso, TX; Dallas, TX; Milwaukee, WI; Philadelphia, PA; Denver, CO; and Fort Collins, Co. In comparison, low-price areas include: Tucson, AR; St. Louis, MO; New Orleans, LA; Peoria, IL; and Louisville, KY.
3. As cautioned by one referee, discussions on the impact of technological change on health-care spending need to acknowledge that technological change may imply treatment expansions affecting quantities and not prices and that prices could be affected when new technology displaces current treatment methods.
4. We thank a referee for pointing out this as a study limitation.

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Appendix

The urban areas included are: Atlanta, GA; Boston – Brockton – Nashua, MA, NH, ME, CT; Chicago – Gary – Kenosha, IL, IN, WI; Cincinnati – Hamilton, OH, KY, IN; Dallas – Fort Worth, TX; Detroit – Ann Arbor – Flint, MI; Houston – Galveston – Brazoria, TX; Kansas City, MO, KS; Los Angeles – Riverside – Orange County, CA; Milwaukee – Racine, WI; New York – Northern New Jersey – Long Island, NY, NJ, CT, PA; Philadelphia – Wilmington – Atlantic City, Philadelphia, NJ, DE, MD, Pittsburgh, PA; Portland – Salem, OR, WA; St. Louis, MO, IL; San Francisco – Oakland – San Jose, CA; Seattle – Tacoma – Bremerton, WA.

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