Money growth and inflation in China: New evidence from a wavelet analysis

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ABSTRACT

This paper provides a fresh new insight into the dynamic relationship between money growth and inflation in China by applying a novel wavelet analysis. From a time-domain view, our findings show strong but not homogenous links between money growth and inflation in the mid-1990s and the period since the early 2000s. Especially since the early 2000s, Chinaś monetary policy has achieved much better performance in terms of inflation management compared to previous years. From a frequency-domain view, we find that money growth and inflation are positively related in one-to-one fashion in the medium or long run whereas they deviates from such a positive relation in the short run due to temporary shocks and significant lag effects. We can also conclude for China that the long-run relationship between M_0 growth and inflation supports the modern quantity theory of money (QTM), while the medium-run relationship between M_1 growth and inflation as well as M_2 growth and inflation supports the modern QTM. In general, however, our results fit well with the fact that China has experienced economic transitions and structural adjustments in monetary policy over the past two decades. Based on the above analysis, this paper provides an overall view of monetary policy operations and some beneficial implications for China.

1. Introduction

China has experienced striking money growth over the past several decades. Statistics from China's central bank, the People's Bank of China (PBoC), show that China's broad money (M_2) reached up to 118.2 trillion Yuan by the end of May 2014. This means that China's M_2 has increased by four times over the last 10 years, with an average year-on-year growth rate of 40.3% during the past decade. On a global scale, China's M_2 has also been 1.7 times as much as that in the U.S. and even 1.5 times as much as that in the Euro area.[1] Moreover, the ratio of M_2 to gross domestic product (GDP) is as high as 194.5% in China at the end of 2013. However, the ratio is just 97.9% in the Euro area and 65.8% in the U.S.,[2] although the two economies have implemented several rounds of Quantitative Easing (QE) in the aftermath of the global financial crisis. As a consequence, many are concerned with such striking money growth coupled with such a high ratio of M_2 to GDP would bring substantial inflationary pressures to the Chinese economy. In addition, a long-run unity relationship between money growth and inflation established by the quantity theory of money (QTM) increases this concern. If the QTM holds true in China, then high money growth would ultimately threaten future price stability and hence the economic growth. Therefore, we are greatly motivated to re-assess the relationship between money growth and inflation in China by using a novel method and the most recent data and with special attention paid to whether such a relationship in China supports the QTM. In addition, as we well know, the money supply has been the intermediate target of monetary policy, while inflation management has been the ultimate target since the mid-1990s in China. As a result, the relationship between money growth and inflation can reflect the effectiveness of monetary policy implementation to a large degree. In this sense, it is worthwhile to explore such a relationship to shed light on what has happened to China's monetary policy over the past several decades.

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[1]Statistics from the U.S. Federal Reserve Bank and the Euro Central Bank show that the stock of M_2 reached 11.23 trillion dollars in the U.S. and 12.73 trillion dollars in the Euro area by the end of May 2014.

[2]Statistics from the U.S. Bureau of Labor Statistics, the Eurostat and the National bureau of statistics of China show that at the end of 2013, the GDP for China is about 9.3 trillion dollars whereas it is 16.8 trillion dollars for the US and 12.9 trillion dollars for the Euro area.

This paper proposes a novel wavelet analysis to revisit the relationship between money growth and inflation in China. Wavelet analysis is greatly distinctive from most conventional mathematical methods such as time-domain methods (correlation analysis and Granger causality, etc.), which cannot identify short-run and long-run relationships between time series, and frequency-domain methods (Fourier analysis, etc.), which cannot reveal how such relationships change over time. It allows us to expand time series into a time-frequency space in which the local correlation and the lead-lag relationship can be read off in a highly intuitive way. Therefore, it is very suitable for assessing simultaneously whether the relationship varies across frequencies and evolves over time. In addition, a wavelet analysis has a significant advantage over the well-known Fourier analysis, especially when the time series under study are non-stationary or locally stationary Roueff and von Sachs (2011).

Wavelet analysis was introduced into economics by Goffe (1994), Ramsey and Lampart (1998a,b) in the mid-1990s. However, its extensive applications in economics did not emerge until recent years. A strand of literature uses wavelet coherency and phase differences based on the continuous wavelet transform (CWT) to assess co-movements between stock markets as well as between energy commodities and macroeconomy (Rua and Nunes (2009); Graham and Nikkinen (2011); Aguiar-Conraria and Soares (2011); McCarthy and Orlov (2012); Vacha and Barunik (2012); etc.). Another strand of literature applies multi-resolution analysis based on the maximal overlap discrete wavelet transform (MODWT) to reexamine some of the most investigated relationships in empirical economics (Gallegati, Gallegati, Ramsey and Semmler (2011); Hacker, Karlsson and Månsson (2014); Reboredo and Rivera-Castro (2014)). For example, Gallegati et al. (2011) test for the stability of the wage Phillips curve relationship across frequencies and over time. Reboredo and Rivera-Castro (2014) provide new evidence of the effects of oil prices on stock returns for the U.S. and Europe. Hacker et al. (2014) revisit the causal relationship between spot exchange rates and nominal interest rate differentials. Wavelet studies that attempt to discuss problems regarding monetary policy and inflation have also been undertaken in recent years. Aguiar-Conraria, Azevedo and Soares (2008) reveal the time-frequency effects of the U.S. monetary policy on its macroeconomy. Dowd, Cotter and Loh (2011) presents a wavelet-based method to estimate the U.S.'s core inflation. Aguiar-Conraria, Martins and Soares (2012) explore the time- and frequency-varying relationship between the yield curve shape and macroeconomy for the U.S. Rua (2012) examines the dynamic relationship between money growth and inflation for the Euro area.[3] To date, no work has utilized wavelet analysis to examine the dynamic relationship between money growth and inflation in China, which is another large motivator for us to make an attempt.

This study differs from those in the existing literature in several important ways. First, wavelet analysis devotes special and full attention to the time-frequency relationship between money growth and inflation in China. Second, this paper employs the most recent monthly data of inflation and money growth, ranging from January 1991 to June 2014. Third, through estimating wavelet power spectrums, wavelet coherencies and phase differences among growth rates of M_0, M_1, and M_2 and inflation rates, respectively, we unravel the extent to which money growth and inflation comprehensively relate to each other, how such a relationship evolves with time, which rate is the leader and whether short-run and (or) long-run relations exist between them in China. Finally, our empirical results show high but not homogenous links between money growth and inflation over time and across frequencies that fit with the fact that China has experienced economic transitions and structural adjustments over the past two decades. In general, this paper provides additional and useful implications for China's monetary policy.

The rest of the paper proceeds as follows. Section 2 briefly reviews the literature on the relationship between money growth and inflation. Section 3 provides an overview of wavelet theory and methods. Section 4 introduces data and plots wavelet power spectrums. Section 5 presents the empirical results and policy implications. Section 6 concludes.

2. Related literature

As mentioned above, it is well known that the relationship between money growth and inflation is historically associated with the QTM. The traditional QTM suggests a unitary relationship between money growth and inflation (Fisher and Brown, 1911). However, the modern QTM argues that money growth impacts both output and inflation in the short run but would be completely reflected on inflation in the long run (Friedman, 1956). Despite the remaining dispute about the short-run relationship, both the traditional and modern QTM, however, reach an agreement with the unitary relationship between money growth and inflation in the long run.

[3] Rua (2012) uses the same kind of methods to analyze a similar problem as the present paper does, but the employed data of these two papers come from different countries, and their focuses of attention are also largely different.

Entering the 1990s, a large number of empirical studies emerged to investigate the relationship between money growth and inflation for different countries. While some studies find a unidirectional or bidirectional causal relationship between money growth and inflation (Assenmacher-Wesche, Gerlach and Sekine, 2008; Hall, Hondroyiannis, Swamy and Tavlas, 2009; Hossain, 2005; Liu, 2002), additional studies that follow the research patterns of the QTM suggest a positive relationship between them from a shortrun and (or) long-run view. Xie (2004), Roffia and Zaghini (2007), Zhang (2012) and Zhang, Zhang, and Wang (2012) claim that money growth has a positive impact on inflation in the short run, whereas Mccandless and Weber (1995), Crowder (1998), Christensen (2001), Grauwe and Polan (2005), and Zhang (2008, 2012) argue that money growth has a positive impact on inflation in the long run. Mccandless and Weber (1995) as well as Grauwe and Polan (2005) reach almost the same conclusion that money growth and inflation are related one-for-one in the long run, which provides strong support for the QTM, particularly for modern QTM. There is also limited work that presents a negative relationship between money growth and inflation. For example, Shuai (2002) and Wu (2002) find that China's money growth has an unusually negative impact on inflation in the 1993–2001 period.

For a further consideration, Lucas (1980) presents for the first time that the frequency level should not be ignored when examining the relationship between money growth and inflation. More recent work has paid special and extensive attention to how money growth and inflation relate at different frequencies (Assenmacher-Wesche & Gerlach, 2008a,b; Benati, 2009; Bruggeman, CambaMendez, Fischer, & Sousa, 2005; Haug & Dewald, 2004; Zhang & Su, 2010). While some researchers focus on the frequency-varying relationship between money growth and inflation, there has been another strand of literature that examines whether such a relationship evolves over time (Basco, D'Amato, & Garegnani, 2009; Christiano & Fitzgerald, 2003; Liu & Chen, 2012; Milas, 2007; Rolnick & Weber, 1997; Sargent & Surico, 2008; Wang, 2010; Zhang, 2009). For example, Zhang (2009) demonstrates that inflation persistence in China has been significantly weakened since 1997 as a consequence of systematic improvements in monetary policy. Wang (2010) reveals that China's money growth drives its inflation change as a hump shape. Liu and Chen (2012) find that their link has become weaker over the past decade in China.

Limited work performs a simultaneous assessment of how money growth and inflation relate at different frequencies and how such a relationship evolves over time, with the exception of Rua (2012), who achieves this using wavelet analysis. Using wavelet coherency and phase difference tools, he finds that the relationship between money growth and inflation is stronger at low frequencies and that money growth in the Euro area seemed to lose its leading properties with respect to inflation in the past decade. In this paper, we have also proposed to apply the wavelet analysis to investigate the dynamic relations between money growth and inflation in both the time and frequency domains. However, despite using a similar method, this paper employs the distinctive monthly data for China spanning from January 1991 to June 2014, which implies that we devote special attention to the world's biggest developing country to the effects of high money growth on inflation, and the ensuing findings would provide some additional and helpful implications for China's monetary policy implementation.

3. Wavelet theory and methods

Wavelet analysis originated in the mid-1980s as an alternative to the well-known Fourier analysis. Although Fourier analysis can uncover the relations across different frequencies by means of spectral techniques, the time-localized information is completely discarded under the Fourier transform. Moreover, Fourier analysis is only suitable for stationary time series. In contrast, wavelet analysis allows us to estimate the spectral characteristics of a time series as a function of time and then extracts localized information in both time and frequency domains (Aguiar-Conraria et al., 2008). In addition, wavelet analysis has significant superiority over the Fourier analysis when the time series under study are non-stationary or locally stationary Roueff and von Sachs (2011).

3.1. The continuous wavelet transform

As the beginning of the wavelet analysis, wavelet transform decomposes a time series into stretched and translated versions of a given "mother wavelet" that is well-localized in time and frequency domains. In this way, the series can be expanded into a timefrequency space where its time- and (or) frequency-varying oscillations are observed in a highly intuitive way. Often, two classes of wavelet transforms exist: discrete wavelet transforms (DWT) and continuous wavelet transforms (CWT). The DWT is useful for noise reduction and data compression, while the CWT is more helpful for feature extraction and data self-similarity detection (Grinsted, Moore, & Jevrejeva, 2004; Loh, 2013). As such, the CWT is widely used in economics and finance (Aguiar-Conraria et al., 2008; Caraiani, 2012; Rua, 2012). Given a time series $x(t) \in L^2(\mathbb{R})$, its CWT in regard to the mother wavelet $\psi(t)$ is defined as an inner product of $x(t)$ with the family $\psi_{\tau,s}(t)$ of "wavelet daughters";

$$W_{x,\psi}(\tau, s) = \int_{-\infty}^{\infty} x(t)\psi^*_{\tau,s}(t)dt, \tag{1}$$

where the asterisk (*) denotes complex conjugation, i.e., $\psi_{\tau,s} \ * \ (t)$ are complex conjugate functions of the daughter wavelet functions $\psi_{\tau,s}(t)$. As mentioned above, $\psi_{\tau,s}(t)$ are derived from the mother wavelet $\psi(t)$ during the decomposition in the sense that $\psi_{\tau,s}(t) = |s|^{-1/2}\tau((t-\tau)/s), \tau, s \in \mathbb{R}, s \neq 0$. Varying the wavelet scale parameter s implies compressing (if $|s| < 1$) or stretching (if $|s| > 1$) the mother wavelet $\psi(t)$ across frequencies, while translating along the localized time index τ implies shifting the position of the wavelet $\psi(t)$ in time. In doing so, one can construct a picture that shows both the amplitude of any features present in $x(t)$ versus the scale and how this amplitude evolves over time (Torrence & Compo, 1998). In addition, because both s and τ are real values that vary continuously (with the constraint $s \neq 0$), $W_{x;\tau}(\tau, s)$ is then named as continuous wavelet transform. To be a mother wavelet of the CWT, $\psi(t)$ must fulfill two indispensable requirements, i.e., $\tau(t) \in L^2(\mathbb{R})$, and the so-called "admissibility condition," which can be written as follows:

$$0 < C_\psi = \int_{-\infty}^{\infty} \frac{|\psi(f)|^2}{|f|} df < +\infty, \tag{2}$$

where $\psi(t)$ is the Fourier transform of the mother wavelet $\psi(t)$ and f is the Fourier frequency (see e.g., Daubechies (1992)). Looking at the formula, it is clear that C_ψ is independent of f and determined only by the wavelet $\psi(t)$. This means that C_ψ is a constant for each given mother wavelet function. Therefore, it is also called the "admissibility constant." The importance of the admissibility condition (2) is that it guarantees the possibility of recovering time series $x(t)$ from its CWT, $W_{x;\psi}(\tau, s)$ as follows:

$$x(t) = \frac{1}{C_\psi} \int_{-\infty}^{\infty} \left[\int_{-\infty}^{\infty} W_{x;\psi}(\tau, s)\psi_{\tau,s}(t)d\tau \right] \frac{ds}{s^2} \neq 0. \tag{3}$$

In this way, we can go from $x(t)$ to the CWT and from the CWT back to $x(t)$, and we hence have reason to believe that $x(t)$ and $W_{x;\psi}(\tau, s)$ are simply two different "representations of the same mathematical entity." [4] More importantly, the original energy of $x(t)$ can also be preserved by its wavelet transform in the sense that

$$\|x\|^2 = \int_{-\infty}^{\infty} |x(t)|^2 \, dt = \frac{1}{C_\psi} \int_{-\infty}^{\infty} \left[\int_{-\infty}^{\infty} |W_{x;\psi}(\tau, s)|^2 \, d\tau \right] \frac{ds}{s^2}. \tag{4}$$

where $\|x\|^2$ is defined as the energy of $x(t)$. There are different types of mother wavelets available for different purposes, such as Haar, Morlet, Daubechies, Mexican hat, and so on. The most popularly applicable mother wavelet for feature extraction purposes is the Morlet wavelet, which was first introduced by Goupillaud, Grossmann and Morlet (1984). Its simplified version can be represented as

$$\psi(t) = \pi^{-1/4} e^{i\omega_0 t} e^{-t^2/2}, \tag{5}$$

where $\pi^{-1/4}$ ensures unity energy of the mother wavelet. Additionally, ω_0 is the dimensionless frequency and usually equals 6 in practice. This is because this value can ensure that the Morlet wavelet is almost an analytic wavelet and make it easy to interpret the relationship between the scale s and Fourier frequency f.[5]

3.2. The wavelet power spectrum

In wavelet theory, the wavelet power spectrum of a time series $x(t)$ is simply given by $|W_{x;\psi}(\tau, s)|^2$, namely, the so-called auto-wavelet power spectrum. It can be interpreted as a measure of the local variance for $x(t)$ at each frequency. Because the cross-wavelet transform of two time series $x(t)$ and $y(t)$ first introduced by Hudgins, Friehe and

[4] See Aguiar-Conraria et al. 2008, p 2

[5] For the particular choice of $\omega_0 = 6$, we can simply get the approximate equation that $f = \omega_0/2\pi s = 6/2\pi s \approx 1/s$. This implies that broad-scale s corresponds to low Fourier frequency f, while fine-scale s corresponds to high Fourier frequency f. See more details on how to get such a relationship in Section 3.3

Mayer (1993) is defined as $W_{xy;\psi}(\tau, s) = W_{x;\psi} W^{*}_{y;\psi}(\tau, s)$, their cross-wavelet power spectrum is accordingly written as $|W_{xy;\psi}|^2 = |W_{x;\psi}|^2 |W^{*}_{y;\psi}|^2$ and presents a measure of the local covariance between $x(t)$ and $y(t)$ at each frequency. In the plots of the wavelet power spectrum, wavelet power is represented by colors, with red corresponding to a high power and blue corresponding to a low power. As discussed above, wavelet power presents a measure of the local volatility. Therefore, the colors similarly correspond to the local volatilities.

3.3. The wavelet coherency and phase difference

To analyze the dynamic relationship between money growth and inflation in China, we should pay greater attention to the wavelet coherency and phase difference. We start with the wavelet coherency, which can be calculated using the cross-wavelet spectrum and the auto-wavelet spectrums as follows:

$$R^2_{xy}(\tau, s) = \frac{\left| S\left(s^{-1} W_{xy;\psi(\tau,s)}\right)\right|^2}{S\left(s^{-1}\left|W_{x;\psi}(\tau, s)\right|^2\right) S\left(s^{-1}\left|W_{y;\psi}(\tau, s)\right|\right)} \tag{6}$$

Here, it is noted that the wavelet coherency under study is represented as a squared type similar to previous studies (AguiarConraria et al., 2008; Grinsted et al., 2004; Rua, 2012). After smoothed by a smoothing operator S, the squared wavelet coherency gives a quantity between 0 and 1 in a time-frequency space.7 It is represented by colors in wavelet coherency plots, with red corresponding to a strong correlation and blue corresponding to a weak correlation. In this way, wavelet coherency allows for a threedimensional analysis that can simultaneously consider the time and frequency components as well as the strength of correlation (Loh, 2013). Therefore, it helps us to distinguish the local correlation between money growth and inflation in China and to identify structural changes over time and the short-run and long-run relations across frequencies.

Because the wavelet coherency is squared, we cannot distinguish between positive and negative correlations. Therefore, we need the phase difference tool to present positive or negative suggestions for correlations and lead-lag relationships between series. Because the Morlet wavelet is a complex function, the CWT with regard to this type of mother wavelet is also complex and can be divided into a real part and an imaginary part. Therefore, following Bloomfield et al. (2004), the phase difference between $x(t)$ and $y(t)$ is defined as follows:

$$\phi_{xy} = \tan^{-1}\left(\frac{\mathfrak{I}\left\{S\left(s^{-1} W_{xy;\psi}(\tau, s)\right)\right\}}{\mathfrak{R}\left\{S\left(s^{-1} W_{xy;\psi}(\tau, s)\right)\right\}}\right), \quad \text{with} \quad \varphi_{xy} \in [-\pi, \pi].$$

where $\mathfrak{I}$ and $\mathfrak{R}$ are the imaginary and real parts of the smoothed cross-wavelet transform, respectively. Furthermore, following Voiculescu and Usoskin (2012) and Aguiar-Conraria and Soares (2013), we can easily convert the phase difference into the instantaneous time lag between $x(t)$ and $y(t)$ in the sense that

$$(\Delta t)_{xy} = \frac{\phi_{xy}}{2\pi f},$$

where $2\pi f$ is the angular frequency with respect to the time scale s, in the sense that the usual Fourier frequency f is given by $f = \omega_\psi / 2\pi s$. Note that the frequency ω_ψ represents the frequency of the mother wavelet, namely, the dimensionless frequency ω_0 of the Morlet wavelet. Using $f = \omega_\psi / 2\pi s$ with the particular choice of $\omega_0 = 6$, we have $f = 6/2\pi s \approx 1/s$. Therefore, the time lag $(\Delta t)_{xy}$ is finally given by

$$(\Delta t)_{xy} = \frac{\varphi_{xy} \cdot s}{2\pi},$$

In this paper, the phase differences are represented as arrows in the wavelet coherency plots. Arrows pointing to the right mean that $x(t)$ and $y(t)$ are in phase (or positively related), while arrows pointing to left mean that $x(t)$ and $y(t)$ are out of phase (or negatively related). Arrows pointing to other directions mean lags or leads between them. For example, arrows pointing straight up mean that $x(t)$ leads $y(t)$ by one-quarter of the corresponding scale or lags behind $y(t)$ by three-quarters of the corresponding scale. It is noteworthy that phase differences can also be suggestive of causality between $x(t)$ and $y(t)$ (Grinsted et al.,2004; Tiwari, Mutascu, & Andries, 2013).

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