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

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ARTICLE INFO

Keywords:
Money growth
Inflation
Wavelet analysis
Time domain
Frequency domain

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, Cai, Shu and Hou (2012a) and Zhang, Xie and Qian (2012b) claim that money growth has a positive impact on inflation in the short run, whereas McCandless, Weber et al. (1995a), Crowder (1998), Christensen (2001), Grauwe and Polan (2005), and Zhang (2008, 2009); Zhang et al. (2012a,b) argue that money growth has a positive impact on inflation in the long run. McCandless, Weber et al. (1995b) 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).

4. Data description

We use monthly data on money growth and inflation in China. We first acquire M_0, M_1, and M_2 from the PBoC and the consumer price index (CPI, 2010 = 100) from the National Bureau of Statistics of China. Second, we transform all original data into natural logarithms to correct for potential heteroscedasticity and dimensional differences between series. Third, we take first-order differences in the end-of-month values relative to the values for the same period of the previous year. In this way, we adjust for seasonal trends within original series and obtain year-on-year growth rates of M_0, M_1, and M_2, and change rates of CPI. Note that the year-on-year rates of change of CPI are defined as inflation rates in this paper. Additionally, because of the availability of original data in China, the growth rates of M_0 and M_1 and inflation rates span from 1991:01 to 2014:06, while the growth rates of M_2 span from 1997:01 to 2014:06.

The time-series plots of the growth rates of M_0, M_1, and M_2 as well as the inflation rates for China are presented in Fig. 1. Periodic properties can be clearly observed within these four series. To explore more details about the periodic properties, we subsequently classify the full samples of these four series into different cycles in terms of the method proposed by Artis, Bladen-Hovell, Osborn, Smith, and Zhang (1995), who define a cycle as a “trough-peak-trough” trend. In doing so, seven cycles can be obtained for money growth series, while six cycles are obtained for inflation series, and furthermore, descriptive statistics are simply used here to identify their main features within each cycle.

Table 1 reports the results of descriptive statistics for money growth and inflation of each cycle. In general, relatively high volatility can be found for money growth series within the first, second and sixth cycles, as represented by greater standard deviation values in the last column of this table. Specifically, M_0 and M_1 growth show the highest volatilities in the first cycle, i.e., the sub-period from the beginning of 1991 to the middle of 1994, with the greatest standard deviation of 0.0843 for M_0 growth and 0.0714 for M_1 growth. Higher volatilities can also be observed within the second cycle, i.e., the sub-period from the middle of 1994 to the middle of 1998. Afterwards, we can see money growth in China shown relatively mild volatilities during the third, fourth, and fifth cycles. Until the sixth cycle, i.e., the period from the end of 2008 to the end of 2011, quite a high volatility reoccurs for money growth series, especially for M_1 growth (with a standard deviation of 0.0736). Very similarly, inflation series also experience relatively high volatilities during three cycles. The highest volatility can be found in the first cycle from 1991 to 1998, with a peak of 24% in late 1994 and a trough below zero in late 1998 as well as a standard deviation of 0.0737. After that, it becomes milder during the next two sub-periods, 1999–2002 and 2002–2006. Until the fourth and fifth cycles of the two periods 2006–2008 and 2009–2012, China suffers sharp ups and downs in inflation rates once again. However, in 2013–2014, China’s money supply begins to grow smoothly, and the rates of inflation remain stable at low levels in the meantime.

Taking advantage of wavelet tools, the rectified wavelet power spectrums of money growth and inflation series are also estimated in Fig. 2.8 The thick black contours designate the 5% significance level estimated from Monte Carlo simulations using a phase randomized surrogate series. The regions below the thin black lines are the cone of influence (COI) in which edge effects cannot be ignored.9 We can see that M_0 growth shows intensive volatilities at shorter time scales (i.e., higher frequencies) in accordance with the highest liquidity of M_0 in comparison to M_1 and M_2. By contrast, M_1 and M_2 growth share similar wavelet power during the 1992–1998 and 2008–2011 periods, corresponding to the first, second, and sixth cycles of them as mentioned above. Moreover, the result that M_1 and M_2 growth mainly varies across 2–4 years’ time scales is much the same with the cycle lengths indicated by Table 1. As for inflation series, higher wavelet power mainly exists in two periods, 1992–1998 and 2007–2011, corresponding to the higher volatilities during its first, fourth, and fifth cycles. Particularly, the result that inflation varies across 1- to 8-year time scales during 1992–1998 is also greatly in line with the 96-month cycle for this period in Table 1.

It may seem that almost the same results are presented in Table 1 and Fig. 2. However, using wavelet-based spectral tools, Fig. 2 provides significant evidence in a time-frequency space where structural changes of money growth and inflation can be read off in a highly visual way. Specifically, the very high volatility of money growth in the first cycle is probably the consequence of the famous talk delivered on Xiao-ping Deng’s south tour in 1992, which greatly stimulated China’s money growth in 1992–1993 followed by a sharp decline in 1994 due to an ever-increasing inflation. In the second cycle, the PBoC begins to make mild but frequent adjustments in money growth, ensuring that China successfully cushioned the economic fallout at the end of 1996. As a result, the volatilities of M_0 and M_1 growth become milder within this cycle. The relatively high volatility in the sixth cycle can be attributed to the global financial crisis of 2008–2009. Under crisis circumstances, an unprecedented expansionary monetary policy is conducted by the PBoC to arrest the economic downturn. Consequently, money growth hits a record high in late 2009. However, after 2010, it starts to fall rapidly due to an overheating economy. According to the estimated wavelet power of inflation in Fig. 2, we find that the wavelet power varies across longer time scales (i.e., lower frequencies) in the 1999–2007 period,

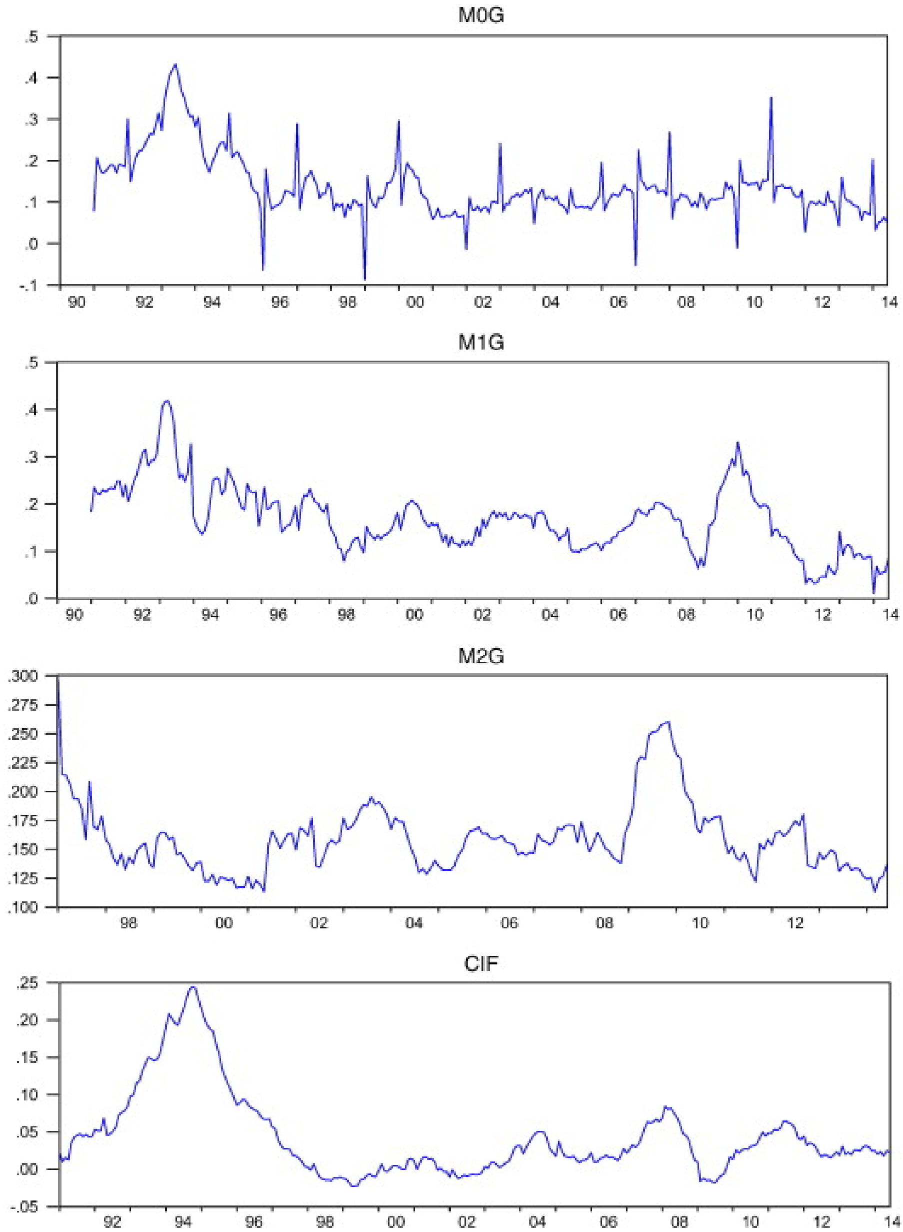

Figure 1: Time-series plots of money growth and inflation in China. M_0G, M_1G, and M_2G represent the growth rates of M_0, M_1, and M_2, respectively, while CIF represents the inflation rates.

which may be indicative of high inflation persistence in a low-inflation environment (Wang & Wang, 2009). However, despite its utility, the wavelet power spectrum cannot reveal any local correlation and lead-lag relationship between time series. Therefore, wavelet coherency and phase-difference tools are proposed in the empirical section to reveal the time- and frequency-varying relationship between money growth and inflation for China.

5. Empirical results

In this section, we plot wavelet coherencies and phase differences between money growth and inflation for China in Figs. 3–5. 10 As mentioned before, the results inside the COI and the regions above the 5% significance level are not reliable indications of correlations and lead-lag suggestion.We classify the frequency on the y-axis into three bands:

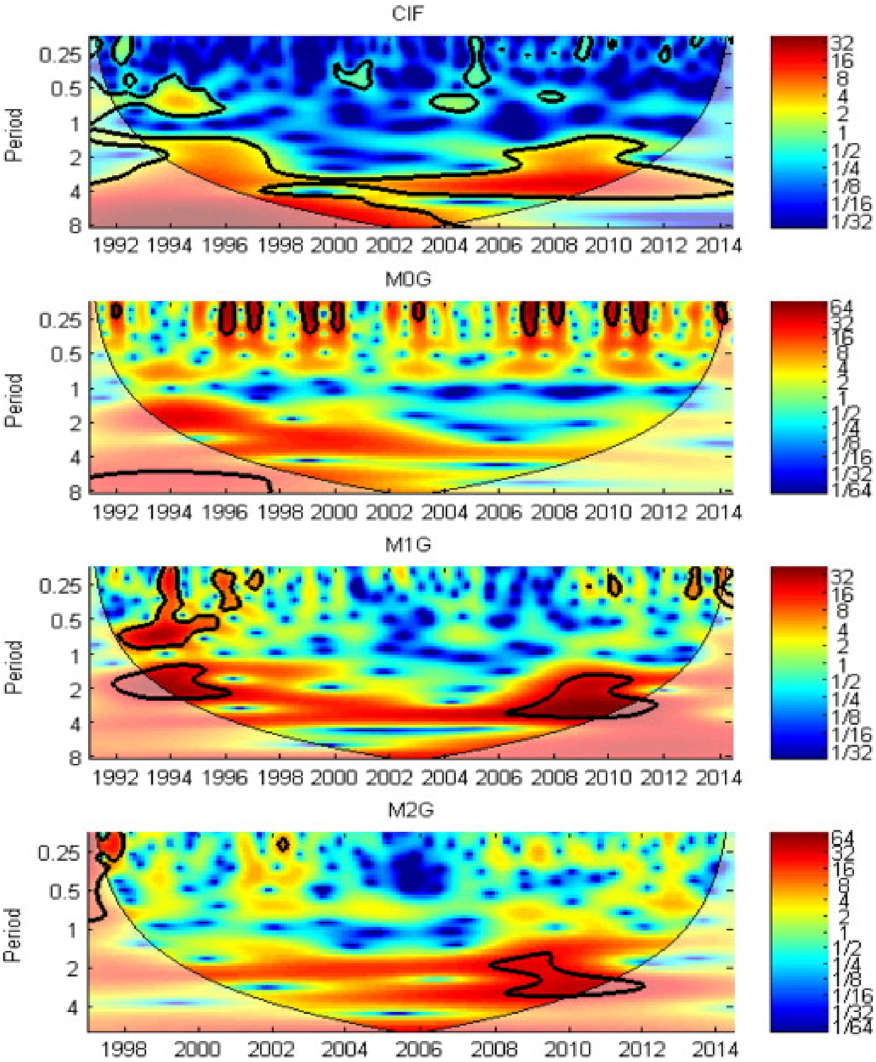

Figure 2: The squared wavelet coherency and phase difference between M_2G and C_IF from 1997 to 2013. M2G represents M2 growth rates, while CIF represents the inflation rates. The x-axis refers to time periods. The y-axis to scales or frequencies (measured in years). The color corresponds to the strength of the correlation.

1-year time scale, 1- to 4-year time scales, and 4- to 8-year time scales, corresponding to short-run, medium-run, and long-run relationships between money growth and inflation. For a better comparison, the relationship of the growth rates of M_0, M_1, and M_2 relative to inflation is analyzed as follows.

6.

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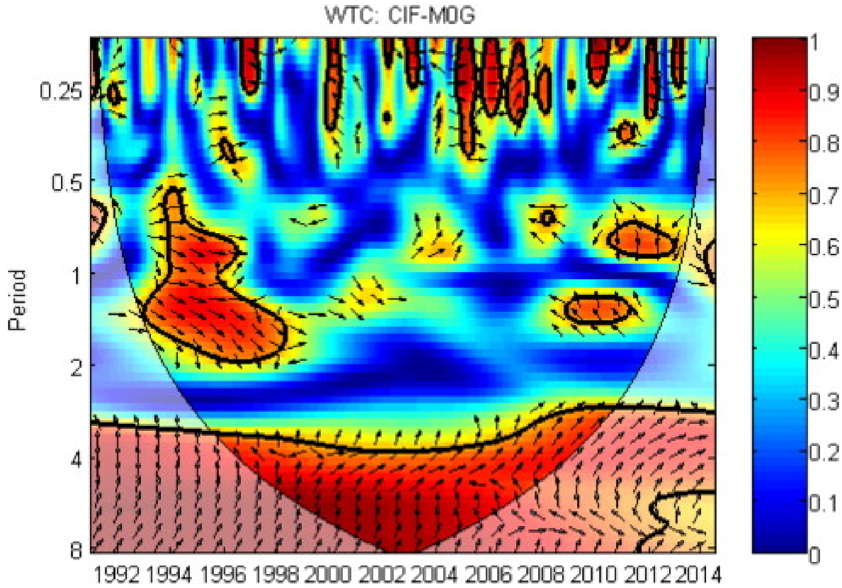

Figure 3: The squared wavelet coherency and phase difference between M_0G and CIF from 1991 to 2013. $M_0$4G represents M_0 growth, while CIF represents the inflation rates. The x-axis refers to time periods. The y-axis is scales (measured in years). The color corresponds to the strength of the correlation.

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