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Abstract

We suggest a new approach to estimating financial cycles, as interactions of real-sector and financial-sector sentiments. We apply this to the U.S. financial indicators over 1973–2014. Based on financial cycle concepts of Schumpeter and Minsky, we motivate the selection of six indicators which capture finance-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 and non-financial corporations. We estimate lead-lag relations and apply principal component analysis on aligned series to construct factors. We find that two factors, capturing corporate and household sentiments, account for over 60% of the cumulative variance in our data. Corporate optimism peaks before crisis episodes while households' sentiment is more persistent and follows with a lag corporate semtiment.

JEL classification: C13, C38, E32, E44
Keywords: Cycles; Corporate sentiment; Household sentiment; Principal components; Factor models

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1 Introduction

The contribution of our paper is to suggest and implement 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 (see Bezemer, 2010, 2011; Eggertsson and Krugman, 2012). This omission has motivated a strand of recent research attempting to summarize financial conditions in a "financial cycle" or in general to define a broader measure for economic conditions which would include financial indicators (see Aruoba, Diebold and Scotti, 2009).

Financial cycles are motivated by their different cyclical properties from business cycles, and their impacts 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 one, commonly agreed definition of a financial cycle, a 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; Ng, 2011; Hatzius, Hooper, Mishkin, Schoenholtz and Watson, 2010; Claessens, Kose and Terrones, 2009).

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

In this paper we build on conceptual work by Minsky (1978, 1986). Financial conditions such as leverage, 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, both older and recent. This approach represents a middle ground between only looking at credit and real estate prices as in Borio (2014), and dozens of potentially relevant indicators as in many other studies. We see our work as complementary to these approaches.

When we summarize these six indicators by principal components analysis in two factors, we find that one loads heavily on household 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 measure against a number of stylized facts documented in the literature, such as the savings and loan crisis beginning at 1984 and the sub-prime crisis 2007 (Reinhart and Rogoff, 2011), and troughs in 1973–1975, 1982–1984, 1988–1991 and 2007 (Lopez-Salido and Nelson, 2010). Overall, we find that the factor representing corporate sentiment conforms to most of these features, and compares well to other indexes we selected from the literature.

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

2 Literature review

2.1 Real-financial linkages and a financial cycle

Increasingly, evidence points to the relevance of financial conditions to real-sector outcomes. Recessions are more severe when they coincide with a downturn of 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; IMF, 2012; Igan et al., 2011, 2011; Claessens et al., 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 financial sector to output. Since banks create purchasing power pro-cyclically, they thereby stimulate output growth and cause fluctuations, instability and recessions (Wicksell, 1889; Keynes, 1930; Fisher, 1933; Schumpeter, 1934; Minsky, 1978). Kumhof and Jakab (2015) show that including bank credit creation in a macroeconomic model helps to capture boom and busts dynamics which would otherwise be hard to account for. This stands in contrast to the common assumption in macroeconomic models that banks re-allocate but do not create purchasing power (e.g., Eggertsson and Krugman, 2012), and that instability originates from exogenous shocks rather than being endogenously generated in the financial sector (e.g., Kiyotaki and Moore, 1997; Boissay, Collard and Smets, 2015). Even with those assumptions, the financial sector may affect output by creating frictions which 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 the wealth distribution or to costs sets in motion interactions between collateral values, borrowers’ net worth and credit limits which amplify, and create persistence in, the 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. This is a starting point for thinking about the interaction of the real and financial sectors. Schumpeter also analysed that in the course of a boom, technical innovations tend to be replaced by financial "innovations". For instance, bank credit for production is being replaced by credit for speculation, and credit is shifting 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 theory on the interaction of the real and financial sectors and the role of expectations, sentiment and leverage. In a nutshell, he explained boom-bust sequences in investment and asset prices by 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 increase liquidity into some asset markets rapidly. The dynamics of financial investment are therefore not constrained 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 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, 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 remained relatively obscure. It has not been formally modelled apart from work by Keen (1995, 2013), Vercelli (2009), Ryoo (2010), Palley (2011), Bhattacharya et al. (2015). For instance Bhattacharya et al. (2015) 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 so increase spending and output until they become vulnerable to small shocks (e.g., some bad news). This causes investor euphoria to collapse, which leads to deleveraging (the downswing of the financial cycle) and then a fall in spending and output (the downswing of the business cycle).

In this paper we undertake an empirical application to the U.S. for 1973-2014 of the

Schumpeter-Minsky conceptualization of financial-real interactions. Building on their ideas, we will additionally take account of the enormous increase in the importance of household sentiments, expressed in stock and real estate marktes, since Minsky's days.

2.2 Formalizing financial-real sector linkages

We will construct an index which captures financial-real sector linkages for the US, 1973–2014. The small empirical literature on financial cycles follows a "let the data speak" methodology (Claessens et al., 2009, Hatzius et al., 2010; Drehman et al., 2012). From a large number of plausible indicators, a small number of common factors is 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 measures, liquidity measures, 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 a real-sector and household sentiment indicators. We so distinguish between three types of economic agents: non-financial corporations, households and financial-maket investors. Changing sentiments in each of these groups guides risk appetite and investment decisions, leading to asset price developments, and these influence sentiments, risk appetite and investment decisions in the other groups. For instance, through the 1990s and 2000s until 2007, household's rising willingness to borrow on mortgage markets stimulated and supported derivative and stock markets. Via financial innovations such as index-linked mortgages, these markets in turn enlarged opportunities for mortgage borrowing. Meanwhile, rising real estate prices 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, is 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 a 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 Methodology

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

3.1 Alignment and dynamic correlation

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

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

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 $i \equiv \sqrt{-1}$. Using the symmetry property of auto-covariances, De Moivre's theorem and trigonometric functions properties, Equation (1) is re-written into the population spectrum of the process X_t, given by

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

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

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

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

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

In selection of the bandwidth M and the lag-window length there are several rules of thumb. For instance, Diebold (2007) and Forni et al. (2000) suggests to use $h = \sqrt{T}$, while Chatfield (1996) suggests $h = 2\sqrt{T}$.

The spectrum can now be defined for a stochastic k-vector process $\boldsymbol{X}_t, t = 1, \ldots, T$. Let this process be covariance-stationary with auto-covariance matrices $\boldsymbol{\Gamma}_j$ which are absolutely summable. The population spectrum of a random process $\boldsymbol{X}_t$ is then given by

$$s_{\boldsymbol{X}}(\lambda) = \frac{1}{2\pi}\left(\boldsymbol{\Gamma}_0 + \sum_{j=1}^{\infty}(\boldsymbol{\Gamma}_j e^{-i\lambda j} + \boldsymbol{\Gamma}_j' e^{i\lambda j})\right), \tag{5}$$

where $\boldsymbol{\Gamma}_j = E(\boldsymbol{X}_t - \boldsymbol{\mu})(\boldsymbol{X}_{t-j} - \boldsymbol{\mu})'$. Just as in the univariate case, a non-parametric estimate such as the Barlett-window can be estimated, given by

$$\hat{\boldsymbol{s}}_{\boldsymbol{X}}(\lambda) = \frac{1}{2\pi}\left(\boldsymbol{\Gamma}_0 + \sum_{h=1}^{M}\left(1 - \frac{|h|}{M+1}\right)\left(\hat{\boldsymbol{\Gamma}}_j e^{-i\lambda j} + \hat{\boldsymbol{\Gamma}}_j' e^{i\lambda j}\right)\right). \tag{6}$$

The cross-spectrum $s_{\boldsymbol{X}}(\lambda)$ 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 $\boldsymbol{X}_t = [Z_t, Y_t]$. The cross-spectrum of the random vector $\boldsymbol{X}_t$ is given by

$$\boldsymbol{s}_{\boldsymbol{X}}(\lambda) = \frac{1}{2\pi}\begin{pmatrix} \sum_{j=\infty}^{\infty}\gamma_j^{(ZZ)}\cos(\lambda j) & \sum_{j=\infty}^{\infty}\gamma_j^{(ZY)}(\cos(\lambda j) - i\sin(\lambda j)) \\ \sum_{j=\infty}^{\infty}\gamma_j^{(YZ)}(\cos(\lambda j) - i\sin(\lambda j)) & \sum_{j=\infty}^{\infty}\gamma_j^{(YY)}\cos(\lambda j) \end{pmatrix} \tag{7}$$

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

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

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

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

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

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

The phase shift in time lead-lag units is equal to $\theta(\lambda)_{Z,Y}/\lambda$. In this paper we will evaluate the phase shift at 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

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

We use signs of dynamic correlation to classify $k-1$ indicators as cyclical or counter-cyclical at 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 below, if an indicator is classified as counter-cyclical, we change its sign, i.e., X inverted is $-X$.

Phase shifts, dynamic correlations and coherence[1] are measures used to compare cyclical properties of time series. All of them require as an input a frequency parameter. Different methodologies are used to decide on the frequency parameter. One approach is to calculate average phase shift, dynamic correlation and coherence measures over a frequency band containing the most dominant frequencies (e.g., Azevedo, 2002). Another approach used by van Niewenhuyze (2006) is to compute phase angle shifts with respect to one reference indicator at 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, e.g., 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 in principle corresponds to a similar cycle concept (e.g., Azevedo, Koopman and Rua, 2006).

To obtain our frequency parameter, we look at pairwise dynamic correlations be-

[1] For a definition of coherence see for example Croux et al. (2001).

tween our reference series and other indicators. For each pair, we select the frequency parameter with the highest dynamic correlation, thus we jointly minimize the phase difference and maximize 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 thereafter we use principal components to obtain the common factor(s).

3.2 Construction of financial factors: Principal components

To construct financial indexes, we work with the phase shift adjusted data (see Section 3.1). 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 diagnolizing data covariance matrix. Symmetric matrices such as covariance matrices are diagonolized using the eigenvector decomposition.

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

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

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).

4 Data

We collected data for the US over the period 1971:Q1–2014Q1, given availability of the real estate price index data. The data include: the slope of the yield curve (SYC_t), i.e. the difference between 10-year and 1-year Treasury annual bond yields in percent; household 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; the growth in the real estate price (REP_t) and stock price (SP_t) indexes and we calculate year-on year growth rates to better capture long-term co-movements; the Purchasing Managers Index (PMI_t) describing expectations regarding new orders, inventory levels, employment and production. All indicators are standardized, i.e., demeaned and divided by their standard deviation. Table 1 reports outcomes of unit root test of financial indicators indicators. Augmented Dickey-Fuller test results in Table 1 indicate that non-stationarity is rejected and we proceed with assumption that constructed financial indicators are stacionary. In Appendix A we provide further details on sources, definitions and data transformations as well as summary statistics of phase shift adjusted data. Figure 1 shows the indicators used in the common financial factors.

Table 1: P-values for the ADF unit root test results on financial indicators.

Indicator	ADF p-value (lags)
SYC_t	$p = 0.003(1)$
PMI_t	$p = 0.000(1)$
REP_t	$p = 0.006(12)$
$NFLEV_t$	$p = 0.000(6)$
$HHLEV_t$	$p = 0.003(4)$
SP_t	$p = 0.000(4)$

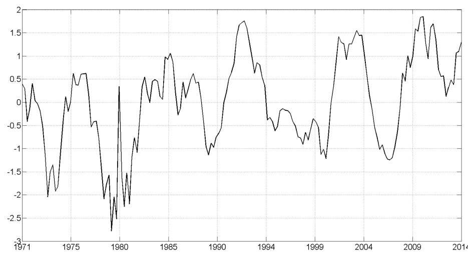
5 Results

5.1 Common movements

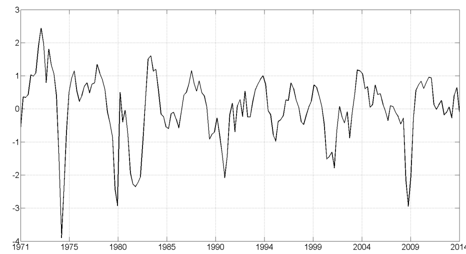
Each indicator introduced in Section 4 is decomposed into its periodic components. We aim to identify the cyclical periodic components with the strongest correlation with the cyclical periodic components of a reference indicator. A financial indicator which has a strong link with the real sector is the slope of the yield curve (SYC_t), hence we choose it 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 (see Appendix B) and the signs of dynamic correlations change depending on the frequency component.

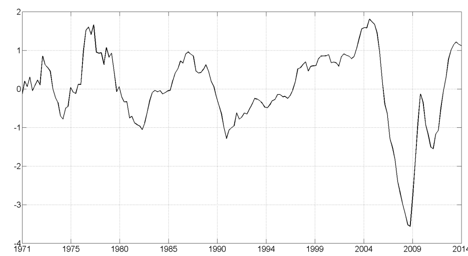
Figure 1: Financial indicators



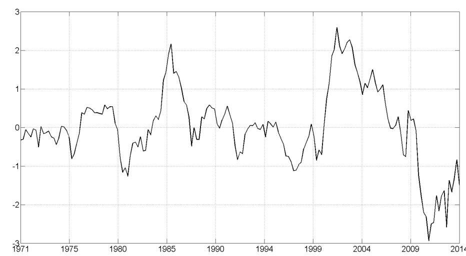
(a) Slope of the yield curve (SYC_t)



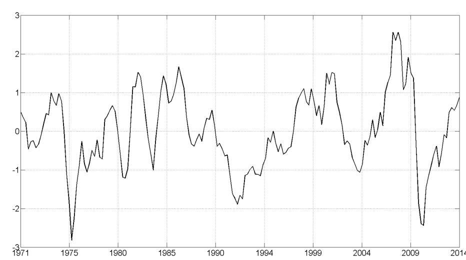
(b) Purchasing Managers' Index (PMI_t)



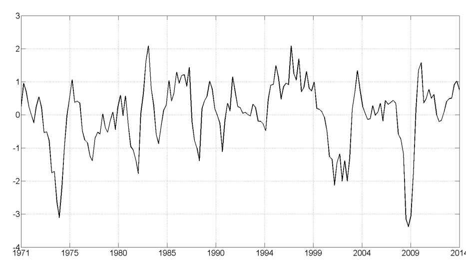
(c) Real estate price index returns (REP_t)



(d) Households' leverage ($HHLEV_t$)



(e) Non-financial corporations' leverage ($NFLEV_t$)



(f) S&P stock price index returns (SP_t)

Following Forni et al. (2000), we classify variables as procyclical 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. We find that PMI_t is procyclical with respect to SYC_t and the other indicators are countercyclical. However, Figure B.5 shows that no indicator can be classified as being either pro- or countercyclical with respect to SYC_t across its entire business cycle frequency band. In particular, PMI_t and $HHLEV_t$ are hard to classify.

Table 2 reports average dynamic correlations, computed over the entire periodic component band, i.e., 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 20-32 quarters have stronger correlations with SYC_t. The fourth column of Table 2 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 opposite phase to SYC_t. Note that SYC_t measures investors' expectations in the long run, i.e., 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 also would be picked-up by managers, i.e., PMI_t should be positive. The dynamic correlation signs support that less sanguine bond investor sentiment, i.e., 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 $HHLEV_t$.

Table 2: Average dynamic correlations and correlations at long-wave periodic components, calculated in reference to periodic components of SYC_t.

Indicator ($X_{i,t}$)	Average corr. ($\bar{\rho}$)	Long Wave (P)	P-period corr. ($\hat{\rho}_{X_{i,t},SYC_t}(P)$)
PMI_t	0.11	20	-0.20
REP_t	-0.09	28	-0.24
$NFLEV_t$	-0.42	32	-0.46
$HHLEV_t$	0.02	24	0.14
SP_t	-0.03	24	-0.14

Note: Wave length is measured in quarters.

Table 3 reports the time shifts for the long-wave periodic components, measured in quarters. Positive signs of the phase shift mean that SYC_t is leading and negative sign that SYC_t is a lagging indicator. We take negative, e.g., sign reversed indicators, where dynamic correlations for the dominant business cycle frequency came out to be negative. We find that SYC_t is lagging negative PMI_t, $HHLEV_t$, and negative SP_t and leading negative $NFLEV_t$ by three quarters. SYC_t is lagging negative REP_t by six quarters.

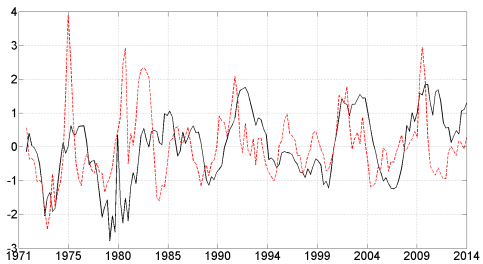
Table 3: Phase shifts measured in quarters with respect to SYC_t.

Indicator ($X_{i,t}$)	Phase shift, $\hat{\theta}(P)_{SYC_t,X_{i,t}}$
$-PMI_t$	-3
$-REP_t$	-6
$-NFLEV_t$	3
$HHLEV_t$	-3
$-SP_t$	-3

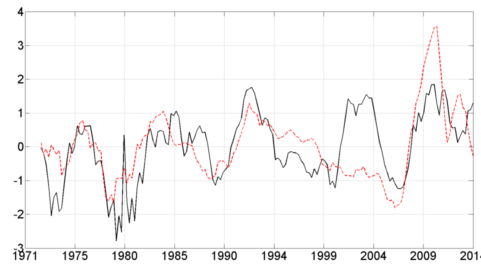
Based on this exploration of phase shifts for 20–32 quarter long cycles, and on the classification of each indicator as "in" or "out" of phase with SYC_t, the indicators are aligned before common factors are extracted, as described in Section 5.2. We describe the details of the alignment procedure in Section 3.1. Figure 2 shows the aligned series. In general, gaps between SYC_t and aligned individual indicators are not large, except for real estate prices after 2000 and for household leverage after 2008. This in line with other evidence on the household 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 household leverage. And also 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 RE_t (i.e., Figure 2) suggests time-variant factor loadings. Also visual inspection of the data suggest that strength of relation between our core indicator SYC_t and other indicators does change over time. We leave to further research the construction of dynamic factor model with time varying factor loadings (see Del Negro and Otrok, 2008).

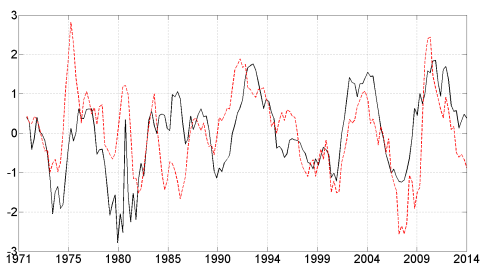
Figure 2: Phase shift and sign adjusted data of the US financial indicators: $PMI_t, HHLEV_t, SP_t$ 1971:Q4–2014:Q1, REP_t, 1972:Q3–2014:Q1 and $NFLEV_t$, 1971:Q1–2013:Q3.



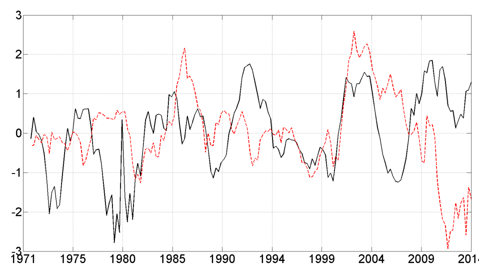
(a) SYC_{t+3} (solid) and $-PMI_t$ (dashed)



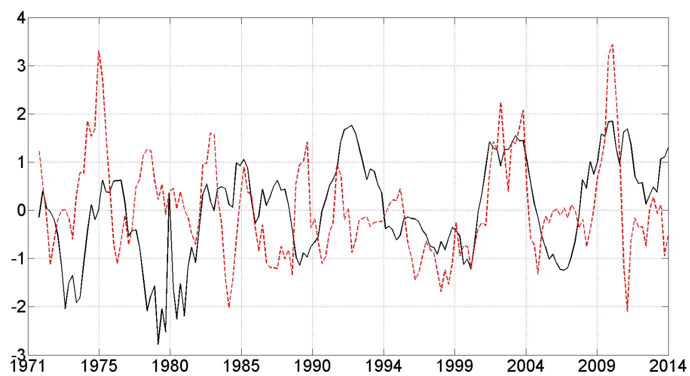
(b) SYC_{t+6} (solid) and $-REP_t$ (dashed)



(c) SYC_t (solid) and $-NFLEV_{t+3}$ (dashed)



(d) SYC_{t+3} (solid) and $HHLEV_t$ (dashed)



(e) SYC_{t+3} (solid) and $-SP_t$ (dashed)

5.2 Household and Corporate Sentiment in the Financial Cycle

We apply the principal components analysis to construct factors capturing the variation in the data, as described in Section 3.2. We find that selecting two factors satisfies Kaiser's criterion and also explains at least 50% of the variance criteria (Table 4).

Table 4: Variance explained by the principal components.

Number of PC	Cumulative variance explained	Eigenvalue
1	0.39	2.35
2	0.63	1.52
3	0.76	0.77
4	0.87	0.68
5	0.96	0.55
6	1.00	0.23

The loadings of the first two principal components in Table 5 suggest that the first factor captures the market sentiments of investors and managers, i.e., corporate sentiments. The second factor places most weight on household leverage and real estate prices, i.e., it captures much of the variation in household sentiment. To check robustness of factor interpretation we redo computations in two and three dimensional factor subspaces after dismissing other factors, as these may contain measurement noise. We also check that Orthogonal-varimax and Oblique-promax factor rotations provide the same qualitative conclusions, since factor correlation is close to zero (Appendix C).

Table 5: Loadings of the first two principal components.

Variable	PC 1	PC 2
$-SYC_{t-3}$	0.49	0.18
PMI_{t-6}	0.42	-0.27
REP_{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

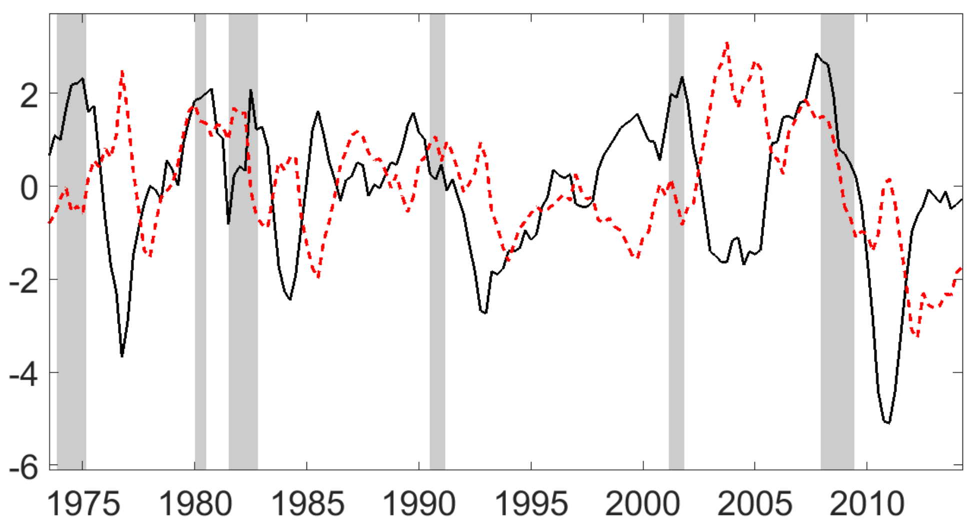
Both factors are interpreted relative to their historic average, which is zero by construction. From now on, we will refer to principal component 1 as corporate sentiment ($Corp\_F$). When $Corp\_F$ takes positive values, this corresponds to an event sequence of high real estate prices followed by positive managers' sentiment, rising stock price returns, positive investors' sentiment and growth of non-financial corporations' leverage. Managers' sentiment is signalled 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 household leverage and real estate price returns. This pattern is even more pronounced when we apply two-factor subspace (Appendix C). We will refer to Factor 2 as households' sentiment (HH_F). When households' sentiment takes positive values, a typical event sequence is rising real estate returns followed by growing households' leverage with falling stock price returns and managers' sentiments, as signalled by PMI_t and SP_t (somewhat more weakly in the two dimensional factor subspace - see Appendix C). After lead and lag adjustments for individual indicators, Figure 3 shows the development over time of the two factors which jointly constitute the new financial cycle index.

In sum, the factor loading and the behaviour of the household and corporate factors over time give some ground to regard the factors we 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 in one indicator, we will study the seperate development and interplay between households and corporate sentiments.

Corporate sentiment is more volatile, but they co-move strongly in most episodes, with the notable exception of the "dot.com" crash. This did not impact households sentiment negatively, in contrast to the Savings and Loans crisis of 1984. Corporate sentiment is peaking before or in NBER recessions and dropping during and after NBER recessions, in line with Minsky's notion that "success leads to excess leads to failure".

Figure 3: Corporate sentiment (solid line) and household sentiment (dashed line) 1973:Q2–2014:Q1 in the US, NBER recessions in gray.



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-banks failures wave of 1982; the 1984 start of the savings and loans crisis; the Black Tuesday stock market crash of 1987; the 1999 "dot.com" crash and the credit crisis and Lehman downfall 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 households' and corporate sentiments, started in 1993 and lasted until 2002, when this was replaced by the debt-burdened regime with low corporate sentiments but still high households' debt levels. The end of this regime came with the financial crisis of 2007-2008. Corporate sentiment recovered from 2012, with continuing low levels of household 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). Lopez-Salido and Nelson (2010) date troughs in 1973–1975, 1982–1984, 1988–1991 and 2007. There are peaks in our corporate factor prior to these periods, and additionally in 2001, just after the dot.com crash and 9/11.

Second, the increase in household mortgage credit is one of the major forces before the financial cycle trough in 2007 (Kemme, 2012). Indeed the household 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 at that time, although the corporate sentiment factor upswing is not uniquely large before 1984: it also peaks in 1977, 1992, 2003 and 2011.

We now continue to probe the validity of our indicators by turning to a number of other indicators.

6 Comparison to other indexes

In this section we ask how the corporate and household sentiment factors relate to other indexes. In comparison to the cycle by Drehman et al. (2012) for the US 1970–2011, 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. Similar to Drehman et al. (2012) our corporate sentiment factors have 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 indexes reflecting financial conditions and two economic conditions based indexes. We first describe them and then discuss their relative performance as measured by lead-lag relations with the GDP growth cycle.

Financial conditions indexes

Brave and Butters (2011) construct an index which measures financial conditions ($NFCI$) 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. Following Hatzius et al. (2010), prior to construction of the index they adjust their time series for inflation and for current and past economic activity (observing that financial and economic time series are highly correlated). The $NFCI$ 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 which 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 et al. (2009). The index consists of seven sub-indexes, describing three financial market segments: banking, securities markets and exchange markets. The seven sub-indexes 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 minus long-term rate), stock market returns, time-varying stock market return volatility, sovereign spreads, exchange market volatility. The methodology 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 implies the historical average of neutral financial market conditions. Positive values imply financial stress, a value of one or higher signals a crisis.

Economic conditions indexes

Aruoba et al. (2008) construct a real-time measure of business conditions (BCI) at the 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-through chronology.

As a second indicator for economic conditions, we will study the real GDP growth cycle, i.e., the annual log-growth rates of real GDP ($100\Delta y$). As discussed in Inklaar et al. (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, i.e., absolute expansions and contractions in the level of economic activity.

Comparison

To obtain an overall impression on how strongly the financial indexes (FSI, $NFCI$ and ours) link to the indexes describing real economic conditions (BCI and Real GDP growth rate cycle), we calculated their correlations. The results are listed in Table 6. Note that $NFCI$ has weak correlation with the real GDP growth cycle by construction, since the authors control 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. We also see that our household sentiment factor does not correlate with other financial or economic condition based indexes. $NFCI$ and FS indexes correlate quite strongly and BCI correlates the strongest with the GDP growth cycle.

Table 6: Correlations between financial condition and real condition based indexes, 1980:Q4–2013:Q2.

	$NFCI$	FSI	$Corp\_F$	HH_F	BCI
$NFCI$	1.000				
FSI	0.508***	1.000			
$Corp\_F$	0.196***	0.330***	1.000		
HH_F	0.030	0.085	0.015	1.000	
BCI	−0.161**	−0.217***	−0.167**	−0.081	1.000
$100\Delta y$	−0.092	−0.129*	−0.086	−0.019	0.480***

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

The beginning of the sample is determined by the availability of FSI index

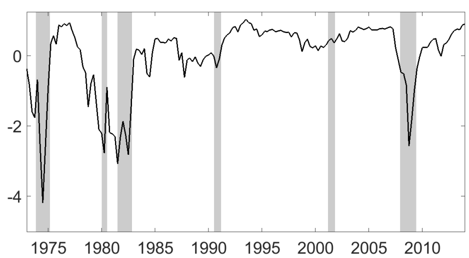
In Figure 4 we present all indexes after standardization to allow for a better comparison. Based on our correlations results with GDP growth rates (Table 6), we choose to invert FSI and $NFCI$. The indexes appear to have quite similar dynamics, with the exception of our household sentiment factor. The largest troughs correspond to the NBER recession dates. We also note that the smoothness of the time series differs, for example $NFCI$ is smoother than the other indexes.

Table 7 more formally compares the turning points of economic condition and financial indexes. The turning points were detected using the BBQ algorithm of Harding and Pagan (2002), extended to quarterly series from the original Bry and Boschan (1971) (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 indexes, however $NFCI$ and FS captures fewer turning points of the GDP growth rate cycle.

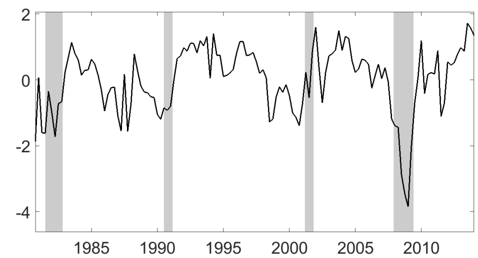
Based on peak-trough dating, we calculate the lead-lag relations between $-NFCI$, $-FSI$, BCI, $-Corp\_F$ and $-HH\_F$ and the GDP growth rate cycle. On average these indexes lead GDP growth by 1–2 quarters but household sentiment is lagging on average by three quarters. However, the lead relation is not always stable. The peaks for $Corp\_F$ 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 $Corp\_F$ 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 growth rate cycle leads $Corp\_F$.

In sum, in this section we explored the common movment and lead-lag relations

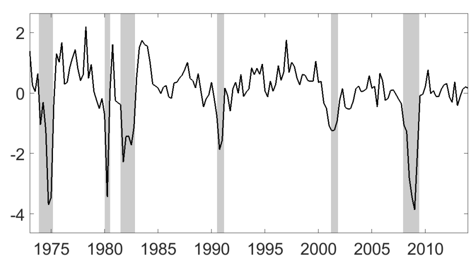
Figure 4: Standardized financial indexes and NBER recessions.



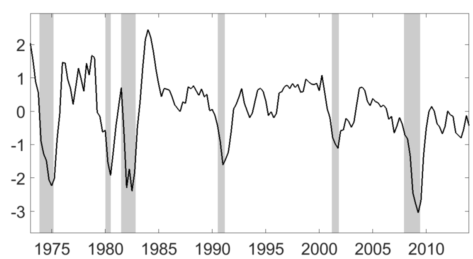
(a) $-NFCI$



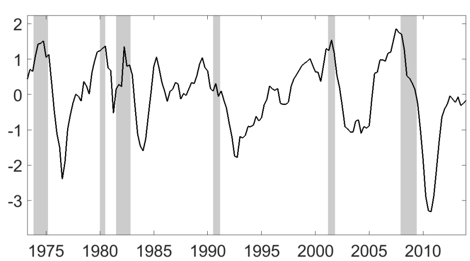
(b) $-FSI$



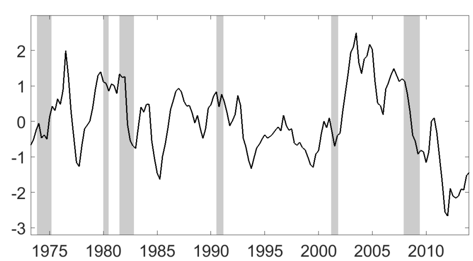
(c) BCI



(d) $100\Delta y$



(e) $Corp\_F$



(f) HH_F

between various indexes. 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 household 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, household debt growth, and descriptions of debt-driven versus debt-burdened growth regimes. We compare these factors to a number of other indexes capturing both real and financial conditions. It is noteworthy that household sentiment persistently leads the GDP growth cycle.

Table 7: Estimated turning points for the Indexes and NBER Business cycle reference points.

	Peaks and Troughs							Leads/Lags with respect to $100\Delta y$				
	$NFCI$ (inverted)	FS (inverted)	BCI	$Corp\_F$ (inverted)	HH_F (inverted)	NBER	$100\Delta y$	$NFCI$ (inverted)	FS (inverted)	BCI	$Corp\_F$ (inverted)	HH_F (inverted)
Peaks	1974:Q3					1973:Q4						
			1978:Q2	1976:Q3		1980:Q4	1978:Q4	M	M	-2	-9	M
	1981:Q3					1981:Q3						
		1983:Q3	1983:Q3	1984:Q1	1985:Q2		1984:Q1	M	-2	-2	0	5
	1987:Q4		1987:Q4		1989:Q2	1990:Q3	1988:Q2	-2	M	-2	M	5
		1994:Q2		1992:Q4	1993:Q4		1994:Q3	M	-1	M	1	-3
	1998:Q4		1997:Q1	1997:Q2								
					1999:Q3	2001:Q1	2000:Q2	M	M	M	M	-3
	2005:Q4	2002:Q1	2005:Q4	2004:Q2	2006:Q1		2004:Q1	7	-8	7	1	8
	2008:Q4		2010:Q2	2010:Q4	2012:Q1	2007:Q4	2010:Q3	-7	M	-1	1	5
Troughs	1977:Q1		1974:Q4	1974:Q4	1976:Q3	1975:Q1	1975:Q1	8	M	-1	-1	6
			1980:Q2	1980:Q3		1980:Q3						
						1982:Q4	1982:Q3	M	M	M	M	
	1986:Q4	1987:Q4	1986:Q2	1985:Q2	1987:Q1		1987:Q1	-1	3	-3	-7	0
			1990:Q4		1990:Q3	1991:Q1	1991:Q1	M	M	-1	M	-2
	1993:Q4			1995:Q4	1996:Q4		1995:Q4	-8	M	M	0	4
		2000:Q4	2001:Q2	2001:Q3		2001:Q4	2001:Q4	M	-4	-2	-1	M
	2004:Q1				2003:Q3							
	2007:Q1	2009:Q1	2009:Q1	2007:Q3	2007:Q1	2009:Q2	2009:Q2	-5	-1	-1	-7	-9
	Average lead-lag							-1.143	-2.167	-0.571	-2.00	3.286
	Standard deviation							6.414	3.656	3.409	4.20	4.424

M: missing values

7 Conclusion

How should the dynamics of the financial side of the economy be captured quantitatively, and how does it 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. Different from 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 since 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 which capture managers', investors' and households' 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 household sentiments, respectively.

Validation of financial indexes and factors is a key challenge in this literature for which there is no consensus approach. We apply both qualitative and quantitative methods. We observe that our corporate sentiment factor has a trough in each of the six NBER-dated recessions. Corporate sentiments rises, peaks and then turns close to financial crisis episodes in the US since 1973. Our indexes also capture the peaks and through as described in the literature. Further, we are able to relate the turning points of our corporate and household sentiment factors to the GDP growth rate cycle. Peaks of Corporate sentiment preceeds throughs in GDP growth cycle but household sentiment mostly is lagging behind GDP growth rate cycle.

Taken together, the corporate part of our index seems to map well onto financial crises, while the household sentiment factor relates more to the business cycle. Given their links, the next step in this paper will be to explore if the household sentiment factor is perhaps linking 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 household consumption becomes increasingly important for growth. A link between financial conditions and the business cycle via household leverage and sentiment is also relevant to monetary policy transmission. Apart from a credit channel through non-financial enterprises, real estate prices and household credit come into play. These issues remain topics for future research.

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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 provided by the Federal Reserve provides quarterly data on seasonally adjusted non-financial businesses' and households' debt securities and loans 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. Households 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 calculate year-on-year logarithmic growth rates of leverage ratios, adjust them to have zero mean and standardize. The resulting indicators are labelled household 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 (REP). The same procedure was applied tot 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 on each quarter on 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). Source: Institute of Supply Management.

In Table A.1 we show summary statistics of phase shift adjusted data. In our sample for PMI, REP, SP indicators normal distribution of the indicators cannot be accepted. Normality assumption is necessary for Principal components to reduce redundancies in the dataset and achieve independence of components, the method is based on the sufficient statistics provided by mean and variance. Multivariate Shapiro-Wilk normality test has value W = 0.86328, p-value = 5.154e-11 which means that we cannot accept normality and the consequence for PCA is that while components are uncorrelated these are not independent.

Table A.1: Summary statistics of the adjusted data, 1973:Q2–2014:Q1.

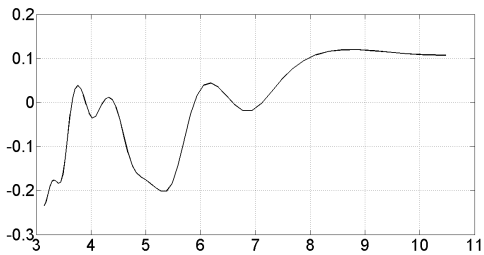
	SYC	$-PMI$	$-REP$	$-NFLEV$	$HHLEV$	$-SP$
Mean	-0.02	0.00	0.04	0.00	0.06	0.01
Median	0.03	-0.11	0.04	0.08	0.02	-0.16
Maximum	1.85	3.90	3.58	2.82	2.59	3.44
Minimum	-2.78	-2.44	-1.81	-2.56	-2.93	-2.09
Std. Dev.	1.01	1.02	1.00	1.02	0.98	1.01
Skewness	-0.27	0.95	0.98	0.04	-0.08	0.88
Kurtosis	2.56	4.39	4.75	2.87	3.81	4.02
Jarque-Bera	3.30	3.82	4.68	0.16	4.65	2.80
Probability	0.19	0.00	0.00	0.92	0.10	0.00
Observations	164	164	164	164	164	164

Table A.2: Description of the dataset

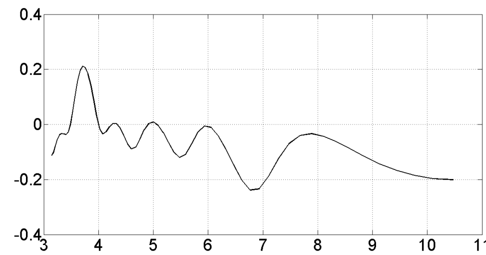
Variable	Data	Code	Source	Transformations	Description
SYC					Slope of the yield curve calculated as the difference between 10 year and 1 year constant maturity rates.
	10-year Treasury Constant Maturity Rates	GS10	Federal Reserve Bank of St. Louis	Monthly data transformed to quaterly by taking values in all months starting a new quarter.	
	1-year Treasury constant Maturity rate	DGS1	Federal Reserve Bank of St. Louis	Monthly data transformed to quaterly by taking values in all months starting a new quarter	
PMI	Purchasing Managers Index	NAPM	Federal Reserve Bank of St. Louis	Quarterly data, log- transformation	A PMI reading above 50 percent indicates that the manufacturing economy is generally expanding; below 50 percent that it is generally declining.
RER			Bank for International Settlements	Quarterly data; variable is adjusted for inflation and log -returns are calculated over 4 quarters as $log(P_t/P_{t-4})100$.	Residential Property prices, existing dwellings, per dwelling, SA: Average sale price of existing single family homes.
	GDPDEF	GDPDEF	Federal Reserve Bank of St. Louis		Gross domestic product: Implicit Price Deflator, seasonally adjusted; Index 2009=100.
HHLEV				Log annual growth rates	Ratio of credit to wages measured in log growth rates.
	Compensation of employees: wages and salaries	A576RC1Q027SBEA	Federal Reserve Bank of St. Louis		Seasonally adjusted annual rate
	Credit Market instruments to households and non-profit organizations, liability, level	CMDEBT			Seasonally adjusted
NFLEV				Log annual growth rates	Ratio of credit to profits measured in log growth rates
	Corporate Profits after tax	CP	Federal Reserve Bank of St. Louis		Seasonally adjusted annual rate without IVA and CCAdj.
	Credit Market instruments to non-financial corporations, liability, level	BCNSDODNS	Federal Reserve Bank of St. Louis		Seasonally adjusted
SP	S& P composite price index	S&P Comp. P.	Online data Robert Shiller	Adjusted for seasonality and GDP deflator before calculating log annual growth rates	Stock Market Data Used in ”Irrational Exuberance” Princeton University Press, 2000, 2005, 2015, updated; R.Shiller.

B Dynamic correlations

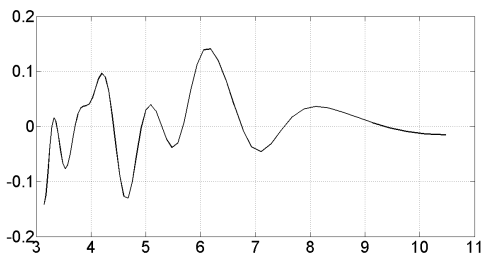
Figure B.5: Dynamic correlations (y-axis) as a function of wave length (x-axis) expressed in years.



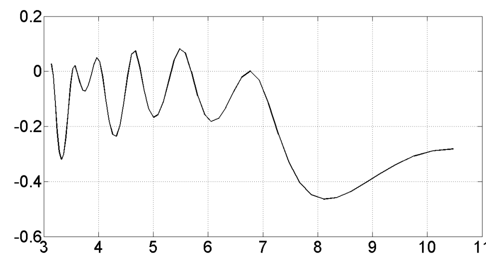
(a) Dynamic correlations between PMI_t and SYC_t



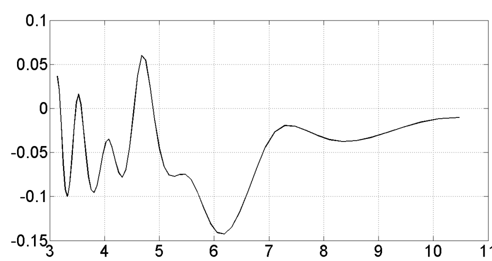
(b) Dynamic correlations between SYC_t and REP_t



(c) Dynamic correlations SYC_t and $HHLEV_t$



(d) Dynamic correlations SYC_t and $NFLEV_t$



(e) Dynamic correlations SYC_t and SP_t

C Robustness checks for factor loadings

We check robustness of factor interpretation in two and three dimensional spaces.

Factor loadings in two dimensional subspace

Table C.3: Factor loadings in original and two dimensional subspace.

	Varimax, 2-Factor space		Promax, 2-Factor space	
Variable	Factor 1	Factor 2	Factor 1	Factor 2
$-SYC_{t-3}$	0.58	0.34	0.57	0.39
PMI_{t-6}	0.55	-0.03	0.55	0.01
REP_{t-9}	0.41	0.91	0.38	0.94
$NFLEV_t$	0.59	0.09	0.59	0.13
$HHLEV_{t-6}$	-0.28	0.62	-0.30	0.60
SP_{t-6}	0.58	-0.13	0.59	-0.09

We use matlab procedure for oblique rotation "promax", where the target matrix is a result of the orthomax rotation raised to the power of four. Estimated correlation under this rotation was close to zero (-0.0382) which implies that factors are orthogonal.

Factor loadings in three dimensional subspace

To check the robustness of factor interpretation, i.e., loadings we redo the computations in three dimensional sub-space. Factor loadings indicate that the first factor can be labeled as investors' sentiment, the second as households' and the third as managers' sentiment. This indicates that the factor interpretation in two-dimensional space remains robust to increasing dimensions of subspace.

Table C.4: Factor loadings in three dimensional subspace.

	Varimax			Promax		
Variable	Factor 1	Factor 2	Factor 3	Factor 1	Factor 2	Factor 3
$-SYC_{t-3}$	0.97	0.00	0.19	1.15	-0.19	-0.19
PMI_{t-6}	0.19	-0.04	0.50	0.06	-0.06	0.50
REP_{t-9}	0.51	0.51	0.23	0.41	0.45	0.11
$NFLEV_t$	0.35	0.07	0.49	0.23	0.03	0.44
$HHLEV_{t-6}$	-0.01	0.98	-0.20	-0.20	1.04	-0.11
SP_{t-6}	0.07	-0.12	0.77	0.25	-0.09	0.89

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