Credit, default, financial system and development[♦]

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ABSTRACT

We use partial wavelet coherency, partial phase-difference diagram and partial regression coefficient to address instrumentalized co-movements across time and frequencies between macro-finance variables and household decisions in terms of consumer loans, home mortgage and its respective delinquency rates in U.S. We provide insights to stock market return prediction and asset pricing puzzles. Our findings are useful to draw public policies to safeguard financial stability and to analyze financial crises drivers. The simultaneous variation of statistics along time and frequencies allow us to detect new stylized facts about the last three decades of U.S. financial development and economic growth.

1. Introduction

Since Solow's (1956) neoclassical growth model, a large literature has thoroughly documented how specific variables are able to drive long-run economic growth. In this context, De Gregorio and Guidotti (1995) have collaborated with the literature on finance and growth by using total credit to the private sector as a share of GDP as proxy to assess possible effects of financial markets development.

With regards the relation between credit and assets, Bordo and Jeanne (2002) suggest an interesting pass-through. They claim that higher credit availability boosts asset prices through liquidity and the expectation of further rises in these prices motivates raising debt. However, during periods of falling asset prices – useful as collateral – one can expect expenditure cut back and borrowing reduction.

Concerning the role of default, Matos (2019) argues that it works as a versatile asset able to span contingent claims. This paper also finds that incorporating investor decisions on credit and delinquency into the CCAPM is useful to price equity premium in U.S. Assuming that borrowers have the option to default enables the analysis to capture the rationality that investors know that stocks do badly at particular times and states of nature. Hence, introducing such decisions works as a recession state variable. Aligned to this argument, delinquency rate on consumer loans increased during NBER recessions in U.S., especially in 2007, with more than 1.1% in 18 months. Delinquency rate on single-family residential mortgages have increased more than 5%, during this last recession in U.S.

Chen et al. (2012) is one of the rare papers in this literature that addresses frequency-varying co-movements between credit market and macro-finance. They use a multivariate analysis accounting for the phase shift mechanism, which enables them to identify causality between financial cycles and business cycles even with raw data at different frequencies. They find that at the business cycle frequency for U.S. over the period from 1965:1 to 2010:3, real output and real stock prices tend to lead total credit in a pro-cyclical fashion.

Our work extends Bordo and Jeanne's (2002) pass-through and is closely related to Chen et al. (2012). In line with this agenda on the role of credit market, we are the first, to our knowledge, to assess the relationship between household credit, home mortgage and both delinquency rates versus macro-finance variables in U.S. in the time-frequency domain. Methodologically speaking, from a positive point of view, wavelet is useful to describe, in a very simple, didactic and parsimonious way, the conditional synchronization and transmission of the credit cycles to financial or macro cycles, for the period from 1991:2 to 2018:1, at a quarterly frequency.

We follow Aguiar-Conraria et al. (2018), by using partial wavelet coherencies, partial phase-difference diagrams and partial gains. It enables us to study in more detail and controlling for a specific set of instruments, when and at what frequencies each credit or delinquency variable is synchronized or not with each financial index or with each macro variable in U.S. This mathematical method also enables us to infer on which credit or delinquency cycle has been leading or lagging each macro or financial cycle. There is also a novelty regarding the data. We use growth and delinquency rates for consumer loans and home mortgages. Our macro data consist of growth of real income, wealth and consumption expenditures on: services, nondurable and durable goods. In the financial market, we use real return on U.S. major stock indices: Russell 2000, Nasdaq and S&P 500. The data source is the Federal Reserve Economic Data.

This letter is structured as follows. Section 2 presents the mathematical method. Section 3 describes the dataset and empirical results. Section 4 is devoted to final remarks.

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2. Mathematical framework

The wavelet transforms, originally explored empirically by Grossmann and Morlet (1984), are a very popular tool deal with economic data, which is usually noisy, nonstationary, with nonlinear relations. Our choice for this framework is well suited to our intent: it enables us to trace transitional changes across time and frequencies, improving the analysis of cycles on the comparison to the traditional methods, as common feature-based approaches. We follow most of the recent empirical contributions, as Lin et al. (2018) by using Morlet as the continuous complex-valued mother wavelet. This function is ideal for the analysis of oscillatory signals, since it provides an estimate of the instantaneous amplitude and instantaneous phase of the signal in the vicinity of each time/frequency location (τ, s).

According this methodology, we measure the dissimilarity between a pair of given wavelet spectra, by using the following equation:

$$dist(W_x, W_y) = \frac{\sum_{k=1}^{K} \sigma_k^2 [d(l_x^k, l_y^k) + d(\mathbf{u}_k, \mathbf{v}_k)]}{\sum_{k=1}^{K} \sigma_k^2} \tag{1}$$

The wavelet transforms of x and y are given by $W_x(.)$ and $W_y(.)$, respectively. Moreover, σ_k^2 are the weights equal to the squared covariance explained by each axis, $\mathbf{u}_k$ and $\mathbf{v}_k$ are singular vectors satisfying variational property and l_x^k and l_y^k are leading patterns.

As usual, the cross-wavelet transform and the respective wavelet coherency of two time-series, $x(t)$ and $y(t)$, are defined as

$$W_{xy}(\tau, s) = W_x(\tau, s)\overline{W_y}(\tau, s) \tag{2}$$

and

$$R_{xy}(\tau, s) = \frac{|S(W_{xy}(\tau,s))|}{\sqrt{S(|W_{xx}(\tau,s)|)S(|W_{yy}(\tau,s)|)}}, \tag{3}$$

where $S(.)$ is a smoothing operator in scale and time. We analyze the time-frequency dependencies, by using phase-difference, given by

$$\phi_{xy}(s, \tau) = tan^{-1}\left(\frac{\Im(W_{xy}(s,\tau))}{\Re(W_{xy}(s,\tau))}\right), \tag{4}$$

where $\Re(.)$ and $\Im(.)$ are the real and the imaginary parts of cross wavelet spectrum.

This is a summary description of the main equations in this wavelet literature, concerning univariate and bivariate tools.

However, our purpose is to discuss the synchronization and the lead-lag conditional relationships between credit or default and macro-finance variables. In other words, besides allowing for the variation of coefficients along time and frequencies, we intend to control each pairwise co-movement for a specific vector of instruments, $\boldsymbol{z}$. We follow Aguiar-Conraria et al. (2018), by using the partial wavelet framework. Hence, the multiple wavelet coherency between y and the series x and $\boldsymbol{z}$, denoted by $R_{y(x\boldsymbol{z})}$ is given by

$$R_{y(x\boldsymbol{z})} = \sqrt{\frac{R_{yx}^2 + R_{yz}^2 - 2\Re(\xi_{yx}\xi_{xz}\overline{\xi_{yz}})}{1 - R_{xz}^2}} \tag{5}$$

The complex partial wavelet coherency between y (macro-finance variable) and x (credit variable) after controlling for $\boldsymbol{z}$ is given by

$$\xi_{yx,\boldsymbol{z}} = \frac{\xi_{yx} - \xi_{yz}\overline{\xi_{xz}}}{\sqrt{(1 - R_{yz}^2)(1 - R_{xz}^2)}} \tag{6}$$

The absolute value and the angle of $\xi_{yx,\boldsymbol{z}}$ are respectively the partial wavelet coherency and the partial wavelet phase difference between y and x, after controlling for $\boldsymbol{z}$. They are analogue of the bivariate metrics given by (3) and (4), and they are denoted by $R_{yx,\boldsymbol{z}}$ and $\phi_{yx,\boldsymbol{z}}$. Regarding the signs, a phase-difference of zero indicates that the time-series move together at the specified frequency. If $\phi_{yx,z} \epsilon \left(0, \frac{\pi}{2}\right)$ the series move in phase, but the time-series y leads x, while if $\phi_{yx,z} \epsilon \left(-\frac{\pi}{2}, 0\right)$ then it is x that is leading. A phase-difference of $\phi_{yx,z} = \pm\pi$ indicates an anti-phase relation. Finally, if $\phi_{yx,z} \epsilon \left(\frac{\pi}{2}, \pi\right)$, then x is leading and time-series y is leading if $\phi_{yx,z} \epsilon \left(-\pi, -\frac{\pi}{2}\right)$.

Finally, Aguiar-Conraria et al. (2018) generalize the concept of wavelet gain (coefficient regression) by defining the partial wavelet gain, which can be interpreted as a regression coefficient in the regression of y on x, after controlling for $\boldsymbol{z}$, given by

$$G_{yx,\boldsymbol{z}} = \frac{|\xi_{yx} - \xi_{yz}\overline{\xi_{xz}}|}{(1 - R_{xz}^2)} \frac{\sigma_y}{\sigma_x} \tag{7}$$

3. Data and empirical results

In terms of sample size, the main limitation for the time-series span used here regards the credit variables. The largest sample available at Federal Reserve Economic Data (RFED) covers the period from 1991:2 to 2018:1, almost three decades, comprising 108 quarterly observations.

Table 1 reports the mean and the standard deviation of each variable x and of its wavelet transform, $W_x(.)$.

Concerning the original time-series, as usual, they seem to corroborate previous data exploratory analyzes in this literature (see e.g. Matos, 2019). Regarding the wavelet cycles, they obviously range around zero. The financial and wealth variables become smoother, while the other cycles are more volatile than the respective series.

Table 1
Summary statistics

	Original time-series		Wavelet transforms	
	Mean	St. dev.	Mean	St. dev.
Financial variables - quarterly returns on indices				
Real Return on Russell 2000	2.11%	9.74%	-0.14%	3.50%
Real Return on Nasdaq Composite Index	2.78%	11.94%	-0.11%	4.51%
Real Return on S&P 500	1.51%	6.39%	-0.05%	4.08%
Macro variables - quarterly growth				
Real Return on Stock market capitalization Wilshire - wealth proxy	1.99%	7.70%	0.12%	4.02%
Real Percapita Seasonally Adjusted Personal Income	0.34%	0.86%	-0.00%	5.07%
Real Percapita Seasonally Adjusted Personal Consumption Expenditures: Durable Goods	0.90%	2.03%	0.01%	3.99%
Real Percapita Seasonally Adjusted Personal Consumption Expenditures: Nondurable Goods	0.20%	0.62%	0.09%	5.35%
Real Percapita Seasonally Adjusted Personal Consumption Expenditures: Services	0.31%	0.36%	0.15%	5.58%
Credit and default variables - quarterly growth and quarterly rates				
Real Percapita Seasonally Adjusted Consumer Loans at All Commercial Banks	0.39%	3.90%	-0.22%	5.95%
Delinquency Rate on Consumer Loans, All Commercial Banks	3.21%	0.69%	0.00%	3.69%
Real Percapita Seasonally Adjusted Households and Nonprofit Organizations; Home Mortgages	1.15%	1.52%	0.04%	2.73%
Delinquency Rate on Single-Family Residential Mortgages, Booked in Domestic Offices, All Commercial Banks	4.19%	3.08%	0.00%	1.57%

Notes: Quarterly series from 1991:2 to 2018:1. Data source: FRED

Instead of observing the correlations, as usual in this literature, for our purposes, it is more relevant and informative observing the dissimilarities between the respective cycles, computed with first equation (See Table 2).

We use the Hermitian angle, so the highest value the dissimilarity can take is $\pi/2$. Value close to zero means that both variables share the same high-power regions and that their phases are aligned. Moreover, the contribution of cycles at each frequency to the total variance is similar between the variables and this contribution happens at the same time in both variables. We may also infer that the ups and downs of each cycle occur simultaneously in both of them. Although they are not significant at 10% (10000 simulations), we highlight the synchronization between the S&P 500 and credit variables, as well as the lower dissimilarities of home mortgage growth with wealth and with income. Credit growth and delinquency are synchronized with wealth and expenditure on durables, respectively.

Table 2
Morlet wavelet dissimilarities

	Credit and default variables			
	Consumer Loans		Home Mortgages	
	growth	delinquency	growth	delinquency
Financial variables - quarterly returns on indices				
Real Return on Russell 2000	0.33	0.39	0.33	0.37
Real Return on Nasdaq Composite Index	0.37	0.37	0.36	0.39
Real Return on S&P 500	0.29	0.28	0.27	0.33
Macro variables - quarterly growth				
Wealth	0.28	0.31	0.27	0.35
Income	0.37	0.43	0.22	0.36
Consumption expenditures on durable goods	0.40	0.27	0.40	0.32
Consumption expenditures on nondurable goods	0.44	0.37	0.41	0.45
Consumption expenditures on services	0.45	0.37	0.38	0.44

Notes: Quarterly series from 1991:2 to 2018:1. Data source: FRED.

Our main findings are based on the partial wavelet method. Considering all 32 possibilities involving each of the four credit market variables versus each of the three financial variables and each of the five macroeconomic variables, we plot and analyze only the figures with higher incidence of regions with strong partial coherency. We also report the respective partial phase-difference and estimations.

As instruments, we follow Cochrane (1996) by using investment to capital stock ratio and dividend-price ratio to explain financial indices. For macro variables, we use two lags of the respective endogenous variable, as usual in the consumption-based asset pricing literature. In Fig. 1, we study credit variables and financial system in U.S., while in Fig. 2, we study credit market and development.

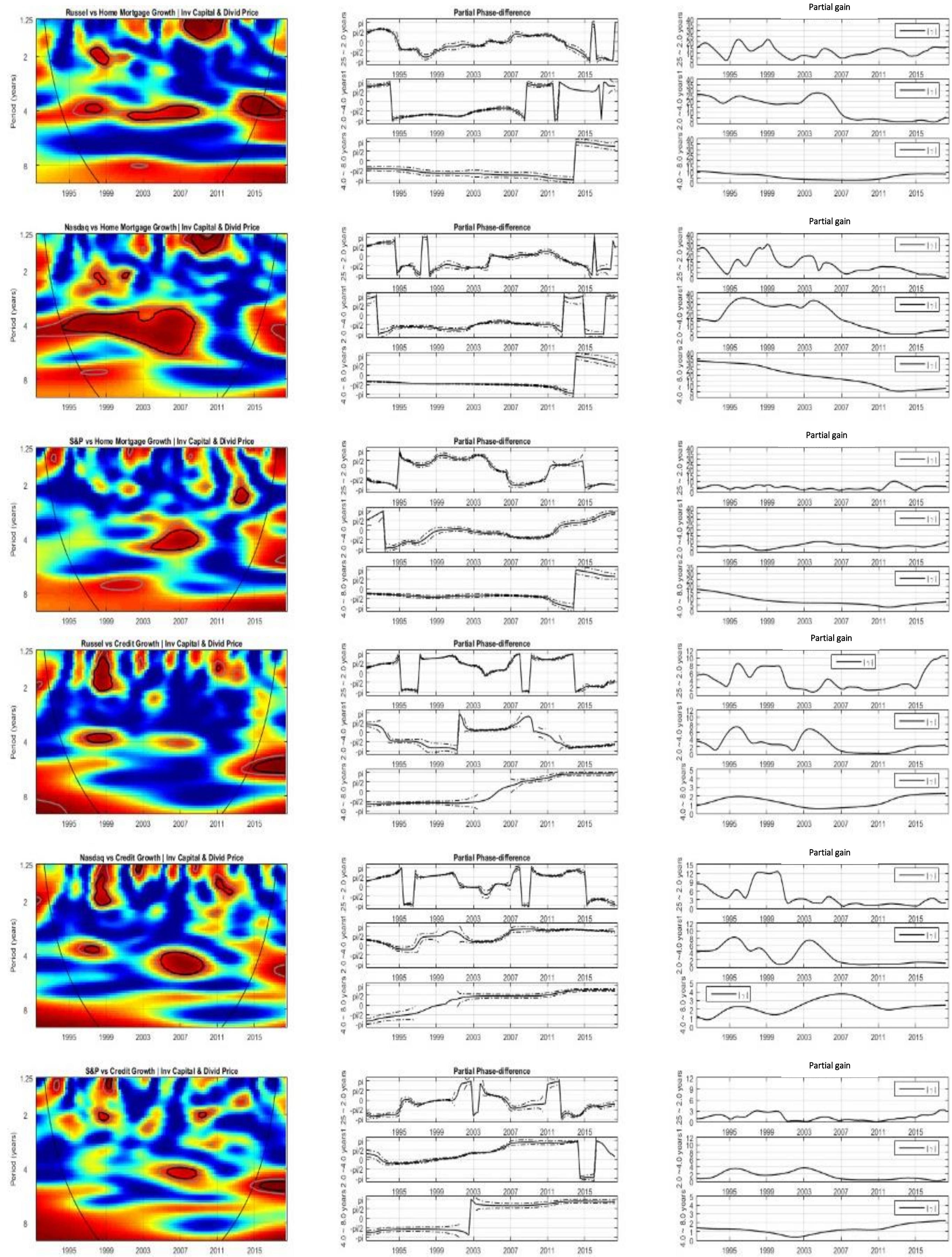

Fig. 1. Credit and financial system in U.S.: partial wavelet coherency (left), phase-difference (center) and regression estimation (right).

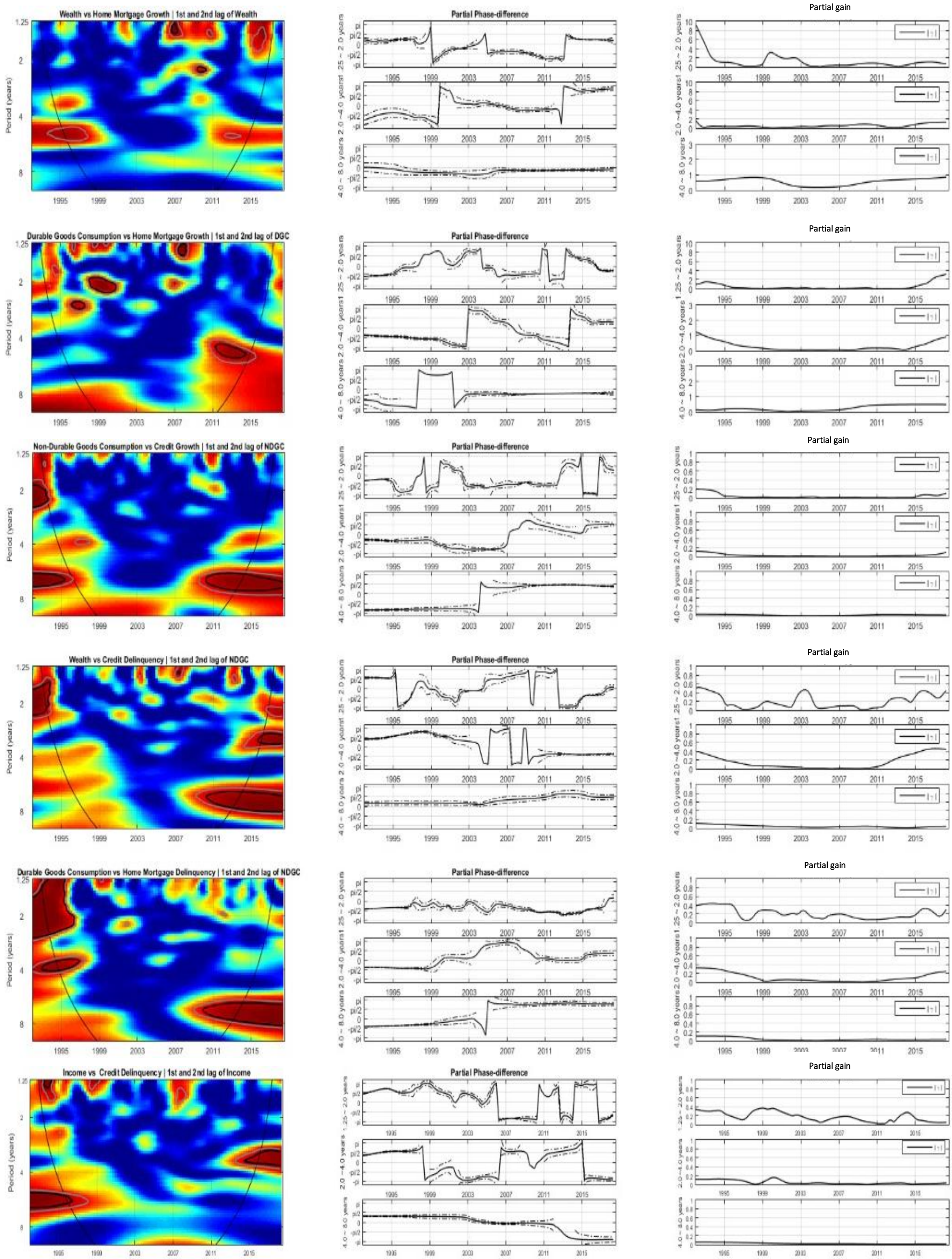

Fig. 2. Credit and development in U.S.: partial wavelet coherency (left), phase-difference (center) and regression estimation (right).

With regards the statistical inference, we follow Aguiar-Conraria and Soares (2018), by relying on Monte Carlo (5000 simulations), since the available tests impose too stringent restrictions to deal with economic data.

The partial wavelet coherencies are plotted as 2-dimensional heat-maps. The colors range from blue (indicating low power/small coherency) to red (high power/high coherency). The cone of influence is shown with a black line at 5% of significance level. In the partial phase-difference and gain diagrams, we display mean values corresponding to three frequency intervals, namely for cycles of period 1.25~2 years (short end of credit cycles), cycles of period 2~4 years (intermediate term fluctuations) and cycles of period 4~8 years (long run relationships). The limits of the confidence intervals are indicated in the pictures with black dashed-lines.

According to Fig. 1, we find isolated regions at short-run frequency with high synchronization between mortgage versus Russell or Nasdaq between 2007 and 2011, while these same indices seem to react to loan growth during the period of 1997 and 1999. The coherency seems to be stronger (significant warm color region) at intermediate to low frequencies (around 4-year cycles) between 1991 and 2008 and after 2014, mainly for home mortgage growth and Nasdaq and even Russell index. The significant causality of home mortgage in S&P 500, as well as the impact of loan growth in this same intermediate frequency are more punctual from 2004 to 2009. To summarize, the partial coherencies between loan or mortgage growth and each of the indices are comparable. Possibly, the main difference is in the temporal extent of these highly coherent regions, which are shorter when the credit variable is consumer loan growth. We must analyze the partial phase-difference and partial gains for the time/frequency locations characterized by these significant coherencies.

Moreover, it is interesting to see the diagrams during the NBER U.S. recessions. In early 1991, in general we find co-movements in-phase at shot-run frequency between financial indices and credit variables, with home mortgage cycles leading S&P 500 cycles while consumer loan cycles are lagging all financial cycles. In the crisis during almost the whole of 2001, both Nasdaq and Russell intermediate-run cycles move out-phase with home mortgage cycles, and both financial cycles are leading the credit cycle. Nasdaq is also moving in-phase and leading consumer loan cycles in the short-run, after 2001. Finally, from December 2007 to June 2009, the world has seen one of the most serious crises in history, during which, home mortgage cycles are lagging financial cycles. Taking into account for the lowest frequency, the diagrams report positive co-movement between Russell and Nasdaq, while the 4-year cycles are out-phase between home mortgage and Russell. On the other hand, we find negative co-movement between Nasdaq or S&P 500 and consumer loan, with the leadership of the cycles of this kind of credit.

Observing partial gains with high-frequency bands of financial indices, mainly for Russell and Nasdaq, there is a strong volatility in the coefficient value, associated with both consumer loan and home mortgage. When we observe the cycles of period 2~4 years, except for the partial gain of S&P 500 over home mortgage, there is a change in the pattern of the reactions of each financial index cycle to the respective credit cycles. The parameters are very volatile and assume high values before 2007, and from there, they become stable and assume a lower value, precisely in the last NBER U.S. recession. The long-run relationship characterized by the partial gains suggest a smooth role of both credit cycles in financial cycles, except for the impact of consumer loan on Nasdaq.

Regarding the analysis of the relationship between credit and development (Fig. 2), except for expenditure on services, all other macroeconomic variables had cycles with strong coherence with any of the credit variables. Home mortgage cycles are capable to lead wealth cycles, in-phase in the 1990s in the long term and out-phase in 2012 in the short term. In both cases, the partial gain is low and ranges between 0 and 2, over time. An innovative result is the high frequency out-phase cycles between loan delinquency and wealth in the 1990s, with the average impact of this type of default being 0.4, with a decreasing trend over the period.

An analysis of the behavior of durable goods shows an undocumented dependence on home mortgage growth and delinquency. Durable goods cycles are lagging the respective credit cycles at all times and frequencies. More specifically, in the short term, at the height of the crisis in 2007, there are positive co-movements with approximately zero partial gain, while in the long term between 2011 and 2015, the reaction of durable goods in-phase cycles is stable around 0.5. It is noteworthy that mortgage default cycles are in-phase in the short term between 1991 and 1997, with a partial gain of 0.4 to 1996, while in the long term, these cycles are out-phase in relation to durable goods cycles from 2010, with seemingly null partial gain. Still according to Fig. 2, the cycles of period 4~8 years of non-durable lead loan growth cycles during the period 1991 to 1995 and from 2011, with null partial gain and phase shift. Finally, the income cycles in U.S. seem to be in-phase in the long run between 1991 and 1996 and out-phase after 2015 in the medium term, relative to loan delinquency cycles. The partial gain is different from zero only in the long run, assuming the value of 0.1.

4. Conclusion

We revisit the discussion on the pass-through between credit and assets addressed by Bordo and Jeanne (2002) and the debate about frequency-varying co-movements between credit and macro-finance variables promoted by Chen et al. (2012). We address the dynamic conditional co-movement between macro-finance variables and household decisions in terms of credit, home mortgage and its delinquency rates. Our wavelet-based exercise offers insights on U.S. stock market return prediction and asset pricing puzzles.

In line with Borio (2012), our findings on the heterogeneity of the co-movements between credit market and macro-finance in terms of the coherency, lead-lag and partial gains are useful to draw public policies to safeguard financial stability and to analyze financial crises drivers, considering that oscillations at different frequencies may have different impacts on growth and social welfare. The simultaneous variation of coefficients along time and frequencies allows for detecting new stylized facts about the last three decades of U.S. financial system and development. This period is particularly notable given the local and world crises with different fundamentals.

References

Aguiar-Conraria, L., Martins, M, Soares, M., 2018. Estimating the Taylor rule in the time-frequency domain. **Journal of Macroeconomics** 57, 122–137.

Bordo, M., Jeanne, O., 2002. Boom-busts in asset prices, economic instability, and monetary policy. **NBER Working Papers** 8966.

Borio, C., 2012. The financial cycles and macroeconomics: what have we learnt? **BIS Working Papers** N. 395.

Chen, X., Kontonikas, A., Montagnoli, A., 2012. Asset prices, credit and the business cycle. **Economics Letters** 117, 857–861.

Cochrane, J., 1996. A cross-sectional test of an investment-based asset pricing model. **Journal of Political Economy** 104, 572–621.

De Gregório, J. and Guidotti, P., 1995. Financial Development and Economic Growth. **World Development** 23 (3), 433–448.

Grossmann, A., Morlet, J., 1984. Decomposition of Hardy functions into square integrable wavelets of constant shape. **SIAM Journal on Mathematical Analysis** 15, 723–736.

Lin, F., Yang, S., Marsh, T., Chen, Y., 2018. Stock and bond return relations and stock market uncertainty: Evidence from wavelet analysis. **International Review of Economics and Finance** 55, 285–294.

Matos, P., 2019. The role of household debt and delinquency decisions in consumption-based asset pricing. **Annals of Finance** 15, 179–203.

Solow, R., 1956. A Contribution to the Theory of Economic Growth. **The Quarterly Journal of Economics** 70, 65–94.