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TIME-FREQUENCY CHARACTERIZATION OF THE U.S. FINANCIAL CYCLE

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Abstract

Despite an increase in research – motivated by the global financial crisis of 2007-08 – empirical studies on the financial cycle are rare compared to those on the business cycle. This paper adds some new evidence to this scarce literature by using a different empirical methodology – wavelet analysis – to extract financial cycles from the data. Our results confirm that the U.S. financial cycle is (much) longer than the business cycle, but we do not find strong evidence supporting the view that the financial cycle has lengthened during the Great Moderation period.

Keywords: time-frequency estimation, wavelets, financial cycle, business cycle, credit, asset prices

JEL classification: C49, E32, E44

1 Introduction

The global financial crisis of 2007-08 has stimulated new interest in the so-called financial cycle and its interaction with the business cycle. A key issue in the current empirical literature is to measure the duration and amplitude of fluctuations in financial variables. Recent empirical studies (see *e.g.* Strohsal et al. (2015)) have found that i) the financial cycle has a much lower frequency than the business cycle and ii) its duration has increased considerably, especially in the course of the Great Moderation starting in the mid-1980s.

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As for the business cycle, standard empirical approaches to analyze the characteristics of the financial cycle rely on i) the analysis of turning points (Claessens et al. (2012)), ii) frequency-based filter methods (Drehmann et al. (2012)), or iii) pure frequency domain methods, *i.e.* the well-known Fourier transform (Strohsal et al. (2015)). The turning point approach requires a prespecified rule which is used to find local maxima and minima of an observed time series. The pure frequency domain approach has the advantage, over frequency-based filter methods, that no *a priori* assumption is needed as to the frequency range at which the financial cycle is assumed to operate. Despite its usefulness, the Fourier transform only provides information regarding how much of each frequency exists in the time series; it does not locate the points in time when these frequency components exist. The Fourier transform does not therefore provide any information regarding how the frequency content of the variable of interest evolves over time. Because of this, one has to split the data into different subsamples in order to analyze possible changes over time in the characteristics of the financial (or business) cycle, as is done by *e.g.* Strohsal et al. (2015).

Against this background, we use here a different empirical methodology – namely wavelet analysis – to extract financial cycles from the data. Wavelet analysis represents a refinement of Fourier analysis and overcomes its aforementioned shortcoming, as it allows one to take into account, at the same time, both the frequency *and* the time variations of a time series. In particular, in what follows we use continuous wavelet tools to analyze the duration of the U.S. financial cycle (*i.e.* at which frequencies the financial cycle operates) and how such duration has evolved over time.[1]

2 The U.S. financial cycle in the time-frequency domain

2.1 The data

The financial cycle is far less well-defined than the business cycle. For our empirical analysis we use data for three of the most common proxies for the financial cycle: i) total credit to the private, non-financial sector; ii) residential property prices; and iii) equity prices. GDP serves as the representative variable for the business cycle.

[1] The pioneer papers in economics using wavelets rely on the discrete wavelet transform (Ramsey and Lampart (1998b,a)). More recently, the literature using the continuous wavelet transform (CWT) has been growing and the CWT is becoming a popular tool in econometric analysis (see Aguiar-Conraria and Soares (2014)). Some recent macro-finance applications using the CWT are Crowley and Mayes (2008), Rua and Nunes (2009), Aguiar-Conraria and Soares (2011), Rua (2012), Caraiani (2012a,b), Aguiar-Conraria et al. (2012), Gallegati and Ramsey (2013), Ko and Lee (2015) and Marczak and Gomez (2015), among others.

We use U.S. quarterly data and, except for residential property prices, the sample period is 1953Q1-2013Q4 (the house price series starts at 1975Q1). To obtain results comparable with those of existing studies, we employ a data transformation similar to that in Comin and Gertler (2006). In particular, all series are measured in logs and deflated by the GDP deflator; then annual growth rates are obtained by taking four-quarter differences for each time series. The upper left graphs in figures 1-4 show the time series of annual growth rates.[2]

2.2 Empirical results [3]

The wavelet power spectrum (WPS) and the global wavelet power spectrum (GWPS) of each series are reported in the lower left and lower right panel, respectively, in figures 1-4. The WPS measures the local variance distribution of a time series around each time and frequency, *i.e.* it gives the relative contributions of a particular frequency to the total variance of the time series at each point in time. The GWPS gives the average wavelet power for each frequency and is obtained by averaging the WPS over all times (so that it can be directly compared with classical spectral methods). In the power spectrum charts, time is on the horizontal axis and period cycles (in years) on the vertical axis, hotter colors (yellow and red) correspond to higher volatility and colder colors (green and blue) to lower volatility, black (gray) contours mark significance at the 5 (10) percent level, and black dashed lines denote the cone of influence (*i.e.* the regions affected by edge effects and where caution is required in interpreting the results). More importantly, for the purpose of this study, the white lines show the maxima of the undulations of the WPS, *i.e.* they provide an estimate of the cycle periods.

Total credit (figure 1) features three main (and statistically significant) cycles: one with a period of 6/8 years (between 1965 and 2000); another starting in 1985 with a period of 12 years, which gradually shortens and becomes a 8-year cycle at the end of the sample; and a third permanent cycle with a period of nearly 20 years. The GWPS further confirms that the majority of the variability of total credit occurs at long period cycles (more than 8 years). Similarly, most of the variability of house prices (figure 2) occurs at frequencies of periods longer than 8 years. Two (almost) permanent cycles characterize house prices fluctuations, one with a period of about 9 years and one with

[2] The data on total credit are from the flow of funds tables available on the Fed Board website (see Contessi et al. (2015) for details). S&P500 data are from Bloomberg, residential property prices data are from OECD.Stat, and data on GDP and its deflator are from the St. Louis Fed FRED2 database. Results are robust using quarterly growth rates.

[3] The results in this paper were obtained using the ASToolbox, a wavelet Matlab toolbox available at https://sites.google.com/site/aguiarconraria/joanasoares-wavelets/the-astoolbox.

a period of about 15 years. Furthermore, a temporary (between 1985 and 2000) and longer (about 24 years long) cycle is also visible. As in Strohsal et al. (2015), the low frequency components of credit and house prices are indeed more important than the short ones. By contrast, figure 3 reveals that most of the variability of equity prices occurs at cycles with periods shorter than 8 years, despite some significant variability starting from the mid-1980s at long period cycles (between 8 and 16 years). Since much of equity price variability concentrates at comparatively higher frequencies, they are not usually considered to be a good representative proxy for the financial cycle. Actually, as Borio (2014) puts it, equity prices can indeed be a distraction.

As regards business cycle fluctuations, the WPS of GDP (figure 4) is somehow similar to that of total credit, as it indicates that GDP features a strong variance at three main cycles: a permanent cycle with a period close to 20 years, another with a period around 12 years, and a third one with a period of about 6 years. Interestingly, the Great Moderation period starting in the mid-1980s is easily seen as the areas of significant power spectrum become narrower and more localized towards cycles of longer duration – *i.e.* GDP becomes less volatile – after 1985. Furthermore, as the GWPS indicates, the medium- and long-term components of GDP fluctuations are also not negligible and seem to be quite as important as the short-term components, thus providing further support for the findings in Comin and Gertler (2006).

So, overall, these empirical results confirm that the financial cycle – when measured using credit or house prices – operates at lower frequencies than the business cycle (though the latter also features important medium- and long-run components). However, it seems difficult to argue (as *e.g.* Strohsal et al. (2015)) that the duration of the financial cycle has increased during the Great Moderation period. The only visible change occurring at the beginning of the Great Moderation period is the appearance of 12-year cycles in total credit and house prices, with the first gradually shortening and the latter gradually lengthening over the sample.

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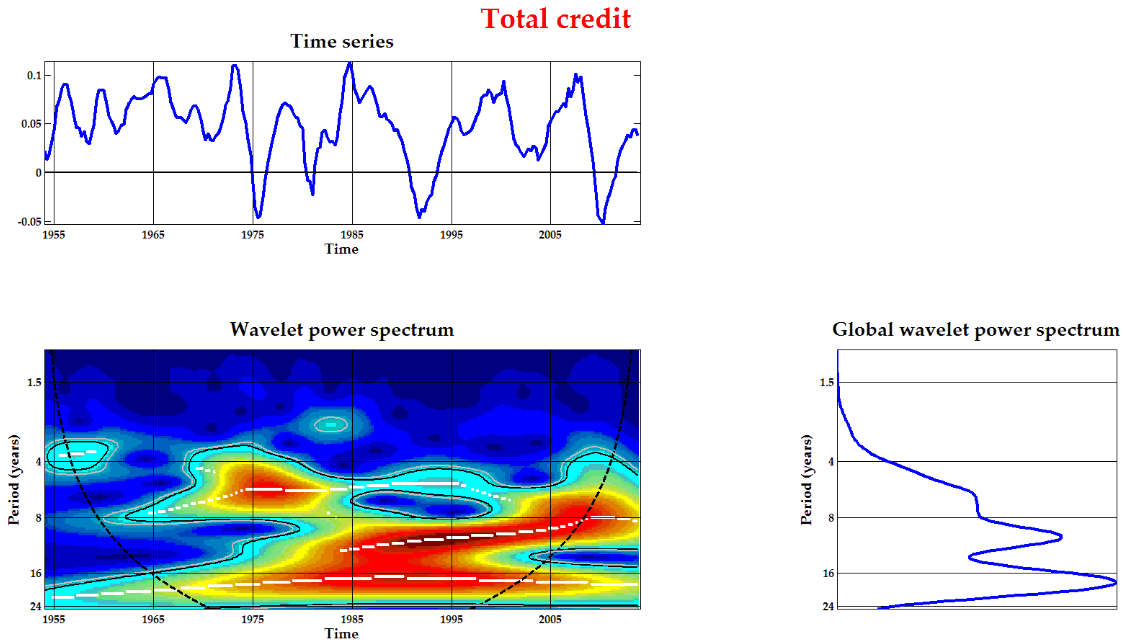

Figure 1: Total credit. Time series (upper panel); wavelet power spectrum (bottom left panel); global wavelet power spectrum (bottom right panel).

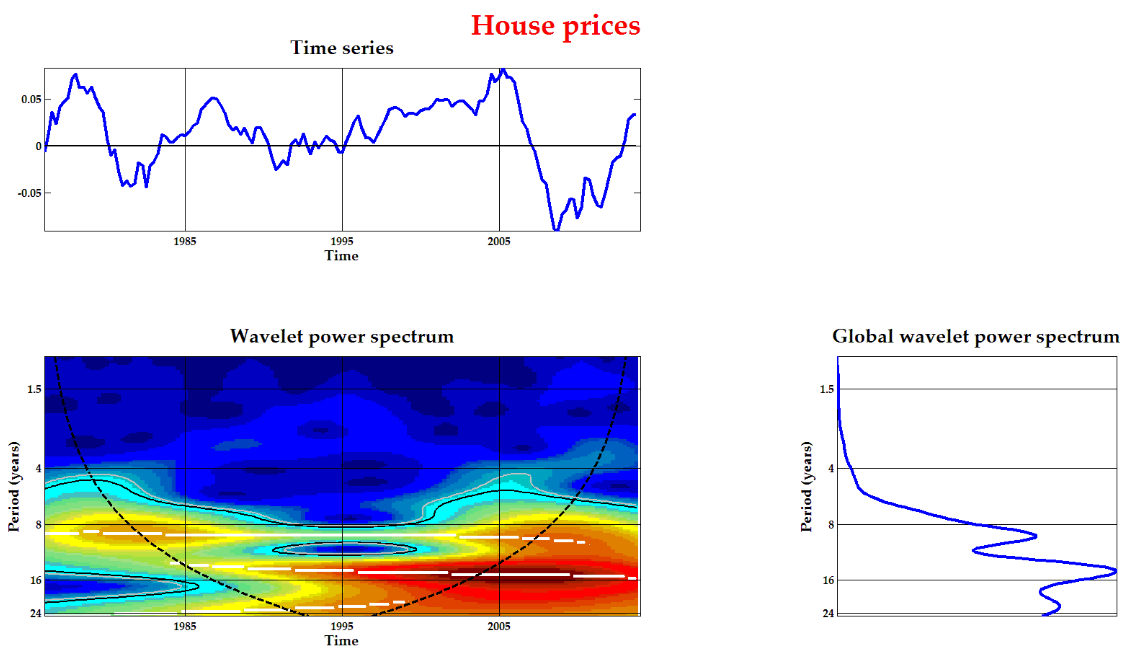

Figure 2: House prices. Time series (upper panel); wavelet power spectrum (bottom left panel); global wavelet power spectrum (bottom right panel).

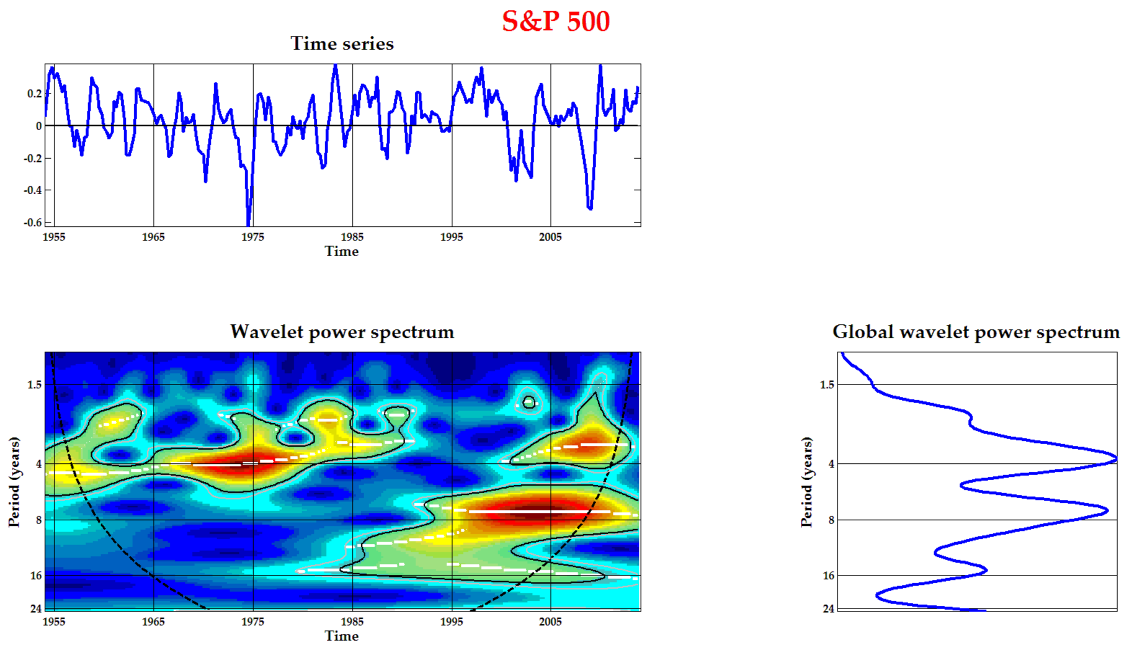

Figure 3: S&P 500. Time series (upper panel); wavelet power spectrum (bottom left panel); global wavelet power spectrum (bottom right panel).

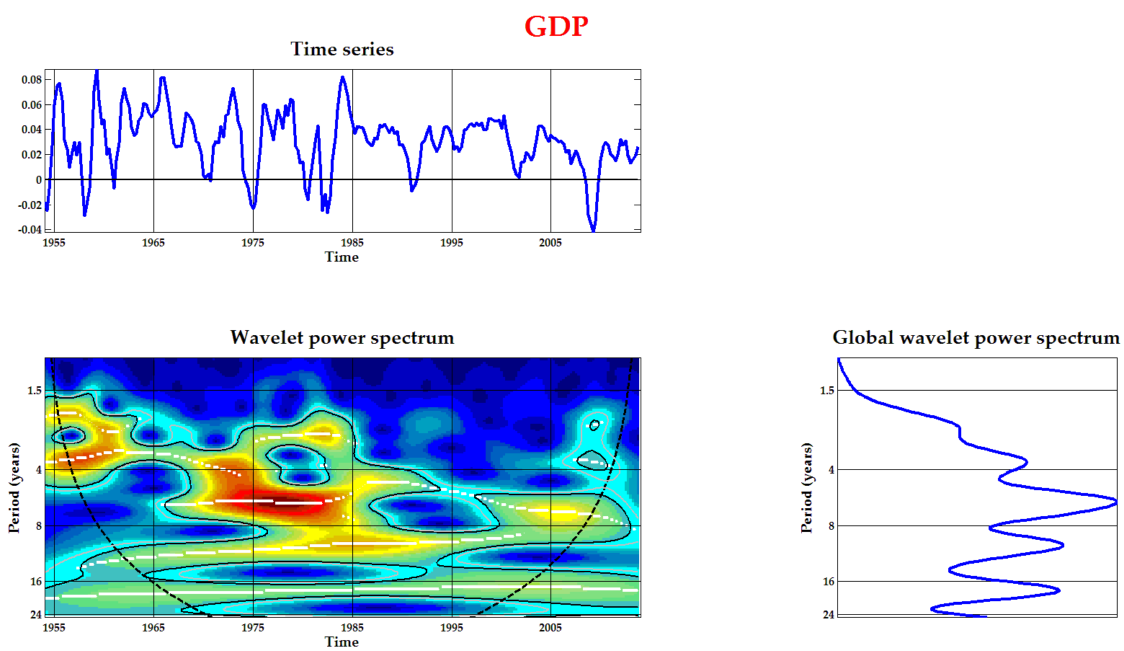

Figure 4: GDP. Time series (upper panel); wavelet power spectrum (bottom left panel); global wavelet power spectrum (bottom right panel).