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Abstract

Recent inflation dynamics in the United States (US) questioned the role of driving forces of inflation in the long run. Although the US recorded one of the longest economic recovery periods and the labor market conditions improved after the Global crisis, the inflation level remained relatively low. Starting from this evidence, the purpose of our paper is to shed light to the influence of inflation uncertainty and labor market conditions on the US inflation level. To this end, we first use two bounded measures of inflation uncertainty, relying on Chan et al.'s (2013) and Chan's (2017) unobserved component models. Second, we compare a linear with an asymmetric Autoregressive Distributed Lag (ARDL) framework. We show that both inflation uncertainty and labor market conditions explain the long-run US inflation. However, these results are sensitive to the way the inflation uncertainty is computed. Moreover, contrary to the recent affirmations regarding the vanishing role of labor market in explaining the US inflation in the long run, we show that the labor market influence is stronger in the post-crisis, compared with the pre-crisis period. Therefore, the monetary policymakers cannot make abstraction of labor market developments in anticipating the US inflation level.

Keywords: US inflation, inflation uncertainty, labor market, bounded series, NARDL
JEL codes: C22, E24, E31, E58.

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1. Introduction

After the 1973 oil crisis and the setup of the stagflation phenomenon in the United States (US), the Phillips curve theory represented the subject of notable debates related to the long-run neutrality of the monetary policy[1]. As a matter of fact, the "monetary-policy invariance hypothesis" advanced by Friedman (1968) in his speech delivered in December 1967 to the American Economic Association, underlines the role of inflation expectations and recommends an augmented right-side hand Phillips curve with inflation uncertainty (Hall and Sargent, 2018). Ten years later, Friedman (1977) explains the non-stable trade-off between inflation and unemployment and argues that higher inflation causes an increase in inflation uncertainty which generates an economic downturn. Nevertheless, the literature dealing with the underlying theoretical mechanisms as well as the empirical works focus mainly on the interactions between inflation and inflation uncertainty, making rather abstraction of labor market conditions[2].

Recently, Janet Yellen[3], the former chair of the Federal Reserve, questions the role of inflation expectations as driving force of inflation. On the one hand, notwithstanding the unexpected movements in oil prices and US dollar exchange rates observed after the crisis which affect the inflation expectations, the long-run inflation projections made by private forecasters were largely stable for a long period. This evidence might witness a low inflation uncertainty climate. On the other hand, the inflation rate remains low after 2009, although the labor market conditions improved in the US[4]. This evidence rises concerns about the reliability of fundamentals forces (e.g. labor market) in explaining the inflation developments on the long run. As Yellen (2017) mentions, the "low inflation likely reflects factors whose influence should fade over time". Starting from this evidence, the purpose of our paper is to inquire the role of driving forces of US inflation in the short and long runs, with a focus on inflation uncertainty and labor market conditions.

The literature on inflation – inflation uncertainty nexus is articulated around two sets of competing theories. The first set of theories addresses the impact the inflation has on the inflation uncertainty level. In this line, Friedman (1977) states that a high level of inflation

[1] According to the FRED database, the inflation rate shifted from 6% in 1973 to more than 10% in 1974, while the US economic contraction installed since 1974 (-0.5%). At the same time, the unemployment rate in the US increased from 4.9% in 1973 to 5.6% in 1974, and afterwards, to 8.5% in 1975.

[2] Please refer to the recent papers of Albulescu et al. (2019), Balcilar and Özdemir (2013), Caporale et al. (2012), Chowdhury (2014), Ferreira and Palma (2016), Kontonikas (2004).

[3] The question was raised during the speech delivered on September 26, 2017 at the 59th Annual Meeting of the National Association for Business Economics in Cleveland.

[4] The Bureau of Labor Statistics shows that the unemployment rate in the US diminished from 9.6% in 2010, to 4.4% in 2017.

creates a strong incentive for the policymakers to counter it generating thus higher uncertainty. Given the existence of two explicit objectives of policymakers, namely a highly stable employment rate and price stabilization, the policy decisions could be controversial and transmit thus confusing signals in the market. According to Friedman (1977), the economic policy "goes from one direction to the other" and determines high variations in the anticipated rate of inflation, which generate an increased uncertainty about the inflation level. Building upon Friedman (1977), Ball (1992) formalizes this mechanism (the Friedman-Ball hypothesis) and shows that, under high inflation regimes, the private agents hardly anticipate the nature of the monetary decisions, i.e. expansionary or restrictive, generating thus highly uncertainty in the market. This theory is validated by several empirical works both for the US (Grier and Perry, 2000; Albulescu et al., 2019), and for the G7 group of countries (Grier and Perry, 1998; Daal et al., 2005). The second theory analyzing the impact of the inflation on the inflation uncertainty is advanced by Pourgerami and Maskus (1987). The authors show that, contrary to the Friedman's (1977) hypothesis, the inflation has a negative impact on the inflation uncertainty. The explanation is based on the pioneering work of Frohman et al. (1981) and relies on the fact that an increasing inflation-associated costs, i.e. during inflationary periods, could straighten the efforts made by the private agents to accurately forecast the inflation rate. Therefore, the inflation uncertainty decreases in periods with high inflation. Hwang (2001) empirically validates this hypothesis for the US.

The second set of theories addresses the impact of inflation uncertainty on the inflation level. The first theory is proposed by Cukierman and Meltzer (1986) and relies on the fact that the monetary authorities could be tempted to generate inflation surprises to encourage economic activity. The perspective of such inflation surprises induces an increased uncertainty regarding the level of inflation. Consequently, even if monetary policymakers have no incentive to stimulate a price increase, i.e. they are only interested in stimulating the economic activity, the inflation appears as an externality of the process. This hypothesis is empirically tested and validated for the US (Berument et al., 2009; Balcilar et al., 2011), for the G7 countries (Fountas and Karanasos, 2007), and for a set of industrial countries (Fountas, 2010). The second theory, developed by Holland (1995), put forward the timing of the relationship between inflation and its uncertainty. Indeed, if inflationary periods precede uncertainty periods, the monetary authority could implement a restrictive policy allowing to reduce the magnitude of inflation. Consequently, a period with high inflation uncertainty might be followed by a reduced inflation period. Balcilar and Özdemir (2013) empirically validate this "stabilization motive" hypothesis in the case of G7 countries.

Based on the second set of theories, the impact of inflation uncertainty on the inflation level can thus be either positive or negative. On the one side, if the uncertainty is high during slow economic growth periods, the inflation might rise following monetary policy surprises created by the policymakers in order to foster the economic activity. On the other side, during and after crisis periods, the uncertainty is generally very high, implying thus a contraction of economic activity (e.g. consumption and investment), generating a reduction in the level of inflation. Therefore, our paper aims to test the impact of inflation uncertainty on the US inflation level by taking explicitly into consideration the role of labor market conditions. As far as we know, none of the previous works addressing the inflation – uncertainty nexus, have investigated the role of labor market conditions as a driving force of inflation dynamics. We can thus test the Yellen's (2017) assumption stating that there is a long run disconnection of the US inflation rate from its fundamentals. The contribution of our paper to the existing literature is threefold.

First, unlike the classic approaches which associate inflation uncertainty with inflation variability and use Generalized Autoregressive Conditional Heteroskedasticity (GARCH) specifications to model the uncertainty, our paper considers an unobserved component approach with stochastic volatility to compute inflation uncertainty. Relying on Chan et al. (2013), this approach presents the advantage that allows the inflation uncertainty to be high, even in low inflation-volatility periods (Evans, 1991). In addition, it presents a better accuracy in forecasting the dynamics of inflation uncertainty (Ftiti and Jawadi, 2019). Moreover, this approach bounds the inflation uncertainty in an interval very closed to an inflation-targeting band US[5]. Another benefit of this methodology is represented by the fact that it leads to a more complete robustness analysis. As alternative measure for the inflation uncertainty, we can thus use the recent approach proposed by Chan (2017). Building upon Stock and Watson (2007), the author proposes an unobserved component model with a stochastic volatility in mean. The benefit of this specification resides in its ability to investigate the inflation volatility feedback, i.e. how the inflation is affected by its volatility. Both Chan et al.'s (2013) and Chan's (2017) approaches are used by Albulescu et al. (2019), which examines the historical relationship between inflation and inflation uncertainty in the US in a time-frequency framework. Nevertheless, this study does not explicitly consider the role of labor market conditions in

[5] According to Thornton (2012), the Federal Reserve implemented a de facto inflation-targeting regime after the global crisis.

influencing this relationship. Moreover, this paper does not take into consideration the recent inflation developments in the US[6].

Second, we use the Labor Market Condition Index (LMCI) as *a proxy* for the labor market conditions in the US. As Yellen (2017) admits, the unemployment rate represents "probably the best single summary measure of labor utilization" but cannot characterize by itself the labor market dynamics. In order to capture these dynamics, several structural indicators can be considered as the number of prime-age and part-time workers, household perceptions of job availability, difficulties encountered by small firms to hire peoples, jobs opening rate, wages, etc. The Federal Reserve has introduced the LMCI in 2014[7] and, even this index is negatively correlated with the unemployment rate, it represents the outcome of a dynamic factor model including 19 individual indicators, offering thus a broader picture of US labor market.

Third, given the presence of a unit root process in our inflation series and the bound characteristics of the inflation uncertainty series, we use an Autoregressive Distributed Lag (ARDL) framework proposed by Pesaran et al. (2001) in order to analyze the long-run relationship between inflation, inflation uncertainty and labor market conditions. Moreover, as inflation uncertainty could theoretically have both a negative or a positive effect on the level of inflation, it is possible that positive shocks in uncertainty could have a significantly different impact on inflation compared with negative shocks. Consequently, in order to capture such potential asymmetries between inflation and its uncertainty, we also use a nonlinear ARDL (NARDL) model proposed by Shin et al. (2014). Previous studies using regime switching models (Kim, 1993), or, more recently, wavelet approaches (Albulescu et al., 2019), underline the nonlinearities that characterize the inflation – uncertainty relationship. However, these studies neither take explicitly into consideration the asymmetries in both short and long-run relationship, nor consider the role of positive and negative changes in uncertainty in explaining the inflation level.

The next section of the paper describes the data used in the empirical approach. The subsequent section presents the methodology employed for computing the inflation uncertainty and the ARDL and NARDL models. Section 4 highlights the main empirical findings and Section 5 the robustness checks. The last part of the paper concludes.

[6] Starting from January 2012, the Federal Open Market Committee's long-run inflation objective was established at 2%.
[7] Backdated data series are available starting with 1976.

2. Data

Our monthly data comes from FRED database and covers the period 1976M08-2017M06.[8] The inflation rate is calculated starting from the Consumer Price Index (CPI) for Urban Consumers, considering a year-on-year percentage change ($\pi_{y\text{-}o\text{-}y}$). For robustness purpose, as in Albulescu et al. (2019) and Ferreira and Palma (2016), we compute the month-on-month percent change in CPI ($\pi_{m\text{-}o\text{-}m}$), using the formula $1200\times\ln(\frac{CPI_t}{CPI_{t-1}})$.

The dynamics of inflation and LMCI are presented in Figure 1. We can notice that an increase in the inflation rate is accompanied by an improvement of the labor market conditions, except for the period 1978-1983 and the beginning of the 1990s. At the same time, Figure 2 shows that the inflation uncertainty computed following Chan et al (2013) is very high when the inflation and LMCI series are decoupling. Further, Chan's (2017) approach allows a higher variability in the uncertainty series and shows that the period before and during the recent Global crisis is characterized by a higher inflation uncertainty in the US.

[Insert Figure 1 about here]

[Insert Figure 2 about here]

We perform two tests to check for the presence of unit root and stationarity in our data series. We use thus ADF and KPSS tests, respectively. The results are presented in Table 1 and shows that the inflation series computed based on a year-on-year percentage change is not stationary (result confirmed by both tests), whereas the LMCI series is stationary. Most of the inflation uncertainty series are stationary, apart from the uncertainty computed following Chan (2017) based on the year-on-year percentage change in CPI ($\vartheta^{2017}_{y\text{-}o\text{-}y}$). Therefore, we conclude that our series are either I(0) or I(1), which requires the use of an ARDL specification to avoid the issue of spurious regressions.

[Insert Table 1 about here]

3. Methodology

3.1. Inflation uncertainty

We use two different approaches to derive the inflation uncertainty, both relying on unobserved component models with stochastic volatility, where the inflation uncertainty is bounded to a specific interval. These approaches allow for a time-varying inflation process in

[8] The timespan is restricted by the LMCI computation, starting with 1976M08. In July 2017, the Board started to discontinued update the index. Therefore, our LMCI series stop in 2017M06.

the state equation (Chan et al., 2013) and in the conditional mean (Chan, 2017). In line with other similar papers, we consider Chan et al.'s (2013) approach as baseline, and we use Chan's (2017) methodology for comparison purpose. The later approach has the advantage to incorporate the inflation volatility feedback and allows for time changes in inflation – inflation uncertainty relationship. However, this method generates a higher variability in the uncertainty series, variability induced by the inflation volatility.[9]

To compute the inflation uncertainty, Chan et al. (2013) start from Cogley et al.'s (2010) approach of modelling the time-varying inflation process. First, this approach allows for stochastic volatility in the state equation. Second, this approach restricts the autoregressive parameter to avoid the generation of "explosive" series. The Cogley et al.'s (2010) inflation specification is:

$$\pi_t=\chi_{0t-1}+\chi_{1t-1}\pi_{t-1}+\varepsilon_t\exp\left(\frac{\vartheta_t}{2}\right), \quad (1)$$

where: π_t is the level of inflation, $\chi_t=\chi_{t-1}+\varepsilon_t^{\chi}$ represents the vector of coefficients, and $\vartheta_t=\vartheta_{t-1}+\varepsilon_t^{\vartheta}$, with $\varepsilon_t\sim N(0,1)$ and $\varepsilon_t^{\vartheta}\sim N\left(0,\sigma_{\vartheta}^2\right)$.

Following Stock and Watson (2007), the inflation series is decomposed in an inflation trend and an inflation gap as follows:

$$\pi_t=\tau_t+\lambda_t, \quad (2)$$

where: $\tau_t=\frac{\chi_{0t}}{1-\chi_{1t}}$ is the inflation trend and $\lambda_t=\tau_{t+1}-\frac{\chi_{0t}}{1-\chi_{1t}}$ is the inflation gap.

The associated model specification for the inflation gap becomes:

$$\lambda_{t+1}=\chi_{1t}\left(\pi_t-\frac{\chi_{0t}}{1-\chi_{1t}}\right)+\varepsilon_{t+1}\exp\left(\frac{\vartheta_{t+1}}{2}\right). \quad (3)$$

Chan et al. (2013) modify the transitory component in Eq. (1) by introducing an autoregressive term. Moreover, like in Stock and Watson (2007), the new specification relies on an unobserved components model:

$$(\pi_t-\tau_t)=\lambda_t(\pi_{t-1}-\tau_{t-1})+\varepsilon_t\exp\left(\frac{\vartheta_t}{2}\right), \quad (4)$$

where: $\tau_t=\tau_{t-1}+\varepsilon_t^{\tau}$ and $\lambda_t=\lambda_{t-1}+\varepsilon_t^{\gamma}$.

However, different from Stock and Watson (2007), Chan et al. (2013) bound both the inflation trend and inflation gap, making an innovation in the state equation. For the inflation trend, we have:

$$\varepsilon_t^{\tau}\sim TN(a-\tau_{t-1},b-\tau_{t-1};0,\sigma_{\tau}^2), \quad (5)$$

[9] See the critic of Evans (1991) showing that higher volatility does not necessarily mean higher inflation uncertainty.

where: $TN(a,b;\mu,\sigma^2)$ represents the normal distribution with the mean μ and the variance σ^2 truncated to the interval (a,b), $E_t[\tau_{t+1}]=\tau_t+\sigma_\tau\left[\frac{\chi\left(\frac{a-\tau_t}{\sigma_t}\right)-\chi\left(\frac{b-\tau_t}{\sigma_\tau}\right)}{\Phi\left(\frac{b-\tau_t}{\sigma_\tau}\right)-\Phi\left(\frac{a-\tau_t}{\sigma_\tau}\right)}\right]$ is the conditional expectation, and $a\leq\tau_t\leq b$.

For the inflation gap, the bounds are generated to satisfy the zero-convergence condition in the long run:

$$\varepsilon_t^{\lambda}\sim TN(a_\lambda-\lambda_{t-1},b_\lambda-\lambda_{t-1};0,\sigma_\lambda^2), \quad (6)$$

where: the conditional expectation becomes $E_t[\lambda_{t+1}]=\lambda_t+\sigma_\lambda\left[\frac{\phi\left(\frac{x_\lambda-\lambda_t}{\sigma_\lambda}\right)-\phi\left(\frac{y_\lambda-\lambda_t}{\sigma_\lambda}\right)}{\Phi\left(\frac{y_\lambda-\lambda_t}{\sigma_\lambda}\right)-\Phi\left(\frac{x_\lambda-\lambda_t}{\sigma_\lambda}\right)}\right]$, with $x_\lambda\leq\lambda_t\leq y_\lambda$, the inflation gap being therefore limited in order to lie inside the unit circle.

The inflation uncertainty is than captured by the posterior mean of volatility (ϑ), starting from Eq. (4).

Different from Chan et al. (2013), Chan (2017) adopts recently a stochastic volatility in mean approach following Koopman and Hol Uspensky (2002). Its approach allows for time-varying coefficients in the conditional mean using the same departure point of unobserved components model of Stock and Watson (2007). Specifically:

$$\pi_t=\tau_t+\alpha_t\exp^{\vartheta_t}+\varepsilon_t^{\pi}, \text{ with } \varepsilon_t^{\pi}\sim N\left(0,\exp^{\vartheta_t}\right), \quad (7)$$

and

$$\vartheta_t=\mu+\phi(\vartheta_{t-1}-\mu)+\beta_t\pi_{t-1}+\varepsilon_t^{\vartheta}, \text{ with } \varepsilon_t^{\vartheta}\sim N\left(0,\sigma_\vartheta^2\right), \quad (8)$$

where: α_t and β_t are time-varying parameters, the log-volatility of inflation ϑ_t represents an AR(1) stationary process, with $\vartheta_1\sim N\left(\mu,\ \sigma^2/(1-\phi^2)\right)$, and ε_t^{π} and $\varepsilon_t^{\vartheta}$ are serially uncorrelated.

The coefficients' vector (δ_t) follows a random walk process:

$$\delta_t=\delta_{t-1}+\varepsilon_t^{\delta}\ , \text{ with } \varepsilon_t^{\delta}\sim N(0,\Omega), \quad (9)$$

where: $\delta_t=(\alpha_t,\tau_t)'$, Ω represents a 2×2 covariance matrix.

Chan (2017) states that, since $\exp^{\vartheta_t}$ represents the transitory component variance, α_t might be associated with the impact of the transitory volatility on the inflation level. Again, inflation uncertainty is captured by the posterior mean of volatility (ϑ).

3.2. ARDL and NARDL bound tests

In order to test the relationship between inflation, uncertainty and labor conditions, we first use the ARDL model of Pesaran et al. (2001). This framework is compatible with both I(0) and I(1) series and allows the integration of short-run adjustments into the long-run equilibrium by resorting to an error correction mechanism (ECM) through a linear transformation:

$$\Delta\pi_t=c+\delta_\pi\pi_{t-1}+\delta_\vartheta\vartheta_{t-1}+\delta_{lmci}lmci_{t-1}+\sum_{i=1}^{p}\alpha_i\Delta\pi_{t-i}+\sum_{i=0}^{p}\beta_i\Delta\vartheta_{t-i}+\sum_{i=0}^{p}\gamma_i\Delta lmci_{t-i}+\theta ECT_{t-i}+\varepsilon_t \quad (10)$$

where: π, ϑ and LMCI represent the inflation, inflation uncertainty and the labor market condition index respectively; c and ε are the intercept and the error term respectively. The short-run relationship is represented by Δ-terms whereas the long-run relationship is represented by δ-terms. p represents the maximum number of lags (established to six in our case) and ECT is the error correction term (θ should have a negative sign and be significant to validate the long-run relationship).

We test the existence of a long-run relationship resorting to the F-statistic where the null hypothesis of no cointegration is $\delta_\pi=\delta_\vartheta=\delta_{lmci}=0$. The optimal number of lags is chosen based on the Akaike Information Criteria (AIC) automatic selection criterion.

The theory and the empirical evidence show that the inflation uncertainty could have both a positive or a negative impact on the inflation level. Hence, we use Shin et al.'s (2014) approach to decompose this variable ϑ_t into positive ($^+$) and negative ($^-$) partial sums. This approach allows to capture the long-run asymmetries by δ^+ and δ^-, whereas the short-run asymmetries are highlighted by β^+ and β^-. Therefore, we obtain a nonlinear (asymmetric) ARDL model (NARDL) as follows:

$$\Delta\pi_t=c+\delta_\pi\pi_{t-1}+\delta_\vartheta^+\vartheta_{t-1}^++\delta_\vartheta^-\vartheta_{t-1}^-+\delta_{lmci}lmci_{t-1}+\sum_{i=1}^{p}\alpha_i\Delta\pi_{t-i}+\sum_{i=0}^{p}(\beta_i^+\Delta\vartheta_{t-i}^++\beta_i^-\Delta\vartheta_{t-i}^-)$$
$$+\sum_{i=0}^{p}\gamma_i\Delta lmci_{t-i}+\theta ECT_{t-i}+\varepsilon_t \quad (11)$$

The long run relationship between inflation (π) and its uncertainty (ϑ) is estimated by computing the long-run coefficients $L^+=-\delta_\vartheta^+/\delta_\pi$ and $L^-=-\delta_\vartheta^-/\delta_\pi$. Given the fact that we compare the ARDL and the NARDL specifications, we test for the asymmetry presence using the Wald test for the null hypothesis that $\beta_i^+=\beta_i^-$ for all i=0,…,p. If the asymmetry is present, the NARDL model offers more insights about the tested relationship. We perform a series of post-estimation tests to check for the residual serial correlation (Breusch-Godfrey LM test)[10], the presence of ARCH effects (Engle ARCH-LM test), and normality (Jarque-Bera test). We also test the stability of our coefficients (Ramsey and CUSUM tests).

[10] Pesaran et al. (2001) show that ARDL models are free from residual correlation. Therefore, there are not endogeneity issues related to appropriate lag selection.

4. Results

Our main results present the relationship between inflation, uncertainty and labor conditions, where the inflation uncertainty is computed starting from the year-on-year inflation series. We compare on the one hand the linear and nonlinear ARDL specifications and, on the other hand, the results of the two approaches measuring the uncertainty, i.e. according to Chan et al. (2013) (Model 1) and Chan (2017) (Model 2) respectively.

We first apply the bound tests (Table 2) to check for the existence of a long-run relationship. The test assumes a lower bound for I(0) series and an upper bound for I(1) series. The critical values are derived from Narayan (2005) and the F-statistics indicate the cointegration if their values are higher than the critical value of the upper bound.

[Insert Table 2 about here]

We notice that the long-run relationship is validated for both ARDL and NARDL models, and for both specifications of inflation uncertainty, relying on Chan et al. (2013) ($\vartheta^{2013}_{\text{y-o-y}}$) and Chan (2017) ($\vartheta^{2017}_{\text{y-o-y}}$).

In the next step, we estimate the ARDL models (Table 3). For Model 1 relying on Chan et al.'s (2013) approach, a positive long run connection between inflation uncertainty and inflation level is observed using the linear ARDL. This result validates the Cukierman and Meltzer's (1986) hypothesis supposing that, during high uncertainty periods, monetary authorities might create inflation surprises leading to an increased inflation rate. These findings confirm the early results reported by Balcilar et al. (2011). The labor market conditions have in turn a positive impact on inflation, although its amount is reduced compared to the impact of the inflation uncertainty. This result holds only in the long run.

The NARDL specification shows that, in the long run, both positive and negative variations of inflation uncertainty have a positive impact on the level of inflation. The Holland's (1995) hypothesis is thus confirmed. Consequently, a period with lower inflation uncertainty might be followed by a period with higher inflation if an expansionary monetary policy is implemented. Our results are thus in line with those reported for the G7 countries by Balcilar and Özdemir (2013), and show in addition that negative shocks in the inflation uncertainty have a slightly larger impact on inflation compared with positive shocks. This result can be explained by the fact that a strong reduction of uncertainty has a direct and strong effect on consumption and investment which could generate inflation pressures. The residual diagnostics tests show no autocorrelation issues, although some ARCH effects persist. Nevertheless, according to the Ramsey and CUSUM tests, the model is stable. The Wald test indicate the presence of

asymmetries and thus, the NARDL specification provides more information about the investigated relationship.

[Insert Table 3 about here]

For the second model (Model 2) relying on Chan's (2017) methodology for computing the inflation uncertainty, we notice that there is no significant relationship in the long run between inflation, its uncertainty and labor market. Nevertheless, in the short run, the uncertainty has a positive impact on inflation. This result confirms the intuition of Yellen (2017), stating that the influence of the factors explaining the level of inflation in the US, fades over time. Nevertheless, Model 2 suffers from the presence of ARCH effects and residual autocorrelation which raise questions about its stability. This can be the result of the feedback effect generated by the inflation volatility on the uncertainty level. Moreover, the two models reveal notable differences in terms of Granger causality between our variables. While Model 1 shows the existence of a bi-directional causality between inflation, its uncertainty and labor market conditions, Model 2 indicates the absence of a such bi-directional causality. Nevertheless, it states that inflation uncertainty and labor conditions Granger cause inflation in the long run.

[Insert Table 4 about here]

All in all, these opposite results between Model 1 and 2 confirm the findings of Albulescu et al. (2019) showing that the results "are sensitive to the way inflation uncertainty is computed". Therefore, several robustness checks are necessary to obtain a clearer picture about the role of uncertainty and labor market in explaining US long-run inflation. On the one hand, the way inflation is computed (i.e. year-on-year basis or month-on-month basis) might also influence the results. On the other hand, during the investigated time horizon, the inflation context has strongly changed. It is especially the case of the recent global crisis affecting the inflation expectations.

5. Robustness check

Two categories of robustness checks will be developed. First, we use month-on-month inflation series to compute inflation uncertainty relying on Chan et al.'s (2013) approach ($\vartheta^{2013}_{\text{m-o-m}}$). Second, we perform a Chow breakpoint tests in the inflation series over the period 1976M08 to 2017M06 which indicates 2008M11 as the moment of a structural break[11].

[11] F-statistic = 146.9 with the associated p-value = 0.000.

Consequently, using the year-on-year base inflation and Chan et al.'s (2013) approach for computing the uncertainty, we investigate the long-run relationship before and after the crisis.

5.1. Month-on-month CPI inflation

We first present the results of the bound tests for the ARDL cointegration. As in the main results, F-statistics show the presence of cointegration for both linear and asymmetric ARDL specifications. Nevertheless, compared to Table 2, the values of F-statistics presented in Table 5 are smaller, indicating a less strong cointegrating relationship.

[Insert Table 5 about here]

Concerning the estimation of linear and nonlinear ARDL models (Table 6), we observe that, in the long run, only the labor market has a positive, but marginal significant influence on the inflation. At the same time, the inflation uncertainty has no significant impact, either we look to the linear or nonlinear ARDL results. In the short run, the inflation uncertainty positively impacts the inflation. The Granger causality tests (Table A1 – Appendix) point in the favor of a bi-directional causality between inflation and its uncertainty, whereas mixed findings can be identified in the case of labor market conditions.

[Insert Table 6 about here]

5.2. Before and after the crisis

In the second set of robustness checks, we use year-on-year inflation rate and Chan et al.'s (2013) measure of uncertainty ($\vartheta^{2013}_{\text{y-o-y}}$) to compare the relationship between inflation, uncertainty and labor market before and after the crisis. Table 7 shows evidence in the favor of a cointegrating relationship for both sub-periods.

[Insert Table 7 about here]

Moreover, Table 8 shows that, before the crisis, both inflation uncertainty and labor market conditions impact positively the level of inflation in the long-run. This results confirm the main findings reported in Section 4 for the Chan et al.'s (2013) approach. Nevertheless, in the NARDL specification, the influence of LMCI is no longer significant before the crisis. These results are validated by the residual diagnostics tests we perform.

After the crisis, opposite findings are revealed by the ARDL and NARDL specifications. Concerning the NARDL asymmetry (recommended by the Wald test), we clearly observe that both an amelioration of labor market conditions and positive and negative variations in the uncertainty, lead to an increase in US price levels. Therefore, it seems that the labor market

conditions better explain the inflation dynamic after the crisis consolidating thus the role of the LMCI for the orientation of the monetary policy decisions. Indeed, as the dynamics of inflation and labor conditions are very closed starting with 2008 (see Figure 1), the fact that the considerably decrease in the unemployment rate is not accompanied by higher inflation could indicate that other structural indicators characterizing the US labor market "shown less improvement since the financial crisis" (Yellen, 2017).

[Insert Table 8 about here]

To sum up, we have noticed that both inflation uncertainty and labor market conditions have a positive impact on inflation in the long run, even if the results seem sensitive to the way inflation and its uncertainty are computed. Moreover, our results suggest that both positive and negative variations in the uncertainty level positively affect the level of inflation, which could explain the mixed findings reported in the earlier literature. Contrary to the recent ideas about the role of labor market conditions in explaining the long-run inflation in the US, we show that LMCI have a positive and a stronger impact on US inflation after the 2008-2009 global crisis.

6. Conclusion

The sustained low US CPI inflation, or more precisely, the lack of inflation dynamics after the global crisis, generated a series of questions about the role of fundamentals in explaining the long-run inflation developments. Whereas the average economic growth rate in the US after the crisis is around 2.5%, the inflation rate remains low, with a small variation between 0 and 2%. A possible explanation of this situation could be represented both by the low inflation expectations, - i.e. the expectations are influenced by relatively stable inflation projections made by private forecasters -, and by a decoupling phenomenon between inflation and US labor market conditions in the long run.

In this context, the purpose of our paper is to test the role of driving forces of US inflation, namely the inflation uncertainty and labor market conditions, according to the distinction between short and long-run time horizon and considering the asymmetric influence that the inflation uncertainty could have on the inflation level. Methodologically, we resort to two recent bounded approaches proposed by Chan et al. (2013) and Chan (2017) to measure the inflation uncertainty, both relying on the unobserved component models with stochastic volatility. Moreover, the analysis is built upon both linear and nonlinear ARDL models and takes explicitly into consideration the crisis structural effect by using two sub-periods of estimation, i.e. before and after the crisis.

Our empirical findings show that both uncertainty and labor market conditions have a positive long-run influence on the US inflation level. Therefore, we state that the driving forces of inflation are still at work in the US, contrary to the recent assumptions. Moreover, the results suggest that both positive and negative variations in the uncertainty level influence the inflation rate. Nevertheless, in line with other researches, we show that the findings are sensitive to the way uncertainty is computed. Although both Chan et al.'s (2013) and Chan's (2017) approaches rely on a bounded unobserved component model and underline an increased uncertainty during the 1973-1974 oil crisis and during the 2008-2009 global crisis, the second approach introduce additional variations in the inflation uncertainty series allowing for time-varying coefficients in the conditional mean. Our robustness checks underline the fact that the results are also sensitive to the way the inflation is computed, using a year-on-year or a month-on-month basis. At the same time, the results are different when we compare the pre-crisis with the post-crisis periods, where the dominant NARDL models show that the labor conditions are important for explaining inflation in the long run, but only after the crisis.

The policy implications derived from our findings are twofold. First, we show that the driving forces of long-run inflation are still at work in the US, and the role of labor market cannot be neglected. Second, our results prove that not only the inflation uncertainty level, but also positive and negative variabilities in the uncertainty series have a positive influence on inflation. Therefore, both positive and negative shocks that characterize the uncertainty might generate a higher inflation. All these mechanisms have to be taken into consideration by the monetary authorities within the framework of the decision-making process.

These findings open some directions for further research issues. As the inflation dynamics are largely influenced by the evolution of oil prices and the US dollar exchange rate, it could be interesting to assess the long-run impact of inflation uncertainty and labor market conditions, making abstraction of these transitory influences. A potential extension can thus focus on US CORE inflation, which has also fallen persistently short of 2%. Moreover, as Istrefi and Piloiu (2014) have stated, the inflation expectations might be largely influenced by the policy-induced economic uncertainty both in the short and long runs. Therefore, an interesting extension of our paper could consist in measuring the impact on the inflation level induced by the monetary policy shocks.

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Appendix

Table A1

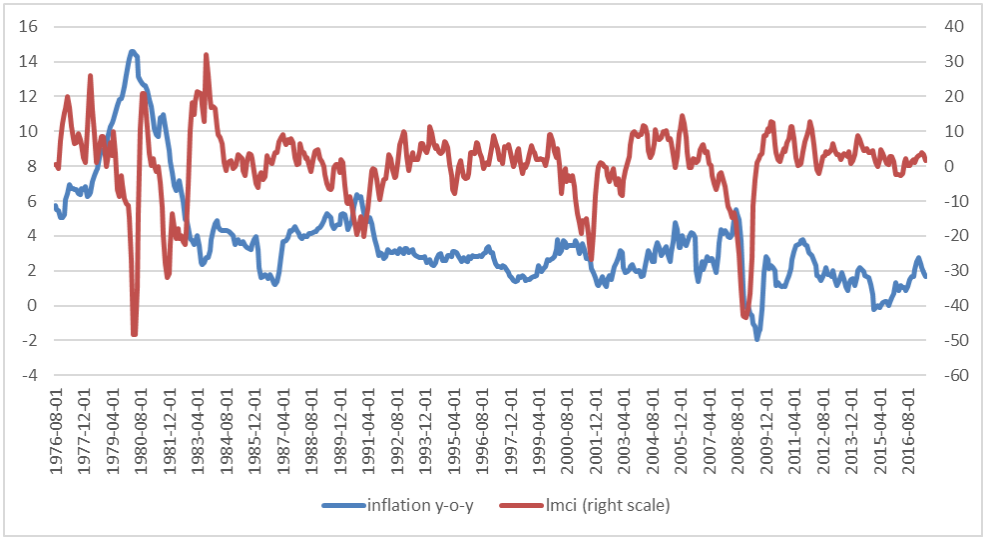
Granger causality results (robustness m-o-m)

Model 1: $\vartheta^{2013}_{\text{m-o-m}}$ – Chan et al. (2013)		
Null hypothesis	F-stat	(p-value)
$\vartheta^{2013}_{\text{m-o-m}}$ does not Granger Cause $\pi_{\text{m-o-m}}$	3.480	(0.002)
$\pi_{\text{m-o-m}}$ does not Granger Cause $\vartheta^{2013}_{\text{m-o-m}}$	4.475	(0.000)
lmci does not Granger Cause $\pi_{\text{m-o-m}}$	1.467	(0.187)
$\pi_{\text{m-o-m}}$ does not Granger Cause lmci	2.176	(0.044)
lmci does not Granger Cause $\vartheta^{2013}_{\text{m-o-m}}$	1.176	(0.317)
$\vartheta^{2013}_{\text{m-o-m}}$ does not Granger Cause lmci	2.606	(0.017)

Figures

Figure 1

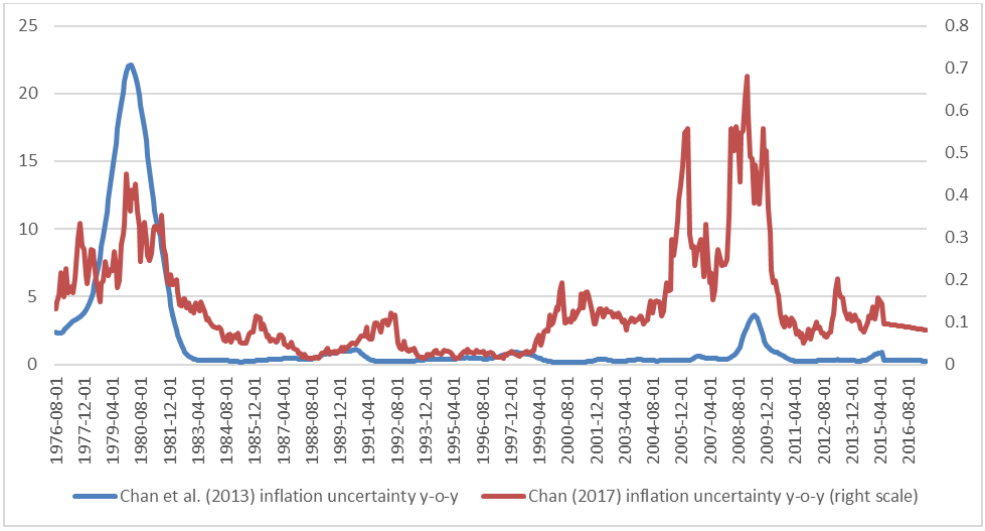
Inflation and labor market conditions in the US



Source: FRED statistics and own computations

Figure 2

Inflation uncertainty



Source: FRED statistics and own computations

Tables

Table 1

ADF unit root and KPSS stationarity tests

	Level		First difference	
	ADF	KPSS	ADF	KPSS
$\pi_{y\text{-}o\text{-}y}$	-1.459	1.465***	-5.232***	0.036
$\pi_{m\text{-}o\text{-}m}$	-3.023**	1.589***	-9.890***	0.406*
$\vartheta^{2013}_{y\text{-}o\text{-}y}$	-3.661***	0.725**	-4.474***	0.037
$\vartheta^{2017}_{y\text{-}o\text{-}y}$	-2.606*	0.307	-21.84***	0.041
$\vartheta^{2013}_{m\text{-}o\text{-}m}$	-2.809*	0.984***	-10.02***	0.035
$\vartheta^{2017}_{m\text{-}o\text{-}m}$	-3.433**	1.113***	-17.59***	0.025
lmci	-6.026***	0.034	-14.52***	0.019

Notes: (i) ***, ** and * means significance at 1%, 5% and 10%; (ii) for the ADF test the null hypothesis is the presence of unit roots whereas for the KPSS the null is the stationarity; (iii) the intercept is included for both test and the optimal lag selection for the ADF test is based on AIC information criterion; (iv) $\pi_{y\text{-}o\text{-}y}$ is the monthly inflation computed on a year-on-year basis, $\pi_{m\text{-}o\text{-}m}$ is the monthly inflation computed on a month-on-month basis, $\vartheta^{2013}_{y\text{-}o\text{-}y}$ and $\vartheta^{2017}_{y\text{-}o\text{-}y}$ are the year-on-year inflation uncertainty following Chan et al. (2013) and Chan (2017) respectively, $\vartheta^{2013}_{m\text{-}o\text{-}m}$ and $\vartheta^{2017}_{m\text{-}o\text{-}m}$ are the a month-on-month inflation uncertainties, lmci is the labor market conditions index.

Table 2

Bounds test results for linear and nonlinear ARDL cointegration (main findings)

Model specification	F-statistics	Lower bound (I(0))	Upper bound (I(1))	Conclusion
$\vartheta^{2013}_{y\text{-}o\text{-}y}$ – Chan et al. (2013)				
Linear	13.40	3.79	4.85	cointegration
Nonlinear	12.77	3.23	4.35	cointegration
$\vartheta^{2017}_{y\text{-}o\text{-}y}$ – Chan (2017)				
Linear	9.77	3.79	4.85	cointegration
Nonlinear	7.24	3.23	4.35	cointegration

Notes: (i) the critical values (at 5% significance level) are derived from Narayan (2005); (ii) the maximum lag for the independent and dependent variables was established at 6 whereas the optimal lag is automatically selected based on AIC criterion; (iii) ϑ is the inflation uncertainty.

Table 3

Estimation on ARDL and NARDL models (main findings)

	Model 1: $\vartheta^{2013}_{y\text{-}o\text{-}y}$ – Chan et al. (2013)					Model 2: $\vartheta^{2017}_{y\text{-}o\text{-}y}$ – Chan (2017)			
	ARDL		NARDL			ARDL		NARDL	
					Long-run specification				
$\vartheta^{2013}_{y\text{-}o\text{-}y}$	0.699***	[0.093]			$\vartheta^{2017}_{y\text{-}o\text{-}y}$	6.466	[18.20]		
lmci	0.174***	[0.058]	0.115***	[0.044]	lmci	1.038	[0.058]	0.504	[0.332]
$\vartheta^{2013^+}_{y\text{-}o\text{-}y}$			0.316***	[0.120]	$\vartheta^{2017^+}_{y\text{-}o\text{-}y}$			-9.819	[25.81]
$\vartheta^{2013^-}_{y\text{-}o\text{-}y}$			0.517***	[0.089]	$\vartheta^{2017^-}_{y\text{-}o\text{-}y}$			-8.427	[25.89]
					Short-run specification				
c	0.095***	[0.022]	0.458***	[0.067]	c	0.013	[0.015]	0.058**	[0.023]
$\Delta\pi_{y\text{-}o\text{-}y_{t-1}}$	0.444***	[0.043]	0.448***	[0.043]	$\Delta\pi_{y\text{-}o\text{-}y_{t-1}}$	0.421***	[0.044]	0.435***	[0.044]
$\Delta\pi_{y\text{-}o\text{-}y_{t-2}}$	-0.158***	[0.043]	-0.145***	[0.043]	$\Delta\pi_{y\text{-}o\text{-}y_{t-2}}$	-0.148***	[0.044]	-0.146***	[0.043]
$\Delta\vartheta u^{2013}_{y\text{-}o\text{-}y}$	0.126**	[0.059]			$\Delta\vartheta^{2017}_{y\text{-}o\text{-}y}$	-0.001	[0.487]		
Δlmci	0.003	[0.004]	0.003	[0.004]	$\Delta\vartheta^{2017}_{y\text{-}o\text{-}y_{t-1}}$	1.138**	[0.486]		
Δlmci$_{t-1}$	-0.006	[0.004]	-0.006	[0.004]	$\Delta\vartheta^{2017}_{y\text{-}o\text{-}y_{t-2}}$	1.975***	[0.482]		
$\Delta\vartheta^{2013^+}_{y\text{-}o\text{-}y}$			-1.368**	[0.535]	$\Delta\vartheta^{2017}_{y\text{-}o\text{-}y_{t-3}}$	0.820*	[0.490]		
$\Delta\vartheta^{2013^+}_{y\text{-}o\text{-}y_{t-1}}$			1.427***	[0.534]	$\Delta\vartheta^{2017}_{y\text{-}o\text{-}y_{t-4}}$	0.945*	[0.496]		
					$\Delta\vartheta^{2017}_{y\text{-}o\text{-}y_{t-5}}$	0.858*	[0.490]		
					$\Delta\vartheta^{2017^+}_{y\text{-}o\text{-}y}$			0.446	[0.846]
					$\Delta\vartheta^{2017^+}_{y\text{-}o\text{-}y_{t-1}}$			1.159	[0.872]
					$\Delta\vartheta^{2017^+}_{y\text{-}o\text{-}y_{t-2}}$			3.137***	[0.864]
					$\Delta\vartheta^{2017^+}_{y\text{-}o\text{-}y_{t-3}}$			1.502*	[0.907]
					$\Delta\vartheta^{2017^+}_{y\text{-}o\text{-}y_{t-4}}$			-0.738	[0.896]
					$\Delta\vartheta^{2017^+}_{y\text{-}o\text{-}y_{t-5}}$			2.256***	[0.858]
					$\Delta\vartheta^{2017^-}_{y\text{-}o\text{-}y}$			-0.389	[0.870]
					$\Delta\vartheta^{2017^-}_{y\text{-}o\text{-}y_{t-1}}$			1.574*	[0.851]
					$\Delta\vartheta^{2017^-}_{y\text{-}o\text{-}y_{t-2}}$			0.840	[0.837]
					$\Delta\vartheta^{2017^-}_{y\text{-}o\text{-}y_{t-3}}$			0.019	[0.827]
					$\Delta\vartheta^{2017^-}_{y\text{-}o\text{-}y_{t-4}}$			2.653***	[0.817]
ECT$_{t-1}$	-0.042***	[0.006]	-0.057***	[0.007]	ECT$_{t-1}$	-0.007***	[0.001]	-0.013***	[0.002]
					Tests				
LM test	0.654		0.705		LM	2.397**		2.839**	
ARCH	6.538**		2.178**		ARCH	1.959*		2.430**	
JB	465.3***		295.6***		JB	212.6***		132.5***	
Ramsey	0.753		2.464		Ramsey	14.59***		21.82***	
CUSUM	stable		stable		CUSUM	stable		stable	
Wald test			4.882** (asymmetry)		Wald			0.003 (symmetry)	

Notes: (i) ***, ** and * means significance at 1%, 5% and 10%; (ii) standard deviations are in square brackets; (iii) Breusch-Godfrey LM test for serial correlation is used; (iv) ARCH effects rely on Engle's (1982) test for conditional heteroscedasticity (with 6 lags); (v) JB means the Jarque-Bera test for normality; (vi) Ramsey and CUSUM are stability tests; (vii) Wald test is applied for detecting long- and short-run asymmetry (if asymmetry, the NARDL specification is recommended); (viii) π is the inflation, ϑ is the inflation uncertainty and lmci represents the labor market conditions index.

Table 4

Granger causality results (main findings)

Model 1: $\vartheta^{2013}_{\text{y-o-y}}$ – Chan et al. (2013)			Model 2: $\vartheta^{2017}_{\text{y-o-y}}$ – Chan (2017)		
Null hypothesis	F-stat	(p-value)	Null hypothesis	F-stat	(p-value)
$\vartheta^{2013}_{\text{y-o-y}}$ does not Granger Cause $\pi_{\text{y-o-y}}$	4.119	(0.000)	$\vartheta^{2017}_{\text{y-o-y}}$ does not Granger Cause $\pi_{\text{y-o-y}}$	4.087	(0.000)
$\pi_{\text{y-o-y}}$ does not Granger Cause $\vartheta^{2013}_{\text{y-o-y}}$	3.440	(0.002)	$\pi_{\text{y-o-y}}$ does not Granger Cause $\vartheta^{2017}_{\text{y-o-y}}$	1.714	(0.115)
lmci does not Granger Cause $\pi_{\text{y-o-y}}$	3.180	(0.004)	lmci does not Granger Cause $\pi_{\text{y-o-y}}$	3.180	(0.004)
$\pi_{\text{y-o-y}}$ does not Granger Cause lmci	2.347	(0.030)	$\pi_{\text{y-o-y}}$ does not Granger Cause lmci	2.347	(0.030)
lmci does not Granger Cause $\vartheta^{2013}_{\text{y-o-y}}$	2.746	(0.012)	lmci does not Granger Cause $\vartheta^{2017}_{\text{y-o-y}}$	0.556	(0.764)
$\vartheta^{2013}_{\text{y-o-y}}$ does not Granger Cause lmci	3.456	(0.002)	$\vartheta^{2017}_{\text{y-o-y}}$ does not Granger Cause lmci	1.725	(0.113)

Table 5

Bounds test results for linear and nonlinear ARDL cointegration (robustness m-o-m)

Model specification	F-statistics	Lower bound (I(0))	Upper bound (I(1))	Conclusion
$\vartheta^{2013}_{\text{m-o-m}}$ – Chan et al. (2013)				
Linear	7.33	3.79	4.85	cointegration
Nonlinear	7.97	3.23	4.35	cointegration

Notes: (i) the critical values (at 5% significance level) are derived from Narayan (2005); (ii) the maximum lag for the independent and dependent variables was established at 6 whereas the optimal lag is automatically selected based on AIC criterion; (iii) ϑ is the inflation uncertainty.

Table 6

Estimation on ARDL and NARDL models (robustness m-o-m)

	$\vartheta^{2013}_{m\text{-}o\text{-}m}$ – Chan et al. (2013)			
	ARDL		NARDL	
Long-run specification				
$\vartheta^{2013}_{m\text{-}o\text{-}m}$	-0.004	[0.009]		
lmci	0.015*	[0.008]	0.008**	[0.004]
$\vartheta^{2013^+}_{m\text{-}o\text{-}m}$			0.010	[0.009]
$\vartheta^{2013^-}_{m\text{-}o\text{-}m}$			0.015	[0.010]
Short-run specification				
c	0.054***	[0.015]	0.149***	[0.029]
$\Delta\pi_{m\text{-}o\text{-}m_{t-1}}$	-0.257***	[0.051]	-0.162***	[0.057]
$\Delta\pi_{m\text{-}o\text{-}m_{t-2}}$	-0.342***	[0.051]	-0.260***	[0.055]
$\Delta\pi_{m\text{-}o\text{-}m_{t-3}}$	-0.231***	[0.050]	-0.158***	[0.053]
$\Delta\pi_{m\text{-}o\text{-}m_{t-4}}$	-0.132***	[0.047]	-0.094*	[0.048]
$\Delta\pi_{m\text{-}o\text{-}m_{t-5}}$	-0.139***	[0.044]	-0.102**	[0.044]
$\Delta\vartheta^{2013}_{m\text{-}o\text{-}m}$	0.041**	[0.019]		
$\Delta\vartheta^{2013}_{m\text{-}o\text{-}m_{t-1}}$	-0.074***	[0.021]		
$\Delta\vartheta^{2013}_{m\text{-}o\text{-}m_{t-2}}$	-0.038*	[0.022]		
$\Delta\vartheta^{2013}_{m\text{-}o\text{-}m_{t-3}}$	0.036*	[0.019]		
$\Delta\vartheta^{2013^+}_{m\text{-}o\text{-}m}$			0.079**	[0.032]
$\Delta\vartheta^{2013^+}_{m\text{-}o\text{-}m_{t-1}}$			-0.084**	[0.035]
$\Delta\vartheta^{2013^+}_{m\text{-}o\text{-}m_{t-2}}$			-0.085**	[0.036]
$\Delta\vartheta u^{2013^+}_{m\text{-}o\text{-}m_{t-3}}$			-0.001	[0.036]
$\Delta\vartheta^{2013^+}_{m\text{-}o\text{-}m_{t-4}}$			0.104***	[0.036]
$\Delta\vartheta^{2013^+}_{m\text{-}o\text{-}m_{t-5}}$			-0.076**	[0.034]
$\Delta\vartheta^{2013^-}_{m\text{-}o\text{-}m}$			0.039	[0.029]
$\Delta\vartheta^{2013^-}_{m\text{-}o\text{-}m_{t-1}}$			-0.067**	[0.029]
ECT_{t-1}	-0.163***	[0.034]	-0.284***	[0.050]
Tests				
LM test	0.654***		3.525***	
ARCH	8.035**		5.693**	
JB	177.1***		278.7***	
Ramsey	1.909		0.236	
CUSUM	stable		stable	
Wald test			9.673*** (asymmetry)	

Notes: (i) ***, ** and * means significance at 1%, 5% and 10%; (ii) standard deviations are in square brackets; (iii) Breusch-Godfrey LM test for serial correlation is used; (iv) ARCH effects rely on Engle's (1982) test for conditional heteroscedasticity (with 6 lags); (v) JB means the Jarque-Bera test for normality; (vi) Ramsey and CUSUM are stability tests; (vii) Wald test is applied for detecting long- and short-run asymmetry (if asymmetry, the NARDL specification is recommended); (viii) π is the inflation, ϑ is the inflation uncertainty and lmci represents the labor market conditions index.

Table 7

Bounds test results for linear and nonlinear ARDL cointegration (robustness structural break)

Model specification	F-statistics	Lower bound (I(0))	Upper bound (I(1))	Conclusion
Before the crisis (1976M08–2008M10)				
Linear	8.17	3.79	4.85	cointegration
Nonlinear	10.75	3.23	4.35	cointegration
After the crisis (2008M11–2017M06)				
Linear	5.24	3.79	4.85	cointegration
Nonlinear	12.77	3.23	4.35	cointegration

Notes: (i) the critical values (at 5% significance level) are derived from Narayan (2005); (ii) the maximum lag for the independent and dependent variables was established at 6 whereas the optimal lag is automatically selected based on AIC criterion; (iii) ϑ is the inflation uncertainty.

Table 8

Estimation on ARDL and NARDL models (robustness structural break)

	Before the crisis (1976M08 – 2008M10)					After the crisis (2008M11 – 2017M06)			
	ARDL		NARDL			ARDL		NARDL	
Long-run specification									
$\vartheta^{2013}_{y\text{-}o\text{-}y}$	0.664***	[0.077]			$\vartheta^{2013}_{y\text{-}o\text{-}y}$	-2.968*	[1.497]		
lmci	0.088*	[0.049]	0.054	[0.041]	lmci	-0.112	[0.101]	0.115***	[0.044]
$\vartheta^{2013^+}_{y\text{-}o\text{-}y}$			0.620***	[0.159]	$\vartheta^{2013^+}_{y\text{-}o\text{-}y}$			0.316***	[0.120]
$\vartheta^{2013^-}_{y\text{-}o\text{-}y}$			0.735***	[0.128]	$\vartheta^{2013^-}_{y\text{-}o\text{-}y}$			0.517***	[0.089]
Short-run specification									
c	0.147***	[0.034]	0.427***	[0.064]	c	0.252***	[0.083]	0.458***	[0.067]
$\Delta\pi_{y\text{-}o\text{-}y_{t-1}}$	0.380***	[0.050]	0.377***	[0.049]	$\Delta\pi_{y\text{-}o\text{-}y_{t-1}}$	0.284***	[0.090]	0.448***	[0.043]
$\Delta\pi_{y\text{-}o\text{-}y_{t-2}}$	-0.223***	[0.051]	-0.204***	[0.050]	$\Delta\pi_{y\text{-}o\text{-}y_{t-2}}$	-0.144	[0.095]	-0.145***	[0.043]
$\Delta\vartheta^{2013}_{y\text{-}o\text{-}y}$	0.361	[0.506]			$\Delta\pi_{y\text{-}o\text{-}y_{t-3}}$	-0.142*	[0.081]		
$\Delta\vartheta^{2013}_{y\text{-}o\text{-}y_{t-1}}$	-1.480	[0.910]			$\Delta\vartheta^{2017}_{y\text{-}o\text{-}y}$	-1.420***	[0.425]	-1.368**	[0.535]
$\Delta\vartheta^{2013}_{y\text{-}o\text{-}y_{t-2}}$	2.913***	[0.907]			$\Delta\vartheta^{2017}_{y\text{-}o\text{-}y_{t-1}}$	-0.401	[0.492]	1.427***	[0.534]
$\Delta\vartheta^{2013}_{y\text{-}o\text{-}y_{t-3}}$	-1.577***	[0500]			$\Delta\vartheta^{2017}_{y\text{-}o\text{-}y_{t-2}}$	-0.690	[0.455]		
Δlmci	-0.001	[0.004]	-0.004	[0.004]	Δlmci	0.041***	[0.012]	0.001	[0.004]
Δlmci$_{t-1}$	-0.006	[0.004]			Δlmci$_{t-1}$			-0.006	[0.004]
$\Delta\vartheta^{2013^-}_{y\text{-}o\text{-}y}$			1.072*	[0.605]					
$\Delta\vartheta^{2013^-}_{y\text{-}o\text{-}y_{t-1}}$			-2.061*	[1.056]					
$\Delta\vartheta^{2013^-}_{y\text{-}o\text{-}y_{t-2}}$			2.276**	[1.015]					
$\Delta\vartheta^{2013^-}_{y\text{-}o\text{-}y_{t-3}}$			0.221	[1.035]					
$\Delta\vartheta^{2013^-}_{y\text{-}o\text{-}y_{t-4}}$			-1.191**	[0.598]					
ECT$_{t-1}$	-0.053***	[0.010]	-0.061***	[0.009]	ECT$_{t-1}$	-0.085***	[0.021]	-0.057***	[0.007]
Tests									
LM test	0.548		0.434		LM	1.527		0.631	
ARCH	0.676		1.489		ARCH	1.760		2.178**	
JB	257.0***		213.8***		JB	0.311		295.6***	
Ramsey	7.773***		0.934		Ramsey	1.868		2.464	
CUSUM	stable		stable		CUSUM	stable		stable	
Wald test			3.100* (asymmetry)		Wald			4.882** (asymmetry)	

Notes: (i) ***, ** and * means significance at 1%, 5% and 10%; (ii) standard deviations are in square brackets; (iii) Breusch-Godfrey LM test for serial correlation is used; (iv) ARCH effects rely on Engle's (1982) test for conditional heteroscedasticity (with 6 lags); (v) JB means the Jarque-Bera test for normality; (vi) Ramsey and CUSUM are stability tests; (vii) Wald test is applied for detecting long- and short-run asymmetry (if asymmetry, the NARDL specification is recommended); (viii) π is the inflation, ϑ is the inflation uncertainty and lmci represents the labor market conditions index.