University of Groningen

Towards a financial cycle for the U.S., 1973-2014

Rozite, Kristiana; Bezemer, Dirk J.; Jacobs, Jan P. A. M.

Published in:
North American Journal of Economics and Finance

DOI:
[10.1016/j.najef.2019.101023](https://doi.org/10.1016/j.najef.2019.101023)

IMPORTANT NOTE: You are advised to consult the publisher's version (publisher's PDF) if you wish to cite from it. Please check the document version below.

Document Version
Publisher's PDF, also known as Version of record

Publication date:
2019

[Link to publication in University of Groningen/UMCG research database](#)

Citation for published version (APA):

Rozite, K., Bezemer, D. J., & Jacobs, J. P. A. M. (2019). Towards a financial cycle for the U.S., 1973-2014. *North American Journal of Economics and Finance*, 50, [101023].
<https://doi.org/10.1016/j.najef.2019.101023>

Copyright

Other than for strictly personal use, it is not permitted to download or to forward/distribute the text or part of it without the consent of the author(s) and/or copyright holder(s), unless the work is under an open content license (like Creative Commons).

The publication may also be distributed here under the terms of Article 25fa of the Dutch Copyright Act, indicated by the "Taverne" license. More information can be found on the University of Groningen website: <https://www.rug.nl/library/open-access/self-archiving-pure/taverne-amendment>.

Take-down policy

If you believe that this document breaches copyright please contact us providing details, and we will remove access to the work immediately and investigate your claim.

Downloaded from the University of Groningen/UMCG research database (Pure): <http://www.rug.nl/research/portal>. For technical reasons the number of authors shown on this cover page is limited to 10 maximum.

Towards a financial cycle for the U.S., 1973–2014

Kristiana Rozite, Dirk J. Bezemer*, Jan P.A.M. Jacobs

University of Groningen, UTAS, CAMA, CIRANO, Netherlands

ARTICLE INFO

JEL classification:

C13
C38
E32
E44

Keywords:

Cycles
Corporate sentiment
Household sentiment
Principal components
Factor models

ABSTRACT

With this paper, we suggest a new approach to estimating financial cycles in terms of interactions of real-sector and financial-sector sentiments. We will apply this to U.S. financial indicators from 1973 to 2014. Based on Schumpeter's and Minsky's financial cycle concepts, we arrive at a selection of six indicators that capture finance and real sector linkages: the slope of the yield curve, a Purchasing Managers' Index, real-estate price returns, the S&P stock price index, and leverage ratios of households (consumer spending) and non-financial corporations. We estimate lead-lag relations and apply principal component analysis to aligned series in order to construct factors. Our conclusion is that two factors, capturing corporate and consumer sentiments, account for over 60% of the cumulative variance in our data. Corporate optimism peaks before crisis episodes, while household/consumer sentiment is more persistent and follows corporate sentiment with a lag.

1. Introduction

The contribution of our paper lies in suggesting and implementing a new approach to estimating financial cycles as interactions of real-sector and financial-sector sentiments. The neglect of the financial sector in macroeconomic research has come to be viewed as a problem, given the apparent impact of financial conditions on economic growth and stability (Bezemer, 2010, 2011; Eggertsson & Krugman, 2012). This omission has motivated a strand of recent research that attempts to summarize financial conditions in a “financial cycle,” or, in general, to define a broader measurement for economic conditions, which would include financial indicators (Aruoba, Diebold, & Scotti, 2009).

Financial cycles are motivated by their differing cyclical properties compared to business cycles, and their impact on real performance indicators. According to Borio (2014), financial cycles are much longer (around 16 years) and have a larger amplitude than business cycles; their peaks coincide with banking crises; they help to predict financial distress risk; and they are dependent on policy regimes. Although there is no single, commonly agreed upon definition of a financial cycle, one useful definition is “self-reinforcing interactions between perceptions of value and risk, attitudes towards risk and financing constraints, which translate into booms followed by busts” (Borio, 2014; Claessens, Kose, & Terrones, 2009; Hatzius, Hooper, Mishkin, Schoenholtz, & Watson, 2010; Ng, 2011).

Empirical estimations of financial cycles differ in terms of the models and financial indicators used. Drehmann, Drehmann, Borio, and Tsatsaronis (2012) empirically estimate a financial cycle for several countries over the period 1960–2011. This estimation is based on a single as well as a composite indicator that includes equity, property prices, and credit. They measure a financial cycle using frequency-based filters or the turning-point method (Harding & Pagan, 2002), which dates peaks and troughs. Other examples of a cycle construction can be found in Brave and Butters (2011), Camacho and Garcia-Serrador (2014), Hatzius et al. (2010), Kose, Otrok, and Whiteman (2003), Sarferaz and Uebele (2009).

* Corresponding author at: Faculty of Economics and Business, PO Box 800, 9700 AV Groningen, Netherlands.

E-mail address: d.j.bezemer@rug.nl (D.J. Bezemer).

In this paper, we build on conceptual work by [Minsky \(1978, 1986\)](#). Financial conditions such as leverage and asset price returns emerge from the interaction of motives and sentiments in the real and financial sectors. Reflecting this, our index will be based on six indicators: the slope of the yield curve, leverage ratios for households and firms, an index for real-sector managers sentiment, S&P stock price returns, and real-estate price index returns. We derive the motivation of these indicators from a careful review of the literature on financial cycles and credit cycles. This approach represents a middle ground between only looking at credit and real estate prices, as in [Borio \(2014\)](#), and studying dozens of potentially relevant indicators, as in many other studies. We see our work as complementary to these approaches. It is also very much in the spirit of [Danielsson, Valenzuela, and Zer \(2018\)](#), the first-ever paper to empirically test Minsky's hypothesis that periods of low return volatility increase risk-taking and the probability of a financial crisis.

When we summarize the six indicators by principal component analysis in two factors, we find that one loads heavily on consumer sentiment-related indicators (real estate prices and household leverage) and the other on indicators related to corporate sentiment. We probe the validity of our new financial cycle measurement against a number of stylized facts documented in the literature, such as the savings-and-loan crisis beginning in 1984 and the sub-prime crisis 2007 ([Reinhart & Rogoff, 2011](#)), and troughs in 1973–1975, 1982–1984, 1988–1991, and 2007 ([López-Salido & Nelson, 2010](#)). Overall, we find that the factor representing corporate sentiment conforms to most of these features and compares well to other indices we selected from the literature.

The remainder of this paper is organized as follows. In the next section, we will explore the theory and measurement of financial cycles in order to motivate our choice of indicators. In Section 3, we will build on this by describing how to extract the factors from the indicators. Sections 4 and 5 will present the data and results, including an assessment of the validity of our factors. Section 6 compares our sentiment indicators to other indices. Section 7 will present our conclusions.

2. Literature review

2.1. Real-financial linkages and a financial cycle

Increasingly, evidence points to the relevance of financial conditions for real-sector outcomes. Recessions are more severe when they coincide with a downturn in the financial cycle. They tend to be longer and deeper if they are preceded by financial booms, with rising mortgage loans and house prices, or if they are associated with credit crunches and house price busts in the contraction phase of the financial cycle ([Drehmann et al., 2012](#); [Igan, Kabundi, De Simone, & Tamirisa, 2011](#); [IMF, 2012](#)). More generally, financial cycles may cause “induced savings” and “induced spending” phases, and so affect the path of output ([Turner, 2013](#)).

Several transmission channels link the financial sector to output. Since banks create purchasing power pro-cyclically, they stimulate output growth and cause fluctuations, instability, and recessions as a result ([Fisher, 1933](#); [Keynes, 1930](#); [Minsky, 1978](#); [Schumpeter, 1934](#); [Wicksell, 1962 \[1898\]](#)). [Jakab and Kumhof \(2010\)](#) show that including bank credit creation in a macroeconomic model helps to capture boom-and-bust dynamics that would otherwise be hard to account for. This is in stark contrast to the common assumption in macroeconomic models that banks re-allocate but do not create purchasing power (e.g., [Eggertsson & Krugman, 2012](#)), and that instability originates from exogenous shocks rather than being endogenously generated in the financial sector (e.g., [Boissay, Collard, & Smets, 2016](#); [Kiyotaki & Moore, 1997](#)). Even with those assumptions, the financial sector may affect output by creating frictions that amplify or dampen exogenous shocks, as in the Credit View and Financial Accelerator literatures, or there may be balance-sheet effects on investment and consumption. In [Bernanke, Gertler, and Gilchrist \(1999\)](#) and related literature, a shock to wealth distribution or to costs sets in motion interactions between collateral values, borrowers' net worth, and credit limits, which amplify and create persistence in their effects on output of shocks to costs and to wealth distribution. In these three ways, the financial cycle affects the business cycle.

Our paper is grounded in the Schumpeter-Minsky theory of the financial cycle. [Schumpeter \(1934\)](#) theorized how financial intermediaries, by mobilizing savings, evaluating projects, managing risk, and monitoring projects, are essential for technological innovations and economic development. Schumpeter also analyzed that in the course of a boom, technical innovations tended to be replaced by financial “innovations.” For instance, bank credit for production is replaced by credit for speculation, and credit shifts from non-financial firms to consumers and financial firms, with a loosening of financing conditions ([Bezemer, 2011](#)). This may cause a prosperity boom followed by a bust and a recovery, preparing the economy for another wave of financial “innovations.” The changing allocation of financial instruments over the productive sectors, real estate, and financial markets produces boom-bust dynamics both in finance and in the real economy.

[Minsky \(1978, 1986\)](#), a student of Schumpeter, developed a theory concerning the interaction of the real and financial sectors, and the role of expectations, sentiment, and leverage. He explained boom-bust sequences in investment and asset prices through the existence of sophisticated financial markets, combined with social psychology. The existence of sophisticated financial markets implies that leverage in one form or another can be used to rapidly increase liquidity in some asset markets. The dynamics of financial investment are therefore not limited by physical constraints (such as resource exploitation, transport, market penetration) that characterize real-sector dynamics. There is no technical or physical upper limit on the price of a financial asset, or on the speed of its increase. Second, Minsky invoked social psychology mechanisms to explain the accelerations, shift, and slowdowns in financial markets and the economy. His point of departure was the Keynesian notion that expectations direct and drive investment. Expectations are based on past experience, are volatile, are subject to herding mechanisms, and they overshoot and undershoot. Investors tend to be too optimistic in a boom and too pessimistic in a bust.

Combined, this implies that, given some productivity shock or new market opportunities offering initial profitability gains, investors in both the real and financial sectors will endogenously increase their leverage in order to accelerate investment, driving up

asset prices in a self-fulfilling process. This leads to a shift of investment from production to speculation, thus increasing financial fragility, since it becomes ever harder to realize returns high enough to maintain increasingly leveraged financing positions. At some point, some bad news or event precipitates an investment flow reversal, fire sales of assets to generate liquidity to pay off debt, falling asset prices, and more investment withdrawal until leverage, prices, and confidence are low enough to start a new growth trajectory.

Minsky's account of the ups and downs of financial conditions and the economy has been formally modeled by [Bhattacharya, Goodhart, Tsomocos, and Vardoulakis \(2015\)](#), [Keen \(1995, 2013\)](#), [Palley \(2011\)](#), [Ryoo \(2010\)](#), [Vercelli \(2009\)](#). [Bhattacharya et al. \(2015\)](#), for instance, develop a model where the financial cycle evolves through increasing investor euphoria. Due to competition, investors increase their risk and leverage in order to increase return to equity. They keep on increasing spending and output until they become vulnerable to small shocks (e.g., some bad news). This causes investor euphoria to collapse, which leads to de-leveraging (the downswing of the financial cycle), and then a fall in spending and output (the downswing of the business cycle).

In this paper, we will undertake an empirical application of the Schumpeter-Minsky conceptualization of financial-real interactions to the U.S. for the period 1973–2014. Building on their ideas, we will additionally take account of the enormous increase in the importance of consumer sentiment, expressed in stock and real estate markets, since Minsky's day.

2.2. Formalizing financial-real sector linkages

We will construct an index that captures financial-real sector linkages for the US from 1973 to 2014. The small empirical literature on financial cycles follows a “let the data speak” methodology ([Claessens et al., 2009](#); [Drehmann et al., 2012](#); [Hatzius et al., 2010](#)). From a large number of plausible indicators, a small number of common factors are derived, and their evolution is considered to be a financial cycle. Indicators include prices of assets (equity, bonds, real estate, derivatives), interest rates and spreads, the shape of the yield curve, credit risk measurements, liquidity measurements, borrower risk and capacity, and willingness to lend.

Our choice of indicators will be consistent with this, but, based on Minsky's theory summarized above, we will add real-sector and consumer sentiment indicators. That way, we can distinguish between three types of economic agents: non-financial corporations, households, and financial-market investors. Changing sentiments in each of these groups guide risk appetite and investment decisions, leading to asset price developments, and these then influence sentiments, risk appetite, and investment decisions in the other groups. For instance, through the 1990s and 2000s until 2007, households rising willingness to borrow on mortgage markets has stimulated and supported derivative and stock markets. In turn, via financial innovations such as index-linked mortgages, these markets have expanded the opportunities for mortgage borrowing. Meanwhile, rising real estate prices have spurred consumption and lifted real-sector sentiments, expressed, for instance, in more positive market evaluations by purchasing managers in the real sector. The interactions of these sentiments, and their expression in leverage levels and returns, are what we view as the essence of the financial cycle. This motivates the collection of data on:

1. leverage: non-financial corporate and household mortgage loans relative to their incomes;
2. asset prices: real estate prices and stock prices;
3. expectations and sentiment: the slope of the yield curve (capturing investors expectations and sentiment) and the Purchasing Managers' Index (capturing real-sector managers' expectations and sentiment).

We measure leverage in relation to income so that we link debt to the means of repaying debt (e.g., non-financial corporations' leverage linked to corporate profit and mortgage loans to households linked to wages).

3. Method

In this section, we will describe how we build our financial cycle indices. We will introduce all the relevant concepts necessary to formalize the definition of dynamic correlation and a phase shift, which is then used to estimate lead-lag relations in our indicators with respect to a reference indicator. Financial cycle indices are the principal components of the aligned indicators.

To measure lead-lag relations in the data, we use spectrum analysis. Consider a covariance-stationary stochastic process X_t , $t = 1, \dots, T$ with absolutely summable auto-covariances. The auto-covariance generating function of the process is given by

$$g_X(z) = \sum_{j=-\infty}^{\infty} \gamma_j z^j, \quad (1)$$

where $\gamma_j = E(X_t - \mu)(X_{t-j} - \mu)$ and $\mu = E(X_t)$, z^j is some complex scalar. The auto-covariance generating function is divided by 2π and evaluated at $z = e^{-i\lambda}$, where λ is a frequency parameter and $i^2 = -1$. Using the symmetry property of auto-covariances, De Moivre's theorem and trigonometric functions properties, Eq. (1) is re-written into the population spectrum of the process X_t , given by

$$s_X(\lambda) = \frac{1}{2\pi} \left(\gamma_0 + 2 \sum_{j=1}^{\infty} \gamma_j \cos(\lambda j) \right), \quad \lambda \in [0, \pi]. \quad (2)$$

We compute sample-based estimates of the spectrum. On the assumption that spectra at similar frequencies are similar, the spectrum of $\hat{s}_X(\lambda)$ is calculated as a weighted average of spectra with frequencies located around the frequency of interest. The weights are

proportional to the difference between nearby frequencies and the frequency of interest. Our frequency of interest belongs to the set characterizing business-cycle length. The general expression for the estimated spectrum at frequency λ_m is given by

$$\hat{s}_X(\lambda_m) = \sum_{h=-M}^M \kappa(\lambda_{m+h}, \lambda_m) \hat{s}_X(\lambda_{m+h}), \quad (3)$$

where the integer M is a band-width (smoothing) parameter proportional to the number of frequencies used in the estimation. Furthermore, $\kappa(\lambda_{m+h}, \lambda_m)$ is a kernel that assigns weights to individual spectra. In our application, we use a triangular window Barlett kernel:

$$\kappa(\lambda_{m+h}, \lambda_m) = \begin{cases} 1 - \frac{|h|}{M+1} & \text{for } |h| \leq M \\ 0 & \text{otherwise.} \end{cases} \quad (4)$$

In selecting the bandwidth M and the lag-window length, there are several rules of thumb. For instance, [Diebold \(2007\)](#), [Forni, Hallin, Lippi, and Reichlin \(2000\)](#) suggest using $h = \sqrt{T}$, while [Chatfield \(1996\)](#) suggests $h = 2\sqrt{T}$.

The spectrum can now be defined for a stochastic k -vector process X_t , $t = 1, \dots, T$. Let this process be covariance-stationary with auto-covariance matrices Γ_j that are absolutely summable. The population spectrum of a random process X_t is then given by

$$s_X(\lambda) = \frac{1}{2\pi} \left(\Gamma_0 + \sum_{j=1}^{\infty} (\Gamma_j e^{-i\lambda j} + \Gamma_j' e^{i\lambda j}) \right), \quad (5)$$

where $\Gamma_j = E(X_t - \mu)(X_{t-j} - \mu)'$. Just as in the univariate case, a non-parametric estimate, such as the Barlett window, can be estimated, given by

$$\hat{s}_X(\lambda) = \frac{1}{2\pi} \left(\Gamma_0 + \sum_{h=1}^M \left(1 - \frac{|h|}{M+1} \right) (\hat{\Gamma}_h e^{-i\lambda j} + \hat{\Gamma}_h' e^{i\lambda j}) \right). \quad (6)$$

The cross-spectrum $s_X(\lambda)$ can be decomposed into a real and an imaginary component. In order to calculate phase shifts, we will apply this decomposition to pairs of indicators. Consider a vector with two indicators $X_t = [Z_t, Y_t]$. The cross-spectrum of the random vector X_t is given by

$$s_X(\lambda) = \frac{1}{2\pi} \begin{pmatrix} \sum_{j=-\infty}^{\infty} \gamma_j^{(ZZ)} \cos(\lambda j) & \sum_{j=-\infty}^{\infty} \gamma_j^{(ZY)} (\cos(\lambda j) - i \sin(\lambda j)) \\ \sum_{j=-\infty}^{\infty} \gamma_j^{(YZ)} (\cos(\lambda j) - i \sin(\lambda j)) & \sum_{j=-\infty}^{\infty} \gamma_j^{(YY)} \cos(\lambda j) \end{pmatrix}, \quad (7)$$

where, for example, $\gamma_j^{(ZY)} = E(Z_t - \mu_Z)(Y_{t-j} - \mu_Y)$. The diagonal elements of $s_X(\lambda)$ include only a real component (called the co-spectrum), while the off-diagonal elements also include an imaginary component. A typical element of the co-spectrum $c_{Z,Y}(\lambda)$ is given by

$$c_{Z,Y}(\lambda) = \frac{1}{2\pi} \sum_{j=-\infty}^{\infty} \gamma_j^{(ZY)} \cos(\lambda j). \quad (8)$$

The co-spectrum between Z and Y is the same as the co-spectrum between Y and Z . It is a symmetric function, since $c_{Z,Y}(\lambda) = c_{Y,Z}(-\lambda)$. The imaginary component of the cross-spectrum $s_X(\lambda)$, or the quadrature spectrum $q_{Z,Y}(\lambda)$, is given by

$$q_{Z,Y}(\lambda) = -\frac{1}{2\pi} \sum_{j=-\infty}^{\infty} \gamma_j^{(ZY)} \sin(\lambda j). \quad (9)$$

The properties of the quadrature spectrum are: $q_{Z,Y}(\lambda) = -q_{Y,Z}(\lambda)$ and $-q_{Y,Z}(\lambda) = q_{Y,Z}(-\lambda)$.

Given the cross-spectrum, a phase difference in radians between the frequency components of two time series is defined as

$$\theta(\lambda)_{Z,Y} = \tan^{-1} \left(\frac{q_{Z,Y}(\lambda)}{c_{Z,Y}(\lambda)} \right). \quad (10)$$

The phase shift in time lead-lag units is equal to $\theta(\lambda)_{Z,Y}/\lambda$. In this paper, we will evaluate that phase shift in the business-cycle frequency component with the highest degree of association between pairs of indicators. The degree of association is measured with the dynamic correlation measure of [Croux, Forni, and Reichlin \(2001\)](#) defined by

$$\rho_{Z,Y}(\lambda) = \frac{c_{Z,Y}(\lambda)}{\sqrt{s_Z(\lambda)s_Y(\lambda)}}. \quad (11)$$

We use signs of dynamic correlation to classify $k - 1$ indicators as cyclical or counter-cyclical, in terms of the frequency of interest with respect to our reference indicator. The time-shifts are estimated for $k - 1$ indicators, and these are aligned with respect to our reference indicator. To aid interpretation further on in this paper, if an indicator is classified as counter-cyclical, we will change its

sign, that is, X becomes $-X$.

Phase shifts, dynamic correlations, and coherence are measurements used to compare cyclical properties of time series (e.g., Croux et al., 2001). All of them require a frequency parameter as an input. Different methodologies are used to decide on the frequency parameter. One approach is to calculate average phase shift, dynamic correlation, and coherence measurements over a frequency band containing the most dominant frequencies (e.g., Azevedo, 2002). Another approach used by Van Nieuwenhuyze (2006) is to compute phase angle shifts with respect to one reference indicator in the typical business-cycle frequency. To obtain the frequency parameter of interest, he calculates an average cycle length for a common component in the reference series, for example, GDP. The common component, in turn, is obtained from a Generalized Dynamic Factor Model. Phase shifts for all indicators are calculated at the frequency parameter of the reference series. Since one common frequency parameter is used for all time series, this corresponds in principle to a similar cycle concept (e.g., Azevedo, Koopman, & Rua, 2006).

To obtain our frequency parameter, we look at pairwise dynamic correlations between our reference series and other indicators. For each pair, we select the frequency parameter with the highest dynamic correlation, thus jointly minimizing the phase difference and maximizing coherence between the series when searching for the strongest signal. We classify our indicators as pro- or counter-cyclical, based on the signs of dynamic correlations at the strongest signal frequency. We calculate phase shifts to classify indicators into leading and lagging, and align them. Only after that, do we use principal components to obtain the common factor(s). PCA assumes that data contain strong signals, i.e. high signal to noise ratio, and hence that variables with the largest variances are the most principal. In order to select the number of factors, we use two criteria. The criteria recommended by Forni et al. (2000) is to include as many factors as necessary to explain at least 50% of the variance in the data. Alternatively, Kaiser's criterion is to include all factors with eigenvalues equal to or exceeding one (i.e., the factor explains at least as much variation as one indicator would). For more details see Appendix C.

4. Data

We collected data for the US for the period 1971:Q1 to 2014:Q1, given the availability of real-estate price index data. The data include: SYC_t , the slope of the yield curve, that is, the difference between 10-year and 1-year Treasury annual bond yields in percent; consumer leverage ($HHLEV_t$), defined as debt liabilities divided by paid wages and salaries; non-financial business leverage ($NFLEV_t$), defined as loans to non-financial corporate business divided by profits before tax; and the growth in the real estate price (RER_t) and stock price (SR_t) indices.¹

We calculate year-on-year growth rates to better capture long-term co-movements, along with the Purchasing Managers Index (PMI_t) that describes expectations regarding new orders, inventory levels, employment, and production. All indicators are then standardized, that is, demeaned and divided by their standard deviation. In Appendix A we provide further details on sources, definitions, and data transformations, as well as summary statistics of data. Table A.2 reports outcomes for a unit root test of financial indicators. Augmented Dickey-Fuller test results indicate that the null hypothesis of non-stationarity is rejected, and so we proceed on the assumption that the financial indicators are stationary. Fig. 1 shows the indicators used in the common financial factors.

5. Results

5.1. Common movements

Each indicator introduced in Section 4 is decomposed into its periodic components. We aim to identify the cyclical periodic components with the strongest correlation to the cyclical periodic components of a reference indicator. A financial indicator that has a strong link with the real sector is the slope of the yield curve (SYC_t). We choose this as the reference indicator.

As noted, we measure the strength of the correlation at different periodicities based on dynamic correlations (Croux et al., 2001). We set the Bartlett lag-window at 13 periods, roughly equal to the square root of our sample size (173 observations). We examine the strength of co-movements for cyclical components of cycles between three and 10 years (12–40 quarters). The strength of co-movements for different pairs of indicators varies substantially along the frequency band and the signs of dynamic correlations change depending on the frequency component (see Fig. B).

Forni, Hallin, Lippi, and Reichlin (2000) classify variables as pro- or countercyclical by calculating the phase angle shifts between each series and the reference variable at the zero frequency, where the long-run correlations between two common components are measured. A positive correlation has a phase angle equal to zero. This means that the indicator is procyclical. If a phase angle equals π , then variables are countercyclical. Following this, we find that PMI_t is procyclical with respect to SYC_t , and the other indicators are countercyclical. However, no indicator can be classified as being either pro- or countercyclical with respect to SYC_t across its entire

¹ Alternatively, stock prices and real estate prices could be normalized by a measure of income. To explore the robustness of our analysis to data selection choices, we collected the Price-to-Earnings ratio (from Robert Shiller's homepage) and Price-to-Rent ratios (calculated by Bart Claassen on the basis of Shiller's data), as alternatives for the stock price index and the real estate price index. As an alternative for the excess bond premium, we collected two indicators provided by Gilchrist and Zakrajšek (AER 102, 1692–1720): Credit Spreads and Business Cycle Fluctuations, with updates from Gilchrist's Boston University homepage. Visual inspection of these series strongly suggests that their normalized movements are very similar indeed to the series used in this paper (i.e. stock price index, real estate price index, and excess bond premium). We thank an anonymous referee for suggesting this exploration.

Fig. 1. Standardized financial indicators. Notes: Data are seasonally adjusted. The abbreviation “GR” denotes growth rates.

business-cycle frequency band (see [Appendix B](#)). In particular, PMI_t and $HHLEV_t$ are hard to classify.

[Table 1](#) reports the average dynamic correlations, computed over the entire periodic component band, that is, wavelength $P \in [12, 40]$ quarters. On average, no indicator, with the exception of $NFLEV_t$, shows strong dynamic correlation with SYC_t . Co-movements between 20 and 32 quarters have stronger correlations with SYC_t . The fourth column of [Table 1](#) lists the largest dynamic correlation across the entire frequency band. The signs of the dynamic correlations imply that all indicators except $HHLEV_t$ are in the phase opposite to SYC_t . Note that SYC_t measures investors' expectations in the long run, that is, when SYC_t is negative, investors are optimistic. One would expect that this sentiment is reflected across different asset markets, such as the real estate market and the stock market, and that it also would be picked up by managers, that is, PMI_t should be positive. The dynamic correlation signs support the fact that less sanguine bond investor sentiment, that is, when SYC_t takes positive values, is consistent with lower leverage in firms and less optimistic managers' sentiments. Thus, the correlation signs are as we expected, except for $HHLEV_t$.

Column six in [Table 1](#) reports the time shifts for the long-wave periodic components, measured in quarters. Positive signs of the phase shift in column five mean that SYC_t is leading and a negative sign that SYC_t is a lagging indicator. We take inverted sign-

Table 1Average dynamic correlations and correlations at long-wave periodic components, calculated in reference to periodic components of SYC_t .

$X_{i,t}$	$\bar{\rho}$	P	$\hat{\rho}^P$	$\text{sign}(X_{i,t})$	$\hat{\theta}^P$
PMI_t	0.11	20	-0.20	-	-3
RER_t	-0.09	28	-0.24	-	-6
$NFLEV_t$	-0.42	32	-0.46	-	3
$HHLEV_t$	0.02	24	0.14	+	-3
SP_t	-0.03	24	-0.14	-	-3

Notes: $X_{i,t}$ is a financial indicator where $i = 2, \dots, 6$, $\bar{\rho}$ is an average correlation across all frequency band, P is the long-term cyclical component estimated in an indicator, $\hat{\rho}^P$ is the estimated correlation between cyclical components of SYC_t and $X_{i,t}$ with periodicity P quarters, $\text{sign}(X_{i,t})$ describes if $X_{i,t}$ is “in” or “out” of phase with SYC_t , $\hat{\theta}^P$ is an estimated phase shift of $X_{i,t}$ with respect to SYC_t after inverting $X_{i,t}$ if necessary.

reversed indicators where dynamic correlations for the dominant business-cycle frequency turned out to be negative. We find that SYC_t is a lagging negative PMI_t , $HHLEV_t$, and negative SP_t , and a leading negative $NFLEV_t$ by three quarters SYC_t is a lagging negative RER_t by six quarters.

Based on this exploration of phase shifts for 20–32 quarter long cycles and on the classification of each indicator as “in” or “out” of phase with SYC_t , the indicators are aligned before common factors are extracted, as described in Section 5.2. We describe the details of the alignment procedure in Section 3. Fig. 2 shows the aligned series. In general, the gaps between SYC_t and aligned individual indicators are not large, except for real estate prices after 2000 and for consumer leverage after 2008. This is in line with other evidence on the consumer-borrowing and house-price booms after the turn of the century. Lead-lag relationships are in line with Minsky’s theory: asset prices lead consumption and investment decisions. The real-estate price index is leading both non-financial corporations and consumer leverage. Moreover, S&P log returns are leading non-financial corporations leverage. In all these respects, financial variables are leading real variables.

The increase in gaps between SYC_t and $HHLEV_t$ and RER_t (i.e., Fig. 2) suggests time-variant factor loadings. Moreover, visual inspection of the data suggests that the strength of the relationship between our core indicator SYC_t and other indicators does change over time. We will leave the construction of dynamic factor model with time varying factor loadings for research at a latter time (see e.g. Del Negro & Otrok, 2008).

5.2. Household and corporate sentiment in the financial cycle

We apply principal components analysis to construct factors capturing the variation in the data. A key finding is that this variation is most parsimoniously described by one factor capturing household sentiment and one factor reflecting corporate sentiment. This outcome is intuitively very attractive, given the large and strongly increasing importance for macroeconomic outcomes in the US economy over the period we study of household debt and of household investment in real estate. The significance of household sentiment adds to the older and longer established importance of corporate sentiment, which was central to Minsky’s theorizing. Thus, the empirical outcome in this section that variation in the data reflects both these sentiments is a finding that appears to be substantially (and not just statistically) meaningful. It is consistent with the theoretical notion that (given the large importance of real estate markets and of household borrowing), the dynamics of household sentiment and their impact on macroeconomic outcomes cannot be reduced to corporate sentiments. We need both for the statistically most parsimonious description of the variation in the data.

Technically, we find that selecting two factors satisfies Kaiser’s criterion (see Fig. 3 and Table C.1). The loadings of the first two principal components in Table 2 suggest that the first factor captures the market sentiments of investors and managers, that is, corporate sentiments. The second factor places greater weight on consumer leverage and real estate prices, that is, it captures much of the variation in consumer sentiment. To check the robustness of factor interpretation, we redid computations in two- and three-dimensional factor subspaces after dismissing other factors, since these might contain measurement noise. We also checked that orthogonal-varimax and oblique-promax factor rotations provided the same qualitative conclusions, since factor correlation was close to zero.

Both factors are interpreted relative to their historic average, which is zero by construction. From now on, we will refer to principal component 1 as corporate sentiment ($CorpF_t$). When $CorpF_t$ takes on positive values, this corresponds to an event sequence of high real estate prices followed by positive managers’ sentiment, rising stock price returns, positive investors’ sentiment, and growth of non-financial corporations’ leverage. Managers’ sentiment is signaled by PMI_t , and investors’ sentiment is indicated by SYC_t (note that with negative SYC_t , current short run treasury yields are above average expected future short run rates).

The second principal component loads heavily on consumer leverage and real-estate price returns. This pattern is even more pronounced when we apply two-factor subspace. We will refer to principal component 2 as consumer sentiment (HHF_t). When consumer sentiment takes on positive values, a typical event sequence consists of rising real estate returns followed by growing consumer leverage with falling stock price returns and managers’ sentiments, as signaled by PMI_t and SP_t (somewhat more weakly in the two dimensional factor subspace). After lead and lag adjustments for individual indicators, Fig. 4 shows the development over time of the two factors that jointly constitute the new financial cycle index.

The factor loadings and the behavior of consumer and corporate factors over time provide some basis for regarding the factors we

Fig. 2. Phase shift and sign adjusted data of the US financial indicators.

constructed as indicative of the upswings and downturns of the US financial markets and economy. The analysis suggests that variation in the underlying distinction is parsimoniously captured in two factors. Rather than attempting to collapse these into one indicator, we will study the separate development and interplay between consumer and corporate sentiments.²

² We undertook an extensive robustness analysis to explore the sensitivity of this key finding (that there are two main and economically meaningful principal components) to selecting alternative indicators, and to excluding the slope of the yield curve. Kaiser's criterion suggests the existence of two principal components also when we use the price-to-rent ratio instead of real estate prices. The result also stands irrespective of whether we include or exclude the slope of yield curve. The movement over time of the two factors is still very distinct also without the slope of the yield curve, and using alternative indicators. This robustness analysis is available on request. We thanks an anonymous referee for suggesting this exploration.

Fig. 3. Scree plot of eigenvalues from principal component analysis. Notes: The y axis shows eigenvalues for six factors.

Table 2
Loadings of the first two principal components.

Indicator	PC 1	PC 2
$-SYC_{t-3}$	0.49	0.18
PMI_{t-6}	0.42	-0.27
RER_{t-9}	0.43	0.52
$NFLEV_t$	0.50	-0.06
$HHLEV_{t-6}$	0.00	0.66
SP_{t-6}	0.38	-0.44

Fig. 4. The US corporate sentiment and household sentiment. Notes: The US corporate sentiment is represented with the solid line and household sentiment with the dashed line. The timing of NBER recession are indicated with gray bars. The sample period is 1973:Q2–2014:Q1.

Corporate sentiment is more volatile, but both indicators co-move strongly in most episodes, with the notable exception of the “dot.com” crash. This did not impact consumer sentiment negatively, in contrast to the savings-and-loan crisis of 1984. Corporate sentiment peaks before or in NBER recessions, and drops during and after NBER recessions, in line with Minsky’s notion that “success breeds excess breeds failure.”

The corporate factor also captures the great financial stress and crisis moments of corporate America in these four decades. They are: the 1973–1974 stock market crash; the deregulated-bank failure wave of 1982; the 1984 start of the savings-and-loan crisis; the Black Tuesday stock market crash of 1987; the 1999 “dot.com” crash, and the credit crisis and Lehman collapse of 2007–2008. At or around each of these moments, the corporate sentiment graph peaks and then declines.

The factors are also consistent with the “debt-led” versus “debt-burdened” growth regimes (Stockhammer, 2013). The regime of consumption financed by debt, with strong growth in consumer and corporate sentiments, started in 1993 and lasted until 2002, when this was replaced by the debt-burdened regime with low corporate sentiment but still high consumer debt levels. The end of this regime came with the financial crisis of 2007–2008. Corporate sentiment recovered starting in 2012, with continuing low levels of consumer sentiment.

To further validate the factors, we identified a number of criteria from a review of the literature. First, according to Reinhart and Rogoff (2011), financial cycle troughs occur in 1984–1991 (the savings-and-loan crisis) and in 2007–2008 (the sub-prime crisis). López-Salido and Nelson (2010) date troughs in 1973–1975, 1982–1984, 1988–1991, and 2007. There are peaks in our corporate factors prior to these periods and additionally in 2001, just after the dot.com crash and 9/11.

Second, the increase in consumer mortgage credit is one of the major forces before the financial cycle trough in 2007 (Kemme & Roy, 2012). In fact, the consumer sentiment factor climbs steeply after 2000 and remains high until 2008.

Third, the increase in corporate mortgage credit is one of the major forces before the financial cycle trough in 1984, according to Reinhart and Rogoff (2011). This is present in our graph for that time, although the corporate sentiment factor upswing is not

uniquely large before 1984: It also peaks in 1977, 1992, 2003, and 2011.

6. Comparison to other indices

In this section, we ask how the corporate and consumer sentiment factors relate to other indices. In comparison to the cycle found by [Drehmann et al. \(2012\)](#) for the US in the period from 1970 to 2011, our financial cycle indicators have more peaks and troughs, display greater stability in amplitude over time, and appear more tightly linked to NBER-dated recessions. As with [Drehmann et al. \(2012\)](#), our corporate sentiment factors share the feature that upturns are longer than downturns ([Claessens et al., 2009](#)); however, note that the length and amplitude of the basic financial cycle have increased since 1980 ([Drehmann et al., 2012](#)).

For a more detailed comparison, we choose two indices reflecting financial conditions and two economic condition-based indices. We first describe them and then discuss their relative performance as measured by lead-lag relations with the GDP growth cycle. In Section 6.4 we consider vulnerability indicators.

6.1. Financial conditions indices

[Brave and Butters \(2011\)](#) construct an index that measures financial conditions (NFCI_t) based on 100 financial indicators with weekly frequency. These indicators represent three data categories: money markets (28 indicators), debt and equity markets (27 indicators) and the banking system (45 indicators). They use time series of varying lengths, available at different frequencies. Series are combined using the dynamic factor model framework. [Hatzius et al. \(2010\)](#), prior to construction of the index, adjust their time series for inflation, and for current and past economic activity (observing that financial and economic time series are highly correlated). The NFCI_t is presented as a broad metric of financial stability, which captures the interactions of financial and economic conditions. A zero value for the index indicates the historic average level of risk, liquidity, and leverage; positive index values indicate tighter-than-average conditions.

The second financial conditions index that we consider is provided by the International Monetary Fund. The IMF compiles a Financial Stress Indicator for advanced economies (AE-FSI), as described in [Balakrishnan, Danninger, Elekdag, and Tytell \(2009\)](#). The index consists of seven sub-indices, describing three financial market segments: banking, securities markets, and exchange markets. The seven sub-indices are: “banking-sector beta,” TED spread defined as the difference between 3-month LIBOR and government short term rate, inverted term spreads for government bonds (short-term minus long-term rate), stock market returns, time-varying stock market return volatility, sovereign spreads, and exchange market volatility. The methodology used to construct the index is to standardize each sub-index (de-mean, divide by its standard deviation), and then sum the seven components. A zero value for the FSI_t implies the historical average of neutral financial market conditions. Positive values imply financial stress; a value of one or higher signals a crisis.

6.2. Economic conditions indices

[Aruoba et al. \(2009\)](#) construct a real-time measure of business conditions (BCI_t) at daily frequency. They use a state-space dynamic factor framework to deal with missing observations so that they can combine time-series available at different frequencies. They use four indicators: the yield curve term premium (the difference between ten-year and three-month Treasury yields), initial claims for unemployment insurance, employees on non-agricultural payrolls, and real GDP. The resulting indicator broadly coheres with the NBER peak-trough chronology.

As a second indicator for economic conditions, we will study the real GDP growth cycle, that is, the annual log-growth rates of real GDP (100Δy). As discussed in [Inklaar, Jacobs, and Romp \(2004\)](#), the turning points for the growth rates correspond to accelerations or slowdowns in economic growth and, in general, lead turning points in the classical cycle, that is, absolute expansions and contractions in the level of economic activity.

6.3. Comparison to business and economic conditions indices

To obtain an overall impression of how strongly the financial indices (FSI_t, NFCI_t and ours) link to the indices describing real

Table 3
Correlations between financial condition and real condition indices.

	NFCI _t	FSI _t	CorpE _t	HHF _t	BCI _t
NFCI _t	1				
FSI _t	0.51 ^c	1			
CorpE _t	0.20 ^c	0.33 ^c	1		
HF _t	0.03	0.09	0.02	1	
BCI _t	−0.16 ^b	−0.22 ^c	−0.17 ^b	−0.08	1
100Δy	−0.09	−0.13 ^a	−0.09	−0.02	0.48 ^c

Notes: ^a $p < 0.10$, ^b $p < 0.05$, ^c $p < 0.01$. The sample period is 1980:Q4–2013:Q2; the beginning of the sample is determined by the availability of FSI index.

Fig. 5. Standardized financial and economic conditions indices. *Notes:* The timing of NBER recession are indicated with gray bars.

economic conditions (BCI_t and Real GDP growth rate cycle), we calculated their correlations. The results are listed in [Table 3](#). Note that $NFCI_t$ has a weak correlation with the real GDP growth cycle by construction, since the authors controlled for past economic growth. The results suggest that our corporate sentiment factor (which loads positively on both real-sector and financial-sector investor sentiments) correlates most strongly to FSI_t . We also note that our consumer sentiment factor does not correlate with other financial or economic condition-based indices. $NFCI_t$ and FSI_t indices correlate quite strongly, and BCI_t correlates the strongest with the GDP growth cycle.

In [Fig. 5](#), we present all indices after standardization in order to allow for a better comparison. Based on our correlation results with GDP growth rates ([Table 3](#)), we choose to invert FSI_t and $NFCI_t$. The indices appear to have quite similar dynamics, with the exception of our consumer sentiment factor. The largest troughs correspond to the NBER recession dates. We also note that the smoothness of the time series differs. For example, $NFCI_t$ is smoother than the other indices.

[Table 4](#) more formally compares the turning points of economic condition and financial indices. The turning points were detected using the BBQ algorithm of [Harding and Pagan \(2002\)](#), extended to quarterly series from the original ([Bry & Boschan, 1971](#))

Table 4

Estimated turning points for the indices in reference to the NBER business cycle turning points.

Peaks and Troughs							Leads/Lags with respect to 100Δy				
− NFCI _t	− FS _t	BCI _t	− CorpF _t	− HHF _t	NBER	100Δy	− NFCI _t	− FS _t	BCI _t	− CorpF _t	− HHF _t
1974-3					1973-4						
		1978-2	1976-3		1980-4	1978-4	M	M	−2	−9	M
1981-3					1981-3						
	1983-3	1983-3	1984-1	1985-2		1984-1	M	−2	−2	0	5
1987-4		1987-4		1989-2	1990-3	1988-2	−2	M	−2	M	5
	1994-2		1992-4	1993-4		1994-3	M	−1	M	1	−3
1998-4		1997-1	1997-2								
				1999-3	2001-1	2000-2	M	M	M	M	−3
2005-4	2002-1	2005-4	2004-2	2006-1		2004-1	7	−8	7	1	8
2008-4		2010-2	2010-4	2012-1	2007-4	2010-3	−7	M	−1	1	5
1977-1		1974-4	1974-4	1976-3	1975-1	1975-1	8	M	−1	−1	6
		1980-2	1980-3		1980-3						
					1982-4	1982-3	M	M	M	M	
1986-4	1987-4	1986-2	1985-2	1987-1		1987-1	−1	3	−3	−7	0
		1990-4		1990-3	1991-1	1991-1	M	M	−1	M	−2
1993-4			1995-4	1996-4		1995-4	−8	M	M	0	4
	2000-4	2001-2	2001-3		2001-4	2001-4	M	−4	−2	−1	M
2004-1				2003-3							
2007-1	2009-1	2009-1	2007-3	2007-1	2009-2	2009-2	−5	−1	−1	−7	−9
Average lead-lag							−1.14	−2.17	−0.57	−2.00	3.29
Standard deviation							6.41	3.66	3.41	4.20	4.42

(monthly) method. After some experimentation, the minimum cycle length was set to 12 quarters, the minimum phase length to two quarters, and a window length to six quarters. We first observe that most peak and trough episodes of the GDP growth rate cycle coincide with the turning points in the indices; however, NFI_t and FS_t capture fewer turning points in the GDP growth rate cycle.

Based on peak-trough dating, we calculate the lead-lag relations between – NFI_t, –FS_t, BCI_t, –CorpF_t and –HHF_t and the GDP growth rate cycle. On average, these indices lead GDP growth by 1–2 quarters, but consumer sentiment is lagging on average by three quarters. However, the lead relation is not always stable. The peaks for CorpF_t seem to lead troughs of the GDP growth rate cycle in a more persistent manner as compared to the lead relation between troughs. Our interpretation of this finding in relation to our CorpF_t is that, when managers and investors are optimistic, this eventually leads to the turning point, which starts the economic slow-down regime. Investors then need a positive signal, potentially provided by a turning point, which starts the acceleration phase in economic growth. This may explain why, in some “peak” episodes in GDP, the growth rate cycle leads CorpF_t.

In sum, we explored the common movement and lead-lag relations between various indices. In line with Minsky’s account, we find that financial variables generally lead real variables. We then presented a new financial cycle index as captured by two factors, representing consumer sentiment and corporate sentiment. The movements of these factors are broadly consistent with a number of key facts observable in the data and literature, including recessions, financial crises, consumer debt growth, and descriptions of debt-driven versus debt-burdened growth regimes. We compare these factors to a number of other indices capturing both real and financial conditions. It is noteworthy that consumer sentiment persistently leads the GDP growth cycle.

6.4. Comparison to vulnerability indicators

In addition to financial indices, we also study the performance of the two principal components compared to several vulnerability indicators. The first is corporate stock returns, used in Danielsson et al. (2018).³ We converted the monthly data on stock returns to quarterly data and compared this to the principal components reflecting household and corporate sentiment. As shown in Fig. 6, there is little correspondence between the series.

We then study the BaaTreasury Credit spread used as a credit-sentiment indicator in López-Salido, Stein, and Zakrajšek (2017). We do not have the underlying data, but their Fig. 1 on p 1384 in their paper suggests large similarities. Strikingly, there is a peak in the López-Salido et al. (2017) Baa Treasury Credit spread close to each of the steep declines ending in a trough of the corporate sentiment graph in our paper in Fig. 4 (around 1977, 1982, 1984, 1987, 1999, 2004 and 2011). Combined with the above comparison with Danielsson et al. (2016), this suggest that spreads, not returns, capture market sentiment in a way similar to our indicator.

Finally, we study the composite indicator of Aikman, Kiley, Lee, Palumbo, and Warusawitharana (2017). Fig. 5 in their paper present their vulnerability indicator, which covers the years 1990–2016. Again, their vulnerability indicator tracks our corporate sentiment indicator quite closely though far from perfectly. There is a rise in the Aikman et al. (2017) indicator from 1995 to 2000

³ We thank corresponding author Marcela Valenzuela who kindly sent us their data on corporate stock returns and volatility sourced from globalfinancialdata.com (Fig. 1 in Danielsson et al., 2016).

Fig. 6. Comparison of corporate sentiment (blue solid line) and household sentiment (red solid line) to the returns series of Danielsson et al. (JFS 2018) (green solid line). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

interrupted by a drop around 1997. In our indicator, that rise starts in 1993 and lasts to 2002, with drops in 1997 and 2001—very similar. In both graphs, there are steep falls to troughs in 2003–4. This is followed in both graphs by a rise that peaks in 2007. Both also show a precipitous decline from 2007 to 2011, and a recovery to a much lower level over 2011–2014. In sum, our corporate index behaves very similarly to vulnerability indicators based on spreads, but not to indicators based on returns.

7. Conclusion

How should the dynamics of the financial side of the economy be captured quantitatively, and how does this relate to real-sector dynamics? These questions have come to the fore since the 2008 crisis, and an emerging literature proposes a number of quantitative indicators for financial and real conditions. Unlike most other papers, in the present paper, we take a small data approach, guided by insights from the literature more than by data availability. Our aim is to construct an index for the financial cycle in the US, starting in 1973.

We survey the literature on financial cycles, and on financial factors and drivers of the business cycle. Inspired in particular by Minsky's account of upswings and downturns governed by investor sentiment and leverage, we select six indicators that capture manager, investor, and consumer sentiments and leverage levels. We apply a static-factor approach to the lead- and lag-adjusted indicators to extract the unobserved leading index for real activity. The factor analysis suggests that the information contained in these indicators can be largely summarized by two factors. We study their loadings, which appear to support an interpretation of the two factors, as capturing corporate and consumer sentiments, respectively.

Validation of financial indices and factors is a key challenge in this literature, and there is no consensus approach for this. We have thus applied both qualitative and quantitative methods. We observe that our corporate sentiment factor has a trough in each of the six NBER-dated recessions. Corporate sentiment rises, peaks, and then turns in close tandem with financial crisis episodes in the US, starting in 1973. Our indices also capture the peaks and troughs as described in the literature. Furthermore, we were able to relate the turning points of our corporate and consumer sentiment factors to the GDP growth rate cycle. Peaks of corporate sentiment precede troughs in the GDP growth cycle, but consumer sentiment generally lags behind the GDP growth rate cycle.

Taken together, the corporate part of our index seems to map financial crises well, while the consumer sentiment factor relates more to the business cycle. Given their links, the next step in this paper would be to explore whether perhaps the consumer sentiment factor links financial conditions to business-cycle movements other than crisis moments (already captured by the corporate factor). This is likely to be more relevant in the later part of our data series, as consumer consumption becomes increasingly important for growth. A link between financial conditions and the business cycle via consumer leverage and sentiment is also relevant to monetary policy transmission. Apart from a credit channel through non-financial enterprises, real estate prices and consumer credit come into play. These issues remain topics for future research.

Acknowledgements

We would like to thank Bart Claassen and Marcela Valenzuela for help with the data; Paul Bekker, Anna Samarina, participants of the 2016 PhD SOM Conference in Groningen (the Netherlands), and an anonymous referee for helpful comments and suggestions. We

gratefully acknowledge the financial support received from the Equilibrio Foundation and the Institute for New Economic Thinking (grant INO11-00053).

Appendix A. Data

The slope of the yield curve (SYC_t) is calculated as the difference between 10-year and 1-year treasury bond annual yields in percent. Source: Federal Reserve of St Louis.

The Z Tables of the US Flow of Funds data, furnished by the Federal Reserve, provides quarterly data on seasonally adjusted non-financial business and consumer debt securities and loan liabilities. In order to calculate leverage, we combined this with seasonally adjusted data at the quarterly frequency on paid wages and salaries and on non-financial corporate business profits before tax. Consumer leverage was calculated as debt securities divided by paid wages and salaries. Non-financial business leverage was calculated as the ratio of loans to non-financial corporate business profits before tax. We calculated year-on-year logarithmic growth rates of leverage ratios, adjusted them so the mean was zero, and standardized them. The resulting indicators are labeled consumer leverage ($HHLEV_t$) and non-financial business leverage ($NFLEV_t$). Source: Board of Governors of the Federal Reserve of St Louis.

The Bank of International Settlements provides quarterly data on residential property as a price index with base year 1995. We adjusted the data seasonally using the X-13ARIMA-SEATS procedure. Year-on-year log growth rates for the real-estate price index were adjusted to have zero mean and unit standard deviation. The resulting indicator is the real estate price (RER_t). The same procedure was applied to Shillers monthly S&P Composite price index, resulting in the indicator stock price (SP_t). Source: Bank of International Settlements.

We used monthly survey data at the start of each quarter regarding the expectations of purchasing managers in manufacturing regarding new orders, inventory levels, employment, and production. The data were seasonally adjusted and taken in logs to yield the Purchasing Managers Index (PMI_t). The source is Institute of Supply Management. We give further details on input data in [Table A.1](#) and summary statistics in [Table A.2](#).

Table A.1
Description of the dataset.

Data	Code	Source	Transformations	Notes
10-year Treasury Constant Maturity Rates	GS10	FRED	Monthly data transformed to quarterly by taking values in all months starting a new quarter.	
1-year Treasury constant Maturity rate	DGS1	FRED	Monthly data transformed to quarterly by taking values in all months starting a new quarter	
Purchasing Managers Index	NAPM	FRED	Quarterly data, log-transformation	The PMI when above 50% indicates that the manufacturing economy is generally expanding; below 50% that it is declining.
Average sale price of existing single family homes	BIS_LPP:Q:US	BIS	Quarterly data; variable is adjusted for inflation and log-returns ($\log(P_t/P_{t-4})100$) are calculated over 4 quarters	Residential Property prices are seasonally adjusted, existing dwellings, index 1995 = 100.
GDP deflator	GDPDEF	FRED		Gross domestic product: Implicit Price Deflator, seasonally adjusted; Index 2009 = 100.
Compensation of employees	A576RC1Q027SBEA	FRED		Seasonally adjusted annual rate
Credit Market instruments to households and non-profit organizations	CMDEBT	FRED		Seasonally adjusted, liability in levels
Corporate Profits after tax	CP	FRED		Seasonally adjusted annual rate without IVA and CCAdj.
Credit Market instruments to non-financial corporations	BCNSDODNS	FRED		Seasonally adjusted, liability in levels
S&P composite price index	S&P Comp. P.	R. Shiller	Adjusted for seasonality and inflation	Stock Market Data Used in "Irrational Exuberance" Princeton University Press, 2000, 2005, 2015, updated; R.Shiller.

Table A.2
Summary statistics.

Statistics	SYC _t	− PMI _t	− RER _t	− NFLEV _t	HHLEV _t	− SP _t
ADF test	0.00 (1)	0.00 (1)	0.01 (12)	0.00 (6)	0.00 (4)	0.00 (4)
Mean	− 0.02	0.00	0.04	0.00	0.06	0.01
Median	0.03	− 0.11	0.04	0.08	0.02	− 0.16
Maximum	1.85	3.90	3.58	2.82	2.59	3.44
Minimum	− 2.78	− 2.44	− 1.81	− 2.56	− 2.93	− 2.09
Std. Dev.	1.01	1.02	1.00	1.02	0.98	1.01
Skewness	− 0.27	0.95	0.98	0.04	− 0.08	0.88
Kurtosis	2.56	4.39	4.75	2.87	3.81	4.02
Jarque-Bera	3.30	3.82	4.68	0.16	4.65	2.80

Notes: Each indicator has 164 observations over 1973:Q2–2014:Q1. ADF test reports p-values for H_0 non-stationary, in brackets are selected lag order using AIC information criteria. In our sample for PMI_t, RER_t, SP_t normal distribution of the indicators cannot be accepted. Normality is necessary for principal components to achieve independence of components, the method is based on the sufficient statistics provided by mean and variance. Empirically, multivariate Shapiro-Wilk normality test has value $W = 0.863$, p -value = 0.000 which means that we cannot accept normality and the consequence for PCA is that while components are uncorrelated these are not independent.

Appendix B. Dynamic correlations as a function of wave length (years)

See Fig. B.1.

Fig. B.1. Dynamic correlations.

Appendix C. Construction of financial factors: principal components

To construct a financial index, we work with the phase shift adjusted data. Redundancies and noise in the data are reduced using the principal component technique which is based on the assumption that data follow Gaussian distribution and hence that mean and variance describe the probability distribution. This implies that removing redundancies equals diagonalizing data covariance matrix. Symmetric matrices such as covariance matrices are diagonalized using the eigenvector decomposition.

Let $\mathbf{x}_t = [x_{1,t}, \dots, x_{k,t}]'$ be a stochastic k -vector process, $t = 1, \dots, T$. $\mathbf{x}_t$ is standardized such that it has zero mean and $\mathbb{E}(\mathbf{x}_t \mathbf{x}_t')$ has ones on its diagonal, i.e., $\text{diag}[\mathbb{E}(\mathbf{x}_t \mathbf{x}_t')] = \mathbf{I}_k$. Let $\hat{\mathbf{C}}_X = \frac{1}{T} \sum_{t=1}^T \mathbf{x}_t \mathbf{x}_t'$ be the estimated covariance matrix with rank $r \leq k$. We search for a basis such that the data matrix $\mathbf{X} = [\mathbf{x}_1, \dots, \mathbf{x}_T]$ can be re-expressed into $\mathbf{F} = \hat{\mathbf{A}}_{C_X}' \mathbf{X}$ where $\mathbf{F} = [\mathbf{f}_1, \dots, \mathbf{f}_T]$ such that $\hat{\mathbf{C}}_F = \frac{1}{T} \sum_{t=1}^T \mathbf{f}_t \mathbf{f}_t'$ is a diagonal matrix and the $(k \times k)$ matrix $\hat{\mathbf{A}}_{C_X}$ is an orthonormal matrix containing the eigenvectors of $\hat{\mathbf{C}}_X$ arranged as columns. $\mathbf{F}$ represents uncorrelated factors.

Table C.1
Variance explained by the principal components

PC number	Cumulative variance explained	Eigenvalue
1	0.39	2.28
2	0.63	1.53
3	0.76	0.76
4	0.87	0.66
5	0.96	0.53
6	1.00	0.23

Diagonal property of $\hat{C}_F$ holds for the covariance matrix decomposition $\hat{C}_X = \hat{\Lambda}_{C_X} \hat{D} \hat{\Lambda}_{C_X}'$, where $\hat{D}$ is a diagonal matrix which contains estimated eigenvalues and $\hat{\Lambda}_{C_X}' \hat{\Lambda}_{C_X} = I_k$. If $\hat{C}_X$ is degenerate, i.e with $r < k$, then $(k - r)$ orthonormal vectors of $\hat{C}_X$ have associated eigenvalues (variances) equal to zero and these vectors do not effect the final solution.

Appendix D. Supplementary data

Supplementary data associated with this article can be found, in the online version, at <https://doi.org/10.1016/j.najef.2019.101023>.

References

- Aikman, D., Kiley, M., Lee, S. J., Palumbo, M. G., & Warusawitharana, M. (2017). Mapping heat in the U.S. financial system. *Journal of Banking and Finance*, 81, 36–64.
- Aruoba, S. B., Diebold, F. X., & Scotti, C. (2009). Real-time measurement of business conditions. *Journal of Business & Economic Statistics*, 27, 417–427.
- Azevedo, J. V. (2002). *Business cycles: Cyclical comovement within the European Union in the period 1960–1999. A frequency domain approach*. Lisboa: Bank of Portugal Working paper series 5.
- Azevedo, J. V., Koopman, S. J., & Rua, A. (2006). Tracking the business cycle of the Euro area: A multivariate model-based bandpass filter. *Journal of Business & Economic Statistics*, 24, 278–290.
- Balakrishnan, R., Danninger, S., Elekdag, S., & Tytell, I. (2009). *The transmission of financial stress from advanced to emerging economies*. Washington, D.C.: International Monetary Fund IMF Working paper 09/133.
- Bernanke, B., Gertler, M., & Gilchrist, S. (1999). The financial accelerator in a quantitative business cycle framework. In J. Taylor, & M. Woodford (Eds.). *Handbook of Macroeconomics* (pp. 1341–1393). Amsterdam: Elsevier Chapter 21.
- Bezemer, D. J. (2010). Understanding financial crisis through accounting models. *Accounting Organizations and Society*, 35, 676–688.
- Bezemer, D. J. (2011). The credit crisis and recession as a paradigm test. *Journal of Economic Issues*, 45, 1–18.
- Bhattacharya, S., Goodhart, C. A. E., Tsomocos, D. P., & Vardoulakis, A. P. (2015). A reconsideration of Minsky's financial instability hypothesis. *Journal of Money, Credit and Banking*, 47, 931–973.
- Boissay, F., Collard, F., & Smets, F. (2016). Booms and banking crisis. *Journal of Political Economy*, 124, 489–538.
- Borio, C. (2014). The financial cycle and macroeconomics: What have we learnt? *Journal of Banking and Finance*, 45, 182–198.
- Brave, S., & Butters, R. A. (2011). Monitoring financial stability: A financial conditions index approach. *Economic Perspectives*, Q1, 22–43.
- Bry, G., & Boschan, C. (1971). *Cyclical analysis of time series: Selected procedures and computer programs*. New York: National Bureau of Economic Research.
- Camacho, M., & Garcia-Serrador, A. (2014). The Euro-sting revisited: The usefulness of financial indicators to obtain Euro area GDP forecasts. *Journal of Forecasting*, 33, 186–197.
- Chatfield, C. (1996). *The analysis of time series: An introduction* (5th ed.). London, UK: Chapman and Hall.
- Claessens, S., Kose, A., & Terrones, M. E. (2009). What happens during recessions, crunches and busts? *Economic Policy*, 24, 653–700.
- Croux, C., Forni, M., & Reichlin, L. (2001). A measure of comovement for economic variables: Theory and empirics. *Review of Economics and Statistics*, 83, 232–241.
- Danielsson, J., Valenzuela, M., & Zer, I. (2018). Learning from history: Volatility and the Financial Crisis. *The Review of Financial Studies*, 31, 2774–2805.
- Del Negro, M., & Otrok, C. (2008). *Dynamic factor models with time-varying parameters: Measuring changes in international business cycles*. New York: Federal reserve bank of New York Staff Report 326.
- Diebold, F. X. (2007). *Elements of forecasting* (4th ed.). Cincinnati: South-Western College Publishing.
- Drehmann, M., Borio, C., & Tsatsaronis, K. (2012). *Characterising the financial cycle: Don't lose sight on the medium term!*. Basel: Bank of International Settlements BIS Working paper 380.
- Eggertsson, G. B., & Krugman, P. R. (2012). Debt, deleveraging, and the liquidity trap: A Fisher-Minsky-Koo approach. *The Quarterly Journal of Economics*, 127, 1469–1513.
- Fisher, I. (1933). The debt-deflation theory of great depressions. *Econometrica*, 1, 337–357.
- Forni, M., Hallin, M., Lippi, M., & Reichlin, L. (2000). The generalized factor model: Identification and estimation. *Review of Economics and Statistics*, 82, 540–554.
- Forni, M., Hallin, M., Lippi, M., & Reichlin, L. (2000). *Reference cycles: The NBER methodology revisited*. London: Centre for Economic Policy Research CEPR Discussion Paper 2400.
- Harding, D., & Pagan, A. R. (2002). Dissecting the cycle: A methodological investigation. *Journal of Monetary Economics*, 49, 365–381.
- Hatzius, J., Hooper, P., Mishkin, F. S., Schoenholtz, K. L., & Watson, M. W. (2010). *Financial conditions indexes: A fresh look after the financial crisis*. Cambridge, MA: National Bureau of Economic Research NBER Working paper 16150.
- Igan, D., Kabundi, A., De Simone, F. N., & Tamirisa, N. (2011). Housing, credit and real activity cycles: Characteristics and comovements. *Journal of Housing Economics*, 20, 210–231.
- IMF (2012). Dealing with household debt. *World Economic Outlook* (pp. 89–124). Washington, D.C.: International Monetary Fund Chapter 3.
- Inklaar, R., Jacobs, J. P. A. M., & Romp, W. E. (2004). Business cycle indexes: Does a heap of data help? *Journal of Business Cycle Measurement and Analysis*, 3, 309–336.
- Jakab, Z., & Kumhof, M. (2010). *Banks are not intermediaries of loanable funds—And why this matters*. London, UK: Bank of England Working paper 529.
- Keen, S. (1995). Finance and economic breakdown: Modeling Minsky's financial instability hypothesis. *Journal of Post-Keynesian Economics*, 17, 607–635.
- Keen, S. (2013). A monetary Minsky model of the great moderation and the great recession. *Journal of Economic Behavior & Organization*, 86, 221–235.
- Kemme, D., & Roy, S. (2012). Did the recent housing boom signal the Global Financial Crisis? *Southern Economic Journal*, 78, 999–1018.
- Keynes, J. M. (1930). *A treatise on money*. London, U.K.: Macmillan and Co.

- Kiyotaki, N., & Moore, J. (1997). Credit cycles. *Journal of Political Economy*, 105, 148–211.
- Kose, A. M., Otrok, C., & Whiteman, C. H. (2003). International business cycles: World, region, and country-specific factors. *American Economic Review*, 93, 1216–1239.
- López-Salido, D., & Nelson, E. (2010). Postwar financial crises and economic recoveries in the United States. Working paper, May 21.
- López-Salido, D., Stein, J. C., & Zakrajšek, E. (2017). Credit-market sentiment and the business cycle. *Quarterly Journal of Economics*, 132, 1373–1426.
- Minsky, H.P. (1978). The financial instability hypothesis: A restatement. Hyman P. Minsky Archive Paper 180.
- Minsky, H. P. (1986). *Stabilizing an unstable economy*. New York: McGraw-Hill.
- Ng, T. (2011). *The predictive content of financial cycle measures for output fluctuations*. Basel: BIS Quarterly Review, Bank of International Settlements.
- Palley, T. I. (2011). A theory of Minsky super-cycles and financial crisis. *Contributions to Political Economy*, 30, 31–46.
- Reinhart, C. M., & Rogoff, K. S. (2011). From financial crash to debt crisis. *American Economic Review*, 101, 1676–1706.
- Ryoo, S. (2010). Long waves and short cycles in a model of endogenous financial fragility. *Journal of Economic Behavior & Organization*, 74, 163–186.
- Sarferaz, S., & Uebele, M. (2009). Tracking down Germany's pre-World War I business cycle: A dynamic factor model for 1820–1913. *Explorations in Economic History*, 46, 368–387.
- Schumpeter, J. (1934). *The theory of economic development: An inquiry into profits, capital, credit, interest, and the business cycle*. New York: Harvard University Press.
- Stockhammer, E. (2013). Financialization and the global economy. In M. H. Wolfson, & G. A. Epstein (Eds.). *The handbook of the political economy of financial crisis* (pp. 512–525). Oxford: Oxford University Press.
- Turner, A. (2013). Credit, money and leverage: What Wicksell, Hayek and Fisher knew and modern macroeconomists forgot. *Presented at the conference on "Towards a sustainable financial system"*.
- Van Nieuwenhuyze, C. (2006). *A generalised dynamic factor model for the Belgian economy*. Belgium, Brussels: National Bank of Belgium Working paper 80.
- Vercelli, A. (2009). *Minsky moments, Russell chickens, and gray swans: The methodological puzzles of the financial instability analysis*. New York: The Levy Institute The Levy Institute Working paper 583.
- Wicksell, K. (1962). *Interest and prices: A study of the causes regulating the value of money*. London, U.K.: Augustus M. Kelley.