Financial Cycles: Characterisation and Real-Time Measurement*

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1 Introduction

This document summarises the replication exercise based on Schüler et al. (2020). I recreate the authors' results based on the US data between 1970:Q1 and 2019:Q4, effectively expanding their sample by a year. Doing so, I succeed in recreating most of their results, with minor differences resulting from the discrepancies between the datasets at hand and the fact that the replication exercise concerns only one country.

Section 2 outlines the data used, with a particular focus on the measure of hours worked based on Raffo and Ohanian (2012). In Section 3, I analyse the cross-spectral densities of the chosen financial and business variables, which provide a foundation for Schüler et al. (2020)'s power cohesion measure introduced in Sub-Section 3.2. This allows me to validate the authors' calculations of the cycles' durations. Then, I study the financial cycle over time in Section 4. Finally, throughout Section 5, I augment the authors' exercise of using the synthetic measure to design warning indicators of a systemic banking crisis. Given that I seek to use this document in my further exploration of financial cycles, I also discuss the key topics adjacent to this study in Appendices A, B, and C. Appendix D features selected original figures and tables from Schüler et al. (2020).

2 Data

With the sensitivity of business and financial cycles measures to the data chosen, I seek to mimic the quarterly dataset for the United States used by Schüler et al. (2020). The exercise's main innovation is expanding the study's span to cover 1970:Q1 through 2019:Q4.

First, I collect the financial cycles data. Total credit is obtained from the BIS database, covering the total loans and debt securities provided to the private non-financial sector. House prices are compiled from the same source. I use the OECD directory to get equity prices and CPI. Moody's AAA corporate bond yields are taken from FRED. All measures are reflected in real terms and seasonally adjusted (X-12).

Second, I gather the data related to business cycles. Schüler et al. (2020) expand the dataset of Raffo and Ohanian (2012). I follow their lead by acquiring the real GDP, real private consumption, and real gross fixed capital formation from the OECD directory, all at the quarterly frequency. Raffo and Ohanian (2012) also design their own quarterly hours worked variable, which is no longer available to the public. To obtain the metric, I follow their technique of deriving the series, as outlined in Section 2.1.

*Schuler, Y. S., Hiebert, P. P., and Peltonen, T. A. (2020). Financial Cycles: Characterisation and Real-Time Measurement. *Journal of International Money and Finance*, 100(1).

2.1 Hours Worked Variable Based on Raffo and Ohanian (2012)

I comply with Raffo and Ohanian (2012)'s method of estimating the average quarterly hours worked per worker in the United States. First, I collect the *Bureau of Labor Statistics*' average weekly hours worked per worker for 1970:1 through 2019:12, adjusting it so that the data reflect the total quarterly hours per worker. Then, mimicking the paper's approach, I follow Denton (1971) by tailoring the series with the following programme;

$$\begin{aligned} \min_{x} \quad & \left\{(x-z)^T A(x-z)\right\} \\ \text{s.t} \quad & \sum x = y \end{aligned} \tag{1}$$

y is the annual estimate of hours worked per worker in the *Total Economy Database*. This allows for developing a series that is comparable across countries (Raffo and Ohanian, 2012). z represents the quarterly BLS series, and A is the weighting matrix: $A = \Sigma \frac{1}{z}(\Delta(x-z)^2)$, which is based on the proportional first difference between the two series. Doing so, I obtain the adjusted quarterly hours worked series.

Then, I compare my results with those obtained from Schuller for 1970:Q1 through 2013:Q4.[1] My output consistently overestimates the series, by 6.4 per cent on average in each quarter. With Raffo and Ohanian (2012) employing the BLS data for the period 1960:Q1 through 2013:Q4, which are not available to the public, the differences between hours worked in the missing periods spanned are likely to be the cause of the consistent discrepancy. Nonetheless, given that Schüler et al. (2020) use the growth rates of all of the variables, the discrepancy is likely to have a minimal impact on the replication's outcome. For further discussion, see Appendix A.

3 Financial Cycle Frequencies

Schüler et al. (2020) depart from the popular methods of analysing cycles. Unlike in the Basel III's methodology or Harding and Pagan (2005), they use the growth rates of the variables. Doing so, they ensure stationarity of the observations, which is necessary for applying spectral analysis. I follow their lead.

In Section 3.1, I reproduce the absolute cross-spectral plots for the financial and business variables, carefully analysing the amplitude and duration of the cycles. I also compare and contrast my findings with those of Schüler et al. (2020) and other relevant literature.

3.1 Cross-Spectral Densities - the Building Block of Power Cohesion

Like Schüler et al. (2020), I investigate the absolute cross-spectral densities of the chosen financial and business variables. I also reach similar conclusions.

I begin by constructing the normalised cross-spectral densities:

$$f_{x_i x_j}(\omega) = \frac{1}{2\pi} \sum_{k=-\infty}^{\infty} \left\{ \frac{\operatorname{Cov}(x_{i,t}, x_{j,t})}{\sigma_{x_i}\sigma_{x_j}} \exp(-ik\omega) \right\} = \frac{S_{x_i x_j}(\omega)}{\sigma_{x_i}\sigma_{x_j}}, \tag{2}$$

where $\{x_{i,t}\}$ and $\{x_{j,t}\}$ are the two series and σ_{x_i} and σ_{x_j} represent their standard deviations. I also derive

[1] This is the most recent Raffo and Ohanian (2012) dataset that the author could find and send to me. I am grateful for his assistance.

the absolute cross-spectral densities, $S_{x_i x_j}(\omega)$. Studying the latter allows for analysing whether different pairs of indicators share not only duration, but also amplitude of common fluctuations between the cycles. Figure 1 plots the absolute cross spectra for the financial and business cycle variables. Schüler et al. (2020)'s graph is attached on Figure 10 in Appendix D.

Comparing Figures 1a and 1b, one immediately sees that the financial cycles are more volatile than their business counterparts. For example, the absolute cross spectral density of the housing and equity prices ($\Delta p_h/\Delta p_e$) reaches the peak of 10. Meanwhile, the GDP-investment duo ($\Delta q/\Delta i$) sees the highest peak of a little over 1.6. In what provides a marginal departure from Schüler et al. (2020)'s result, only the "least moving" plots for the financial indicators, the total credit-bond prices pair ($\Delta cr/\Delta p_b$) observe a similar rate of volatility as the most shifting pair for the business cycle variables. I also note that the second peak of the consumption-investment ($\Delta co/\Delta i$) cross spectral density, located at about 6-years frequency, is characterised with a lower amplitude than its counterpart from the original study.[2]

The picture of the indicators' duration is similar to that of Schüler et al. (2020). That is, the financial variables have similar levels of cyclical covariance at the medium-term frequencies. For example, the credit-housing prices ($\Delta cr/\Delta p_h$), equity prices-housing prices ($\Delta p_e/\Delta p_h$), and housing prices-bond prices ($\Delta p_h/\Delta p_b$) pairs have their peaks in the window between 8 and 20 years. That the most significant common cycles for the financial data are at the medium-term frequencies also echoes the seminal results of Borio et al. (2012) who point out similar interdependencies using a different dataset and methodology. At the same time, the business cycle covariates see more co-movement at the short-term frequencies. One can observe that especially the GDP-investment ($\Delta q/\Delta i$), consumption-investment ($\Delta co/\Delta i$), and investment-hours worked ($\Delta i/\Delta h$) display comparable durations in the 2-8 window of frequencies.

Having concluded that my absolute cross-spectra are in line with the findings of Schüler et al. (2020), I proceed towards investigating financial cycles. Given the obtained evidence, as well as the referenced studies (Schüler et al., 2020; Borio et al., 2012), I expect the financial and business cycles to have most mass located at the the medium and short-term frequencies respectively.

3.2 Financial Cycle Frequencies

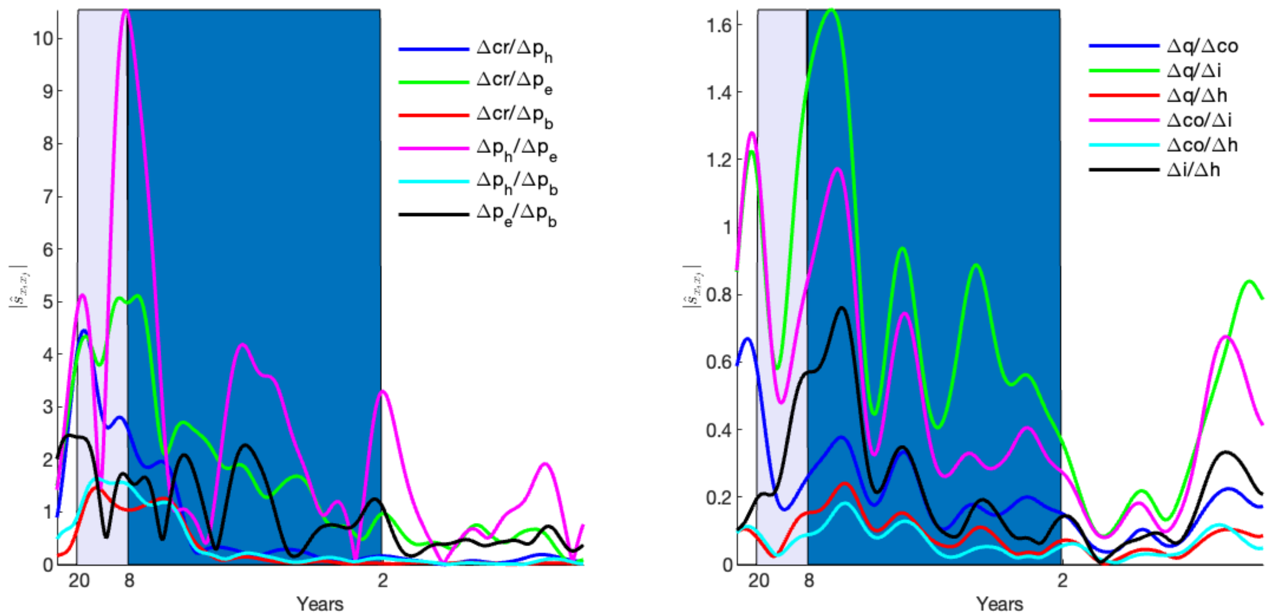
Schüler et al. (2020) identify the financial cycle frequencies with the so-called *power cohesion* (PCoh). The multivariate measure evaluates the contribution of different cycle durations to the total covariance between the chosen variables. Using it, one can capture the shared cycle frequency for the analysed set.

I start by constructing the PCoh. For $X = (x_1, ..., x_M)$, with $M \geq 2$, it is defined by:

$$\mathrm{PCoh}_X(\omega) = \frac{1}{M(M-1)} \sum_{i \neq j} \left| f_{x_i x_j}(\omega) \right|, \tag{3}$$

where $f_{x_i x_j}(\omega)$ comes from Equation (2). I distinguish between the narrow and broad financial cycles. The former captures the co-movements in the credit and housing prices. The latter encompasses all of the financial variables studied.

[2] This minor difference significantly impacts the maximum length of the business cycle frequency in Table 1. That is, the power cohesion measure picks up the 40-year frequency as the dominant element for the $\Delta co/\Delta i$ pair, despite the fact that the difference between the two largest amplitudes is minimal.



(a) Financial Cycle

(b) Business Cycle

Figure 1: Absolute Cross Spectra for the United States: Replication (Original Plots Can Be Found in Appendix D, Figure 10).

Figure 2 presents the plots for the three types of cycles. First, I note that the business cycle pattern is similar to that of Schüler et al. (2020). Namely, the peak is located at about 6 years. The only difference to the original study is that my plot exhibits less smoothness at the frequencies above 8 years. For example, the original version does not show a trough at about 16 years. On the other hand, both narrow and broad financial cycle measures display almost an identical pattern to that of Schüler et al. (2020). Like in their case, I observe that the broad and narrow definitions of financial cycles envelop the medium-term frequencies. Especially in the latter case, most of the mass is centred at around 16 years.

In Table 1, I confirm the results above by calculating the duration of the most important cycle, as well as the minimum and maximum cycle lengths. While slightly underestimating the maximum narrow and broad financial cycle frequencies, I match Schüler et al. (2020) in the values representing the peaks of the two types of financial cycles, as well as the business cycle. The main difference remains the maximum business cycle frequency (marked with †) which significantly exceeds the original finding. A closer inspection of Figures 1b and 2 leads me to conclude that this anomaly is caused by the co-movement of the consumption-investment ($\Delta co/\Delta i$) and consumption-GDP ($\Delta q/\Delta co$) pairs at the lowest frequencies.

4 Financial Cycles Across Time

Done with analysing the cyclical properties of pairs of variables, I emulate Schüler et al. (2020) in identifying financial and business cycles with the so-called power cohesion. In this section, I outline the steps taken to derive the synthetic measure and provide a brief analysis of my results.

Seeking to follow Schüler et al. (2020) as closely as possible, I standardise the variables by creating arrays

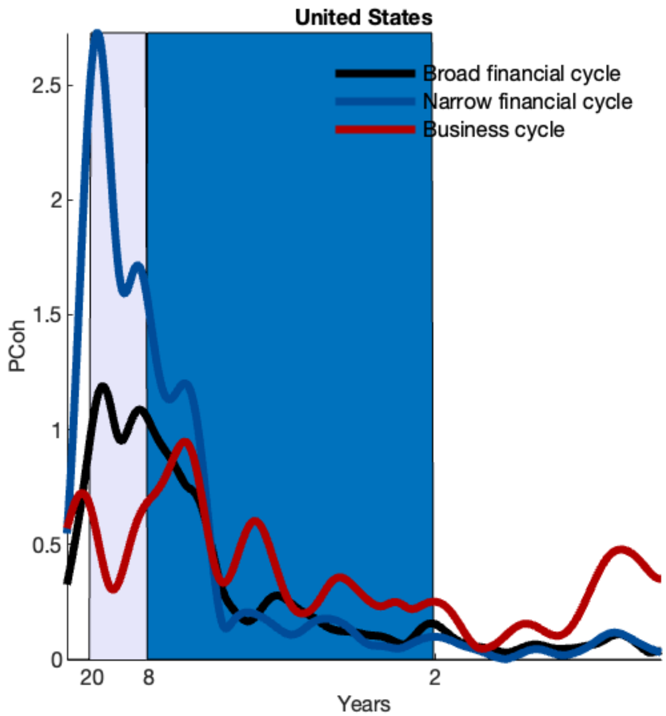
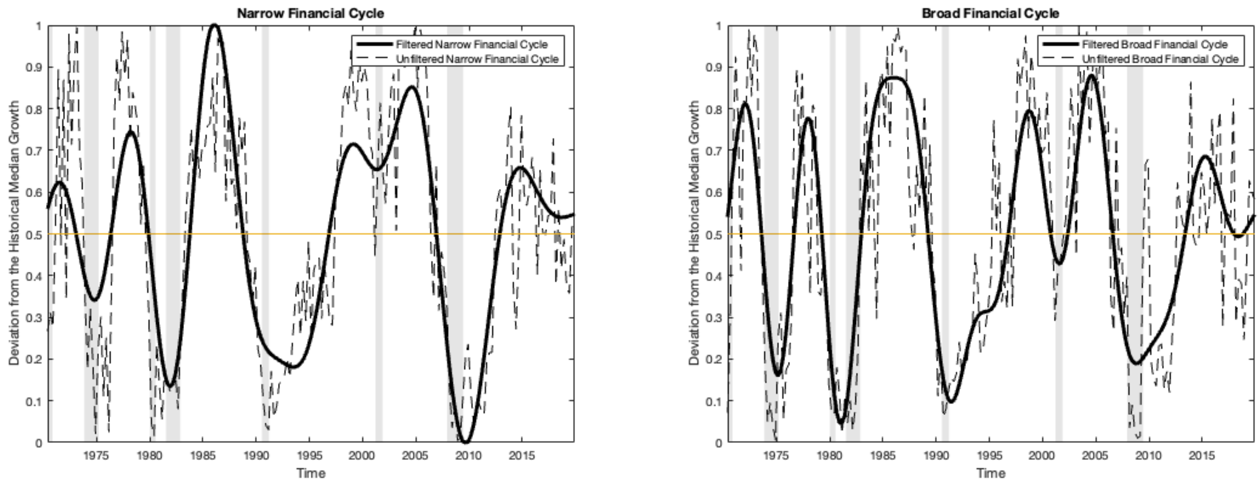


Figure 2: Power Cohesion, as Defined by Equation (3), for the United States (Original Plots Can Be Found in Appendix D, Figure 11).

	Narrow Financial Cycle			**Broad Financial Cycle**			**Business Cycle**		
Measure	Max.	Peak	Min.	Max.	Peak	Min .	Max.	Peak	Min
Schüler et al. (2020)'s Results (1970Q1-2018Q4)									
Years	28.1	16.9	7.1	33.6	15.0	4.9	15.4	5.7	2.6
Replication (1970Q1-2019Q4)									
Years	26.6	16.9	5.9	26.7	15.0	4.7	45.6†	5.7	2.5

Table 1: The Peak, Maximum, and Minimum Cycle Lengths as Defined by the Power Cohesion in Equation (3) Compared with the Results of Schüler et al. (2020).



(a) Narrow Financial Cycle

(b) Broad Financial Cycle

Figure 3: Narrow and Broad Financial Cycles for the United States: Replication (Original Plot for the Broad Cycle Can Be Found in Appendix D, Figure 12).

of their empirical cumulative density functions:

$$y_{i,t} = \hat{F}_{i,T}\left(x_{i,t}\right) = \begin{cases} \frac{r}{T} & x_{i,[r]} \leq x_{i,t} < x_{i,[r+1]} \\ 1 & x_{i,t} \geq x_{i,[r+1]} \end{cases} \tag{4}$$

where $\left\{x_{i,[r]}\right\}_{r=1}^{T}$ is the ordered sample of variable $\left\{x_{i,t}\right\}_{t=1}^{T}$. Then, I linearly combine the standardised indicators in order to construct the synthetic cycle, ζ_t. Let Y_t be a vector of the standardised variables at time t: $Y_t \equiv (y_{1,t}, ..., y_{M,t})$. Then, the composite cycle indicator is derived from:

$$\zeta_t = \frac{1}{\iota^T C_t \iota} \iota^T C_t Y_t^T, \tag{5}$$

where ι is an $M \times 1$ vector of ones and C_t an $M \times M$ time-varying weighting matrix with each term defined by:

$$c_{ij,t} = \begin{cases} \frac{\sigma_{ij,t}}{\sqrt{\sigma_{ii,t}\sigma_{jj,t}}} & \sigma_{ij,t} \geq 0 \\ 0 & \sigma_{ij,t} < 0 \end{cases} \tag{6}$$

where $\sigma_{ij,t} \equiv \lambda\sigma_{ij,t-1} + (1-\lambda)(y_{i,t} - 0.5)(y_{j,t} - 0.5)$, with $\lambda = 0.89$ representing the so-called "decay factor" (Schüler et al., 2020). Note that the policy indicators based on the quarterly observations are characterised by a high degree of volatility due to the fact that growth rates are likely to "pick up" too many cycle durations. This is why the filtered (smoothened) cycle series are constructed with the use of Christiano and Fitzgerald (2003)'s bandpass filter. For each series, the bounds from Table 1 are applied.

Figures 3a and 3b depict the original and smoothened versions of narrow and broad financial cycles. My results are nearly identical to that of Schüler et al. (2020). Irrespective of the definition of the financial cycle employed, its duration is unchanged, with the peaks located around 1971, 1978, 1985, 1998, 2004, and 2015 in both cases. On the other hand, the narrow financial cycle displays lower amplitudes with the exception of the systemic banking crises starting 1988 and 2007, as defined by Laeven and Valencia (2012, 2018), and

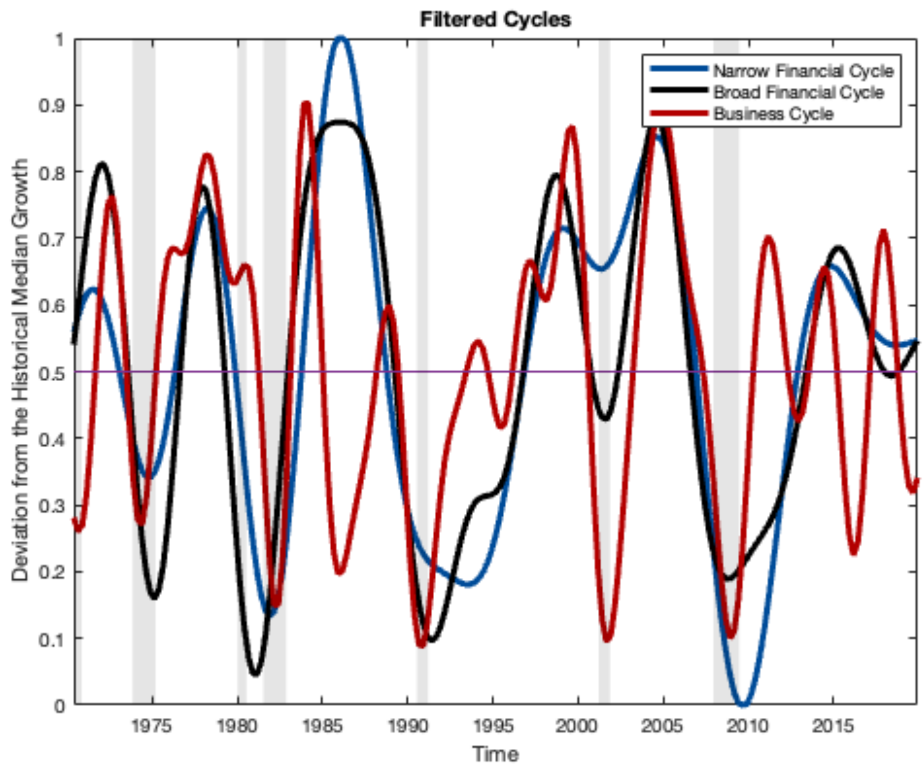


Figure 4: Financial & Business Cycles for the United States: Replication (Original Plot for the Broad Cycle Can Be Found in Appendix D, Figure 12).

the 2015 peak. This is likely to originate from different levels of volatility of the equity and bond prices as compared with the total credit and house prices, echoing Ng (2011) who observes different predictive behaviour of the financial cycle measures.[3] Further, the plots of both types of definitions of financial cycle indicators are exactly in the middle of the transition between their peaks and troughs in 1988 and 2007. Both dates are associated with the onsets of systemic banking crises in the US (Laeven and Valencia, 2012, 2018). This lends further credibility to the composite cycle measures applied in this section.

Figure 4 allows one to compare the business cycles with its financial counterparts. As previously shown, the relationship resembles that of Schüler et al. (2020)'s study. First, notice the different durations of the financial and business cycles. In what validates the evidence in Table 1, the business cycles have $5-6$ year-long durations. At the same time, irrespective of the measure used, the financial cycles are less monotonous. While the PCoh-based results indicate the duration to stand at around $15-16$ years, the findings are clearly a weighted average of what one observes on Figure 4. Before the end of the 1980s, the financial cycles coincide roughly with their business counterpart. Later, however, the cycle duration expands. This is in line with Borio et al. (2012) who posit that the average length of a financial cycle is 16 years. The observation about the "early days" overlap between both types of cycles resembles the argument of Hiebert et al. (2018). They point out that business and financial cycles coincide only $\frac{2}{3}$ of times (albeit, they base

[3] I further compare variability of all of the financial variables used in Appendix B. I conclude that the differences in variability of the housing and equity prices before 2000 allows one to understand the distinct amplitudes of the narrow and broad financial cycle measures. This reasoning is congruent with Breitung and Eickmeier (2014); Rey (2015), who also stress the importance of the housing prices in defining the financial cycle.

it on the study of the EU member states).

Confident that my results match those of Schüler et al. (2020), I proceed to investigating whether the results can be used by policymakers as an early warning indicator of systemic banking crises.

5 Coincident and Early Warning Indicators of Systemic Banking Crises

5.1 Econometric Methodology

I augment Schüler et al. (2020)'s approach of validating the financial cycle measure. That is, I conduct a similar signalling exercise in which I test whether the synthetic cycle index performs better than the underlying indicators as a coincident or an early warning indicator of the systemic banking crises. Using the Laeven and Valencia (2012, 2018)'s database of such events, I set the first quarter of 1988 and the third quarter of 2007 as the milestones indicating the onsets of crises.

While the authors employ a pooled logit model to the data of 7 countries in the sample to calculate the predicted probabilities of a systemic banking crisis, I use a similar approach only for the United States. In what follows, I estimate multiple versions of:

$$\tilde{\pi}_t = \mathbf{\Lambda}^{-1}\left(\phi_\star + \sum_{k=1}^{K} \tilde{X}_{t-k}^T \phi_k\right), \tag{7}$$

where $\tilde{\pi}_t \equiv \mathbb{P}(Y_t = 1|\mathcal{F}_{t-1})$ represents the probability of a systemic banking crisis taking place at t given the information contained at time $t-1$, $\mathcal{F}_{t-1}$. $\mathbf{\Lambda}^{-1}(\cdot)$ represents the inverse of the log of the odds ratio: $\mathbf{\Lambda}(x) = \frac{\mathbb{P}(x)}{1-\mathbb{P}(x)}$. $\tilde{X}_{t-k}$ is a chosen $M \times 1$ vector of predictors at $t-k$. $\phi_\star$ and ϕ_k are parameters. Unlike Schüler et al. (2020) who allow for the maximum of 6 lags, varying them based on the area under the curve measure, I stick to using only one lag due to a much smaller sample size.[4] Table 2 outlines the explanatory variables used and summary statistics collected.[5] I also add a column indicating what dummies are investigated in my regressions. I split the study into three sections, which allows me to gauge the measure's predictive power at the onset of a systematic banking crisis, as well as its usefulness as an "early warning indicator."

Following Schüler et al. (2020), I depart from the filtering method applied in Section 4 (which leads to the results plotted on Figures 3a, 3b, and 4). Instead of using Christiano and Fitzgerald (2003)'s bandpass approach, I compile the filtered synthetic cycle indicator based on a one-sided Bartlett window with weights: 1 for ζ_t, $\frac{5}{6}$ for ζ_{t-1}, $\frac{4}{6}$ for ζ_{t-2}, $\frac{3}{6}$ for ζ_{t-3}, $\frac{2}{6}$ for ζ_{t-4}, and $\frac{1}{6}$ for ζ_{t-5} (normalised so that they add up to 1). Doing so, I give the highest weight to the most recent observations and avoid the end-point bias of the bandpass filter. The results can be seen on Figure 5. When it comes to both measures of financial cycles, they match those of Schüler et al. (2020). The business cycle composite cycle real time measure, however, sees slightly lower amplitudes before 1990, which is most likely caused by the marginal discrepancy between the hours worked variable I construct and that of Raffo and Ohanian (2012).

[4] Given that I collect only the US data, I work with 80 observations, whilst the authors operate the same data, but for 7 countries, which allows them to identify more parameters of lagged variables.

[5] Note that, unlike Schüler et al. (2020), I do not use Δcr & Δp_h, and Δcr, Δp_h, Δp_e, & Δp_b as explanatory variables due to the small number of observations in the sample. Using more than 2 explanatory variables with their lags and a constant leads to a failure of identification of the crucial coefficients.

Expl. Variables ($\tilde{X}_{t-k}$)	**Summary Statistics**	**Dummies** (Y_t)
Narrow financial cycle	True positive	Crisis onset
Broad financial cycle	False positive	$1-4$ quarters before crisis
Business cycle	True negative	$5-12$ quarters before crisis
Δcr	False negative	
	Type I error	
	Type II error	
	Noise-to-signal ratio	
	Area under the curve	
	Usefulness	

Table 2: Summary of Explanatory Variables, Summary Statistic, and Dummies Used in Estimating Various Versions of Equation (7). Summary Statistics Are Defined in Equations (8), (9), (10), (11), and (12) in Appendix C.

Importantly, seeking to avoid the "post-crisis" bias while deriving the early warning indicators, I follow Anundsen et al. (2016) in removing the onset of the crisis as well as 6 quarters thereafter from the samples used in the vulnerability-centred samples (where Y_t is a $1-4$ or $5-12$ quarters before crisis dummy).

5.2 Out-of-Sample Experiment Results

Equipped with this methodology, I follow Schüler et al. (2020) in conducting an out-of-sample experiment. I estimate the logit model for 1980Q1-1999:Q4, with the 1970s data used as a training sample for the algorithm from Section 4. Then, I use my results to calculate the fitted probabilities for 2000:Q1-2019:Q4. Analysing the summary statistics, I keep in mind that the authors stress that the strongest point of their specification is aggregation. That is, with a very few systemic banking crises happening among G7 countries, let alone the US, only thanks to pooling observations from multiple interconnected economies can one make meaningful inferences. As a result, I approach the following results with caution.

In what constitutes an expansion of the original study, I plot the fitted probabilities obtained in the exercise and present them in Appendix C.[6] My analysis indicates that the synthetic financial cycle measures can serve as insightful early warning indications of an incoming systemic banking crisis. What's more, the so-called coincident measure based on the broad financial cycle appears to be the most reliable indicator, which is in line with the authors' argument.

Then, in Table 3, I present the summary results. For the calculation of statistics, I use the threshold value of 0.3 to make the results across variables more comparable.[7] The picture is mixed, mostly due to the small sample size and using the period with only one systemic banking crisis in calculating the fitted values. In all variations of the experiment, true negatives prevail. Interestingly, unlike in Schüler et al. (2020), the coincident indicator appears to have little predictive power compared to the $5-12$ quarters-ahead warning. This likely indicates that its power in the original study is brought by the financial cycle measures of other economies, which provides an interesting study extension idea. The early warning indicator for

[6]This allows me to compare and contrast predictions made with the use Schüler et al. (2020)'s variables as compared with the standard predictors.

[7]Schüler et al. (2020) use a threshold value that minimises the sum of probabilities of both types of errors. I decide against applying this method as, in certain cases, it leads to the choice of excessively low threshold values. I pick the threshold value based on the discussion in Appendix C.

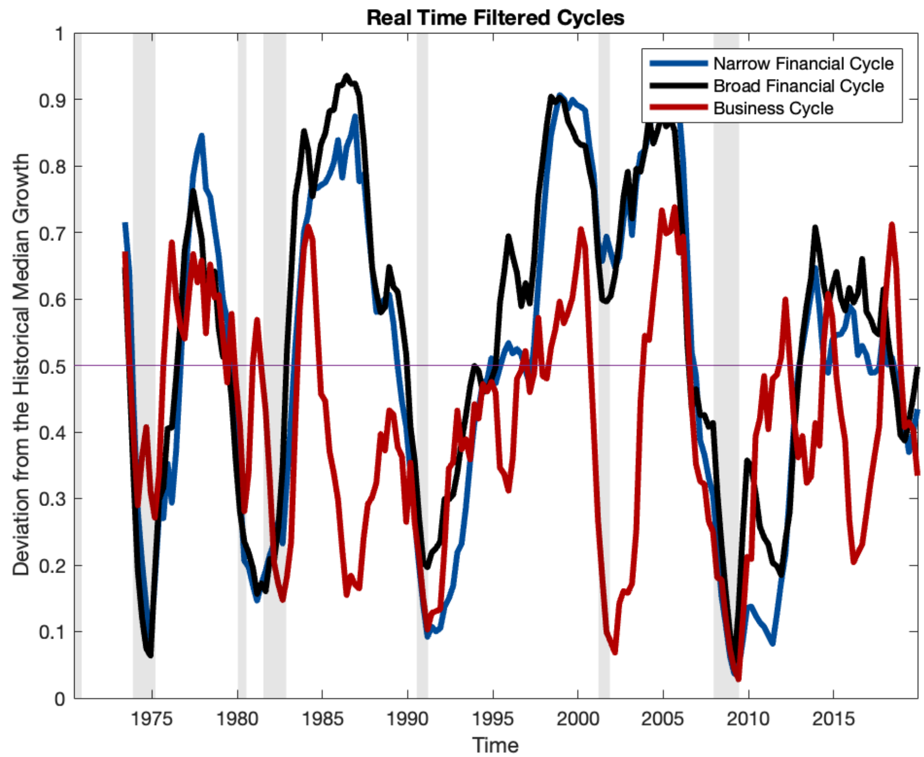


Figure 5: Real Time Composite Cycles for the United States: Replication (Original Plot for the Real Time Composite Cycles Can Be Found in Appendix D, Figure 13)

$1-4$ quarters ahead of the crisis does even more poorly, achieving more false positives than the coincident approach. Finally, the "very" early warning experiment, creating a $5-12$ quarters-ahead warning, achieves the best results, which is exactly opposite to the results based on the G7 sample.

The discrepancy between the results based on the US alone and those derived from the G7 data speaks volumes. In what echoes the argument about the global financial cycle of Miranda-Agrippino and Rey (2021), I conclude that predicting a systemic banking crisis based on the observations of one country alone, even if it is the US, is likely to have less predictive power than applying the data of multiple major economies.

6 Concluding Remarks

Replicating the study allows one to see the merits of using spectral densities and the measures based on them in analysing financial cycles. In Section 3, adopting an expanded dataset, I analyse the cross-spectral densities for the leading financial and business variables in the US. In doing so, I succeed in replicating Schüler et al. (2020)'s results and understanding the inner mechanics of the power cohesion measure introduced in Section 4. There, I compare and contrast different versions of the derived variable to those of the authors. Despite using my own extended dataset, I match their results, which again lends credibility to the study. Finally, Section 5 gives me the taste of applying the synthetic measure in real-time policy analysis, highlighting the limitations of relying on one country's data alone in analysing financial cycles in the ever-more integrated world.

	Out-of-Sample									
Indicators	Obs.	K	TP	FP	TN	FN	TI	TII	U^r	NtS	AUC
Panel A: At Start of Crisis											
Narrow fin. cycle	79	1	0	1	77	1	1	0.013	-1.03	0.013	0
Broad fin. cycle	79	1	0	0	78	1	1	0	-1	0	0
Business cycle	79	1	0	0	78	1	1	0	-1	0	0
Δcr	79	1	0	0	78	1	1	0	-1	0	0
Panel B: Early Warning (1-4 Quarters)											
Narrow fin. cycle	79	1	0	0	75	4	1	0	-1	0	NaN
Broad fin. cycle	79	1	0	2	73	4	1	0.027	-1.05	0.027	0
Business cycle	79	1	0	0	75	4	1	0	-1	0	NaN
Δcr	79	1	0	0	75	4	1	0	-1	0	NaN
Panel C: Early Warning (5-12 Quarters)											
Narrow fin. cycle	79	1	5	6	65	3	0.38	0.085	0.081	0.23	0.45
Broad fin. cycle	79	1	1	1	70	7	0.88	0.014	-0.78	0.016	0.50
Business cycle	79	1	0	11	60	8	1	0.15	-1.31	0.15	0
Δcr	79	1	0	0	71	8	1	0	-1	0	NaN

Table 3: Signalling Exercise: Coincident & Early Warning: Augmented Replication. For the Original See Table 2 in Schüler et al. (2020).

The work on replicating Schüler et al. (2020) has given me ideas of further research of financial and business cycles. For example, I am interested in using the power cohesion measure in investigating the convergence of the Eurozone with the Eastern European EU member states that are on the verge of adopting the Euro as their currency.

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A Hours Worked - Further Discussion

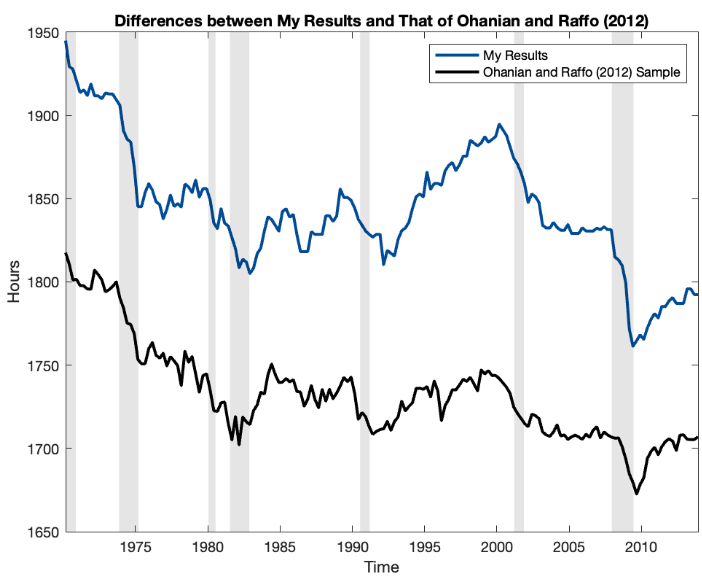


Figure 6: Quarterly Values of the Measure of Annual Hours Worked Based on Raffo and Ohanian (2012).

Figure 6 presents my estimate of annual hours worked based on Raffo and Ohanian (2012)'s methodology compared with their original sample between 1970 and 2013, kindly provided to me by Schüller. I note that there exists a persistent difference of about $5-6$ per cent of the original value between both series. Having experimented with the algorithm used to derive them, I conclude that there might be 2 reasons behind the discrepancy.

First, the gap is likely to originate from the BLS datasets used. Raffo and Ohanian (2012) have access to a longer BLS series, spanning the 1960s. My publicly-accessible version starts in 1970. Given that American workers tended to work slightly longer hours in the 1960s (for example, see the estimates from the *Total Economy Database*), the algorithm in Equation (1) is likely to underestimate the negative trend in hours worked for my sample, which in turn leads to the consistent overshooting pattern.

Second, there can exist an exogenous reason behind the discrepancy. This could relate to an adjustment of methodology at the BLS between 2013 and now, Raffo and Ohanian (2012) failing to mention one of the manipulations used to clean the data, a minor difference in the way of applying Denton (1971)'s algorithm, or another reason.

With Schüler et al. (2020) using growth rates of variables, I also check if there is a significant difference between the series' growth rates. I find that the mean difference between the growth rates of annual hours worked in both cases stands at 0.2 per cent.

B Volatility of Financial Variables

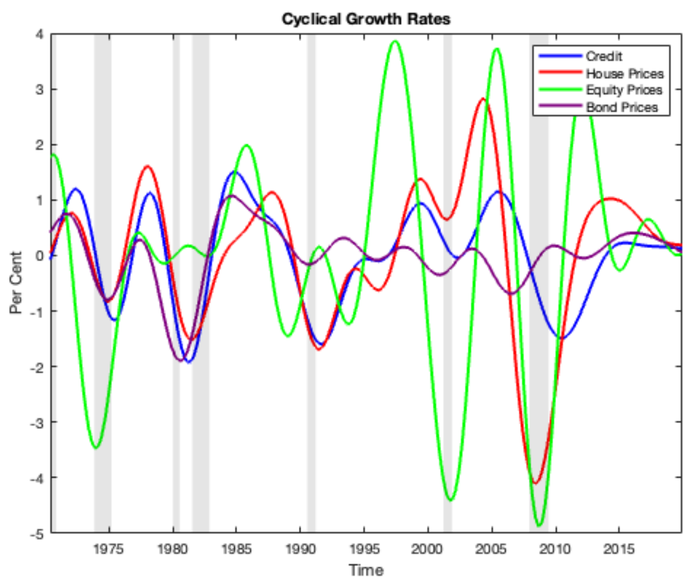


Figure 7: Cyclical Components of the Financial Variables; Detrended with Christiano and Fitzgerald (2003)'s Bandpass Filter Using Maximum & Minimum Frequencies from Table 1.

In Section 4, I discuss the differences between the composite cycle indicator for broad and narrow financial cycles. Referring to a similar analysis of Ng (2011), I note that the amplitude disparities between the narrow and broad financial cycles (see Figures 3a and 3b) likely originate from the distinct sensitivities of the variables used. Recall that the narrow financial cycle composes only of the total credit and housing prices. At the same time, the broad measure encompasses all of the financial measures.

The first impression of Figure 7 is that the narrow financial cycle's variables are characterised by lower volatility than their peers. The only exception remains the housing prices on the onset and during the systemic banking crises, as defined by Laeven and Valencia (2012, 2018). This is likely to be one of the explanations behind the discrepancy between the narrow and broad financial cycle measures seen on Figures 3a and 3b.

Analysing the growth rates' amplitudes on Figure 7, one can immediately notice that the equity prices are the series that varies most across the financial cycles only in three cases. That is, its deviations are the starkest in 1973 (negative), in the late 1990s during the run-up to the dot-com bubble (positive), in the late 2000s during the great financial crisis (negative), and around 2013 (positive). Note that, especially up to 2000, the equity prices see a higher growth rates than the housing prices. This is likely to be the second ingredient of the differences between what one see on Figures 3a and 3b. Namely, by feeding only into the broad financial cycle, the equity prices make its amplitudes higher than those of the narrow financial cycle outside the systemic crises before 2000.

This line of analysis is congruent with such studies as Breitung and Eickmeier (2014); Rey (2015). Both of them stress the importance of housing prices in propagation of the financial cycles, its global version in the latter case.

C Pseudo Out-of-Sample Exercise: Fitted Probabilities

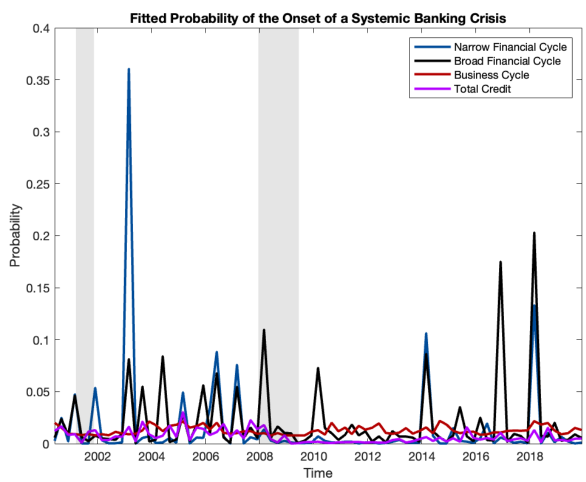
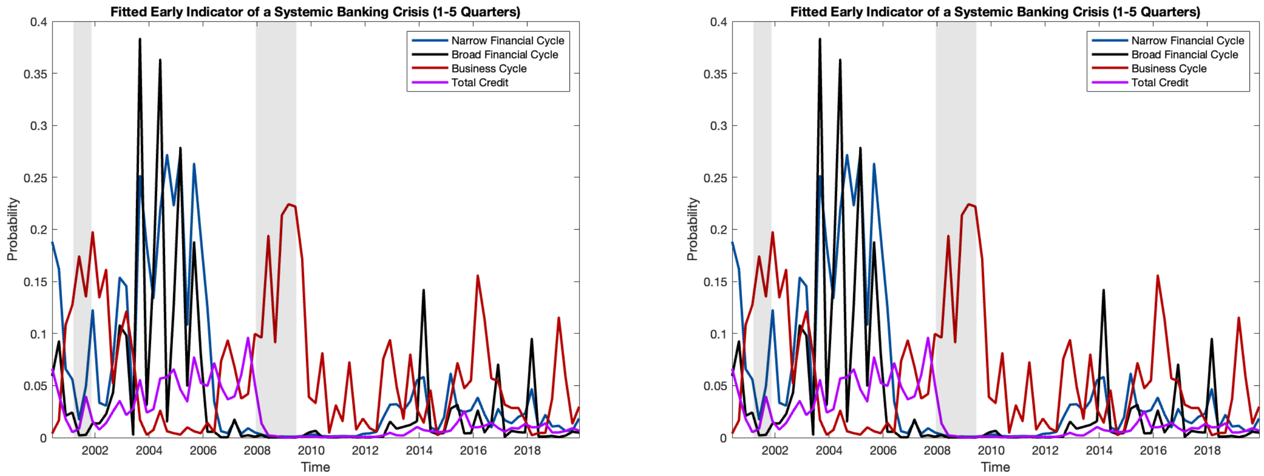


Figure 8: Fitted Probabilities of the Onset a Systemic Banking Crises Obtained with the Methodology from Section 5.



(a) Early Indicator (b) Very Early Indicator

Figure 9: Fitted Probabilities of Early and Very Early Indicators of a Systemic Banking Crises Obtained with the Methodology from Section 5.

Figures 8, 9a, and 9b present the fitted probabilities obtained in the pseudo out-of-sample exercise conducted in Section 5. Analysing the plots, I reach three conclusions: (1) the narrow and broad financial cycle measures of Schüler et al. (2020) can help in early detection of looming systemic banking crises; (2) they are more informative than the business cycle index or the total credit measure (which is popularly used to investigate financial cycles); and (3) my results are only remotely in line with the findings about G7 countries.

Below, you can find the expressions used to derive the statistics introduced and presented in Tables 2 and 3 respectively. Let FP $\equiv$ false positive, TP $\equiv$ true positive, TN $\equiv$ true negative, and FN $\equiv$ false negative.

$$\text{Type I Error} \equiv \frac{\text{FN}}{\text{FN} + \text{TP}} \tag{8}$$

$$\text{Type II Error} \equiv \frac{\text{FP}}{\text{FP} + \text{TN}} \tag{9}$$

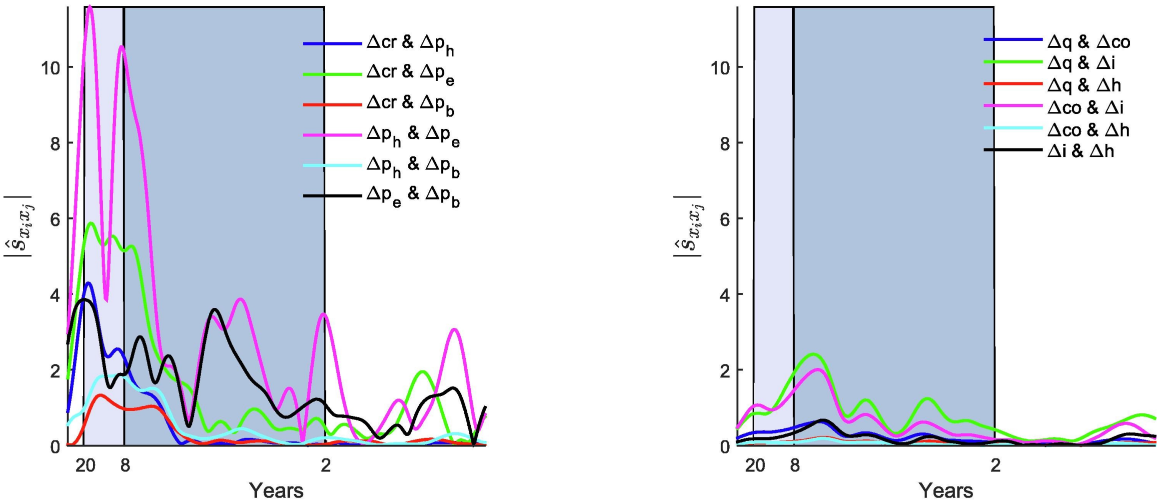
$$\text{Noise-to-Signal Ratio} \equiv \frac{\text{Type II Error}}{1 - \text{Type I Error}} \tag{10}$$

$$\text{Usefulness} \equiv \frac{0.5 - \text{Type I Error} - \text{Type II Error}}{0.5} \tag{11}$$

$$\text{AUC} \equiv \frac{\text{TP}}{\text{TP} + \text{FP}} \tag{12}$$

D Schüler et al. (2020)'s Original Figures

This section presents the original figures from Schüler et al. (2020)'s work.



(a) Financial cycle indicators **(b) Business cycle indicators**

Figure 10: Absolute Cross Spectra for the United States: Original (Schüler et al., 2020, Figure 1).

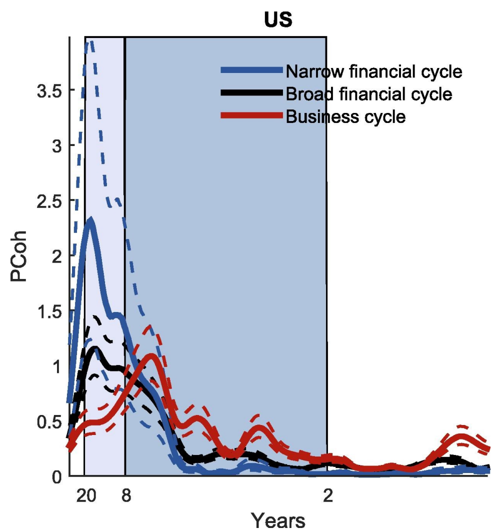
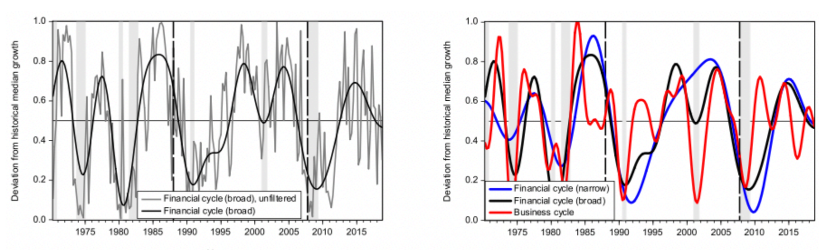


Figure 11: Power Cohesion for the United States: Original (Schüler et al., 2020, Figure 2).



(a) Filtered and unfiltered financial cycle, broad (b) Filtered composite cycle indices

Figure 12: Power Cohesion for the United States: Original (Schüler et al., 2020, Figure 5).

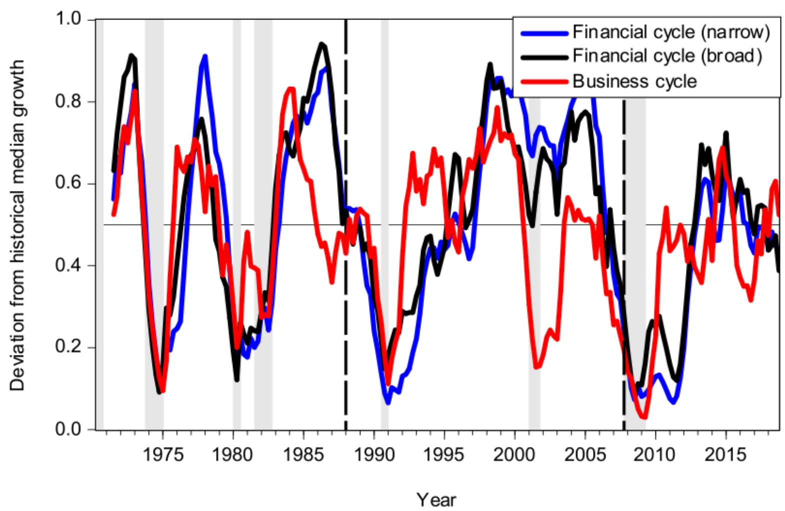


Figure 13: Real Time Composite Cycles for the United States: Original (Schüler et al., 2020, Figure 7).