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Unobserved components model estimates of credit cycles: Tests and predictions☆

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ABSTRACT

This paper estimates unobserved components (UC) models with real and financial trends and business and credit cycles to assess different measures of the credit cycle used by policymakers. The permanent components of the real and financial sectors are a Beveridge–Nelson and local linear trend, respectively. The business and credit cycles evolve jointly as a second-order vector autoregression. Bootstrap methods are applied to UC model estimates retrieved from classical optimization of the predictive likelihood of the Kalman filter. Results indicate the slope of the financial trend better predicts the credit to GDP ratio in the United States than the estimated business and credit cycles and the Basel gap. This suggests policymakers should consider permanent shocks to the financial sector when gauging the state of financial stability.

1. Introduction

The effectiveness of the CCyB depends on accurate measurement of the business cycle on the real side of an economy and similar transitory fluctuations in its financial markets. The credit cycle is the label often given to the hidden state variable that captures the response of financial markets to transitory disturbances. The Basel Committee on Banking Supervision (2010) recommends measuring the credit cycle by applying a one-sided Hodrick–Prescott (HP) filter to the quarterly credit to GDP ratio.

The choice by the Basel Committee on Banking Supervision (BCBS) to use the HP filter has drawn criticism. Along with the well known critiques of the HP filter by Harvey and Jaeger (1993), King and Rebelo (1993), Cogley and Nason (1995), Canova (1998), and Hamilton (2018) among others, there is an extensive literature showing the BCBS-HP filtered credit cycle can exhibit excess volatility and persistence and its conditional mean can be biased. A subset of this literature includes (Edge and Meisenzahl, 2011; Alessandri et al., 2015; Barrell et al., 2018; Darracq Pariès et al., 2019; Jokipii et al., 2021; Alessandri et al., 2022). An interesting aspect of these critiques is provided by Galán and Mencía (2021), Schüler (2020), and Jylhä and Lof (2022). They draw attention to the BCBS (2010) suggesting the HP smoothing parameter be set to 4×10^6 instead of the conventional value of 1600 for quarterly data.

Despite these issues, the Basel Committee on Banking Supervision (2017) reports that its HP filtered credit cycle, which is also known as the Basel gap, is widely used by national financial market regulators. Support for the Basel gap is found in Drehmann et al. (2010), Drehmann and Juselius (2014), and Borio et al. (2016). Drehmann et al. (2010) contend the Basel gap is a leading indicator of financial distress. Drehmann and Juselius (2014) support this finding over long horizons, while an alternative measure, the debt service ratio, performs better over shorter horizons. Borio et al. (2016) find incorporating the Basel gap into estimations of potential output improves the precision and robustness of real time output gap estimates.

This paper presents an alternative approach to estimating and testing the credit cycle motivated by the lack of consensus about the Basel gap. I obtain estimates of the credit cycle by imposing restrictions associated with the permanent income hypothesis (PIH) and a macro-finance theory of leverage on unobserved components (UC) models. The PIH predicts a decomposition of consumption and income into the common PI trend and business cycle. I extend the ideas of Brunnermeier and Sannikov (2014) to place restrictions on the financial sector. Brunnermeier and Sannikov (2014) construct a macro-finance model

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in which the demand for credit originates in the optimal choice of leverage by borrowers. This choice predicts a long-run equilibrium that jointly restricts movements in capital and the level of debt held by the productive sector. Similar to the PIH, the long-run relationship in the stock of nonfinancial assets and credit supply predicts a permanent-transitory decomposition, which I refer to as the financial trend and the credit cycle.

The UC models embed the trend-cycle restrictions of the PIH and the Brunnermeier and Sannikov theory of leverage in the measurement equations. The measurement equations are grounded in a vector of constant dollar observables consisting of non-durable goods and services consumption expenditures, disposable income, nonfinancial credit, and nonfinancial assets. These variables are sufficient to recover the state variables, which are the PI and financial trends and business and credit cycles, given an appropriate specification of the system of state equations. I assume the PI trend evolves as a random walk with drift while a local linear trend produces the permanent financial component. As a result, the PI trend is interpreted as the permanent component of the Beveridge and Nelson (1981) decomposition while the permanent component of the financial sector consists of the levels trend and its time-varying I(1) slope.

An unrestricted second-order bivariate autoregression generates the business and credit cycles. This is my baseline UC model. I create five additional UC models by placing restrictions on the lag coefficients of the business and credit cycles or covariance matrix of the errors of the reduced-form VAR(2). The UC models are estimated using the Kalman filter and its predictive likelihood and classical optimization methods on a quarterly U.S. sample from 1960 to 2018. However, bootstrapped methods are employed to construct the empirical sampling distributions of the UC model parameters, state variables, and test statistics.

Estimating the UC models yields five main contributions. First, bootstrapped likelihood ratio (LR) tests favor the baseline UC model that lacks exclusion restrictions on the lags of the cycles in the reduced-form VAR(2). Nonetheless, joint tests of these lag coefficients suggest Granger causality does not run in either direction between the business and credit cycles.

Second, estimates of the slope of the financial trend and the business cycle display troughs during almost every NBER dated recession between 1960 and 2018. The credit cycle has three troughs. The first two troughs are in the mid 1960s and mid 1990s, but the third occurs at the end of the 2007–2009 recession and financial crisis. My estimated credit cycle is more persistent and volatile than the business cycle, but less volatile and smoother than the Basel gap.

Third, mapping the reduced-form VAR(2) into a structural VAR (SVAR) yields impulse response functions (IRFs) for the business and credit cycles with respect to their shocks. When the business cycle is ordered after the credit cycle, its IRF to a credit cycle shock is hump-shaped. However, the uncertainty bands around this IRF include zero at every forecast horizon except between the 1- and 2-year horizons. Reversing the order of the SVAR results in substantial uncertainty surrounding the equivalent IRF of the business cycle to a credit cycle shock.

Fourth, I report predictive regressions of the h-quarter ahead bootstrapped business cycles on the bootstrapped credit cycle. Tests show the credit cycle is a useful predictor of the h-step ahead business cycle only at horizons longer than two years. In contrast, the business cycle has predictive power for the credit cycle at every forecast horizon from one quarter to four years.

Fifth, regressing the h-quarter ahead growth rate of the credit to GDP ratio on the Basel gap results in serially correlated residuals at all forecast horizons. This reinforces results in Alessandri et al. (2022), Galán and Mencía (2021), and Schüler et al. (2020) that the Basel gap is a weak predictor of the future path of the credit to GDP ratio. Adding the bootstrapped business and credit cycles to the regression yields serially uncorrelated residuals at low-order forecast horizons. Interestingly, my estimate of the slope of the financial trend is the best predictor of the growth of the credit to GDP ratio considered. Regressing the h-quarter ahead growth rate of the credit to GDP ratio on the bootstrapped slope of the financial trend produces serially uncorrelated residuals at forecast horizons of up to one year. This finding suggests permanent shocks to the financial sector matter for financial stability. Plots of the coefficient from this regression estimated with rolling windows demonstrate the slope of the financial trend could have provided a signal of financial instability to policymakers prior to the 2007–2009 financial crisis in the United States.

My estimates contribute to a large and growing empirical literature on credit cycles. Important work on this topic includes (Demirgüç-Kunt and Detragiache, 1998; Kaminsky and Reinhart, 1999; Mendoza and Terrones, 2008; Schularick and Taylor, 2012; Claessens et al., 2012; Aikman et al., 2014). This literature points out the importance of growth in the credit to GDP ratio as a precursor of financial instability. Recent contributions to the literature by Lo Duca and Peltonen (2013), Aikman et al. (2017), Alessi and Detken (2018), and Schüler et al. (2020) demonstrate that broader sets of financial indicators improve upon the Basel gap's ability to gauge financial stability. Hartwig et al. (2021) consider a number of different indicators from the literature. The authors conclude that ex ante systemic risk can only be measured consistently after turning points in the indicators have been observed. Since turning points are unpredictable, Hartwig et al. (2021) suggest using leverage cycle theory in the vein of Brunnermeier and Sannikov (2014) to explain systemic risk.

This paper is distinct from existing literature in two aspects. First, I recover estimates of a financial trend and credit cycle from a structural model with restrictions informed by theory. Theory for the joint consideration of variables is provided by the PIH for the real sector and Brunnermeier and Sannikov (2014) for the financial sector as suggested by Hartwig et al. (2021). Second, I jointly estimate credit and business cycles and examine their comovement. This is important for policymakers because the link between the financial sector and the real sector is the focus of the CCyB as stated by the BCBS (2010). My results indicate that omission of business cycle information when estimating the credit cycle leads to model misspecification.

My approach to studying the credit cycle within a structural time series model is closest to Galati et al. (2016) and Rünstler and Vlekke (2018). Galati et al. (2016) estimate UC models to recover estimates of the credit cycle. Rünstler and Vlekke (2018) jointly estimate business and credit cycles. The results in this paper support the claim made by Rünstler and Vlekke (2018) that there is important information in the credit cycle for the business cycle. A key difference in my work is the imposition of a common trend and cycle on two variables in each sector. The use of multiple variables for each sector is necessary to properly identify a trend-cycle decomposition. Carreras et al. (2018) demonstrate the importance of taking long-run relationships between financial variables into account. Loading additional observable information into UC models that restrict the joint process generating the real and financial sides of the U.S. economy gives estimates of the credit cycle that are more efficient and economically interesting. Further, estimates of the slope of the financial trend and business and credit cycles are used to assess their and the Basel gap's predictive content. The predictive regressions indicate my estimates of the business and credit cycles and especially the slope of the financial trend provide better signals of the state of the financial markets, as measured by the credit to GDP ratio, than the Basel gap. Hence, my results lend support to a growing literature that recommends policymakers exercise caution if using the Basel gap to assess the state of the financial markets for which they are responsible.

Section 2 lays out the UC models. Section 3 describes the data. My estimation methods are discussed in Section 4. Section 5 presents the estimates of the PI and financial trends and business and credit cycles, estimates of the SVARs of these cycles, the IRFs and forecast error variance decompositions (FEVDs), and predictive regressions. Section 6 concludes.

2. The UC models

I estimate PI and financial trends and business and credit cycles using UC models. The UC models are described by measurement and state transition equations. The measurement vector, Y_t, contains the n observed variables in the model. The system of measurement equations is

$$Y_t = CX_t + De_t. \tag{1}$$

In Eq. (1), the measurement error, e_t, is a white noise process with $var(e_t) = I_n$. The states are placed in the k-dimensional vector X_t, which evolves as the system of state transition equations

$$X_t = AX_{t-1} + H + B\varepsilon_t. \tag{2}$$

Static drift parameters are stored in the vector H, which also contains zeros. In Eq. (2), the state transition error is a white noise process with $var(\varepsilon_t) = I_m$, $m \le k$.

2.1. The PIH and the business cycle

The PIH identifies the common trend of the consumption–income pair. Households consume their PI level which is their current expected discounted level of future income. By assuming a random walk with drift drives the PI trend, it is identified with the Beveridge and Nelson (1981) trend as in Morley (2007). The consumption–income pair yields the business cycle as the common transitory component that remains after removing the common PI trend.

2.2. Leverage, the financial trend, and the credit cycle

Much of the literature measures credit cycles from the perspective of firms' and households' ability to pay their debt obligations. For example, Drehmann et al. (2012) calculate a credit cycle using a band-pass filter on the ratio of credit to GDP. In this interpretation, the credit cycle is in an expansionary phase when credit growth outpaces income growth. Their story is increasing debt, relative to income, increases default risk in financial markets and the likelihood of a credit contraction in the future.

My models innovate by identifying a long-run relationship between credit supply and nonfinancial assets. This long-run relationship is motivated by the macro-finance theory of Brunnermeier and Sannikov (2014). Their model begins with productive agents borrowing from non-productive agents to purchase physical capital. Productive agents seek to maximize growth in net worth by targeting a level of leverage. Leverage is defined as the percentage of net worth borrowed to fund physical capital expenditures. Leverage is stationary in this model, which predicts there is a long-run relationship between debt and physical capital. Similar to Brunnermeier and Sannikov (2014), deviations from this long-run relationship are identified as the credit cycle.

The permanent financial component is a local linear trend as in Rünstler and Vlekke (2018). This specification implies the level of the trend and its slope are I(1) processes. A local linear trend nests the financial trend of Galati et al. (2016) which sets the level disturbance equal to zero to form an integrated random walk. Further, a local linear trend is consistent with the HP and Baxter-King filters, as discussed by Harvey and Trimbur (2003), among others. This assumption makes for straightforward comparisons with studies using these filters to estimate credit cycles as, for example, by Borio et al. (2018).

2.3. The measurement equations

Restrictions on the real and financial sectors of Model 1 are embedded in the system of measurement equations

$$\underbrace{\begin{bmatrix} con_t \\ inc_t \\ nfc_t \\ nfa_t \end{bmatrix}}_{Y_t} = \underbrace{\begin{bmatrix} 1 & 0 & 0 & \kappa & 0 & 0 & 0 \\ \alpha & 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & \lambda & 0 \\ 0 & \beta & 0 & 0 & 0 & 1 & 0 \end{bmatrix}}_{C} \underbrace{\begin{bmatrix} \tau_t \\ \psi_t \\ \xi_t \\ \delta_t \\ \delta_{t-1} \\ \phi_t \\ \phi_{t-1} \end{bmatrix}}_{X_t} + De_t, \tag{3}$$

where $e_t = [e_{con,t} \quad e_{inc,t} \quad e_{nfc,t} \quad e_{nfa,t}]' \sim N(0_{4\times1}, I_{4\times4})$, and D is a square matrix with the volatility of measurement errors $\sigma_{con,t}$, $\sigma_{inc,t}$, $\sigma_{nfc,t}$, and $\sigma_{nfa,t}$ on the diagonal and zeros elsewhere. The real sector, consumption and income, is composed of the PI trend, τ_t, and business cycle, δ_t. Similar to Morley (2007), I normalize the response of consumption, con_t, to the PI trend. The factor loading of income, inc_t, on the business cycle is also normalized to one. In Eq. (3), α is the factor loading of income on the PI trend, and κ is the factor loading of consumption on the business cycle. Further, I normalize the response of credit supply, nfc_t, to the financial trend, ψ_t, and the response of nonfinancial assets, nfa_t, to the credit cycle, ϕ_t. The response of nonfinancial assets to the financial trend is described by β. The response of the supply of credit to the credit cycle is measured by λ.

2.4. The state equations

The trends and cycles of the UC models make up the state vector. The PI trend is a random walk with drift μ, which is consistent with a Beveridge–Nelson trend. As already mentioned, the financial trend evolves as a local linear trend.[1] The level of the financial trend is ψ_t and ξ_t is its slope. The business and credit cycles, δ_t and ϕ_t, are a reduced-form VAR(2). This structure is summarized in the system of state transition equations of Model 1

$$\underbrace{\begin{bmatrix} \tau_{t+1} \\ \psi_{t+1} \\ \xi_{t+1} \\ \delta_{t+1} \\ \delta_t \\ \phi_{t+1} \\ \phi_t \end{bmatrix}}_{X_t} = \underbrace{\begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & \theta_1 & \theta_2 & \vartheta_1 & \vartheta_2 \\ 0 & 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & \zeta_1 & \zeta_2 & \gamma_1 & \gamma_2 \\ 0 & 0 & 0 & 0 & 0 & 1 & 0 \end{bmatrix}}_{A} \underbrace{\begin{bmatrix} \tau_t \\ \psi_t \\ \xi_t \\ \delta_t \\ \delta_{t-1} \\ \phi_t \\ \phi_{t-1} \end{bmatrix}}_{X_{t-1}} + \underbrace{\begin{bmatrix} \mu \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \end{bmatrix}}_{HZ_t} + B\varepsilon_t, \tag{4}$$

where $\varepsilon_t = \begin{bmatrix} \varepsilon_{\tau,t} \\ \varepsilon_{\psi,t} \\ \varepsilon_{\xi,t} \\ \varepsilon_{\delta,t} \\ \varepsilon_{\phi,t} \end{bmatrix} \sim N(0_{5\times1}, I_{5\times5})$,

and $BB' = \begin{bmatrix} \sigma_\tau^2 & 0 & 0 & \sigma_{\tau,\delta} & 0 & 0 & 0 \\ 0 & \sigma_\psi^2 & 0 & 0 & 0 & \sigma_{\psi,\phi} & 0 \\ 0 & 0 & \sigma_\xi^2 & 0 & 0 & 0 & 0 \\ \sigma_{\tau,\delta} & 0 & 0 & \sigma_\delta^2 & 0 & \sigma_{\delta,\phi} & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & \sigma_{\psi,\phi} & 0 & \sigma_{\delta,\phi} & 0 & \sigma_\phi^2 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix}$.

In the system of state Eqs. (4), innovations to the trend and cycle within a sector are correlated. The PI trend and the financial trend are independent. In Model 1, the real and financial sectors are connected by the VAR(2) specification of the business and credit cycles. Similar restrictions on the state equations are found in Lee and Nelson (2007).

[1] Attempts to model the financial trend as a random walk with drift were not supported by the data. See Appendix F.2 for further discussion.

Table 1
Summary of model restrictions.

Model	Cycle description	Restrictions
Reduced-form VAR specifications		
Model 1	Granger causality runs in both directions.	none
Model 2	Business cycle does not Granger cause credit cycle.	$\zeta_1 = \zeta_2 = 0$
Model 3	Credit cycle does not Granger cause business cycle.	$\vartheta_1 = \vartheta_2 = 0$
Model 4	Cycles do not Granger cause each other.	$\zeta_1 = \zeta_2 = \vartheta_1 = \vartheta_2 = 0$
Recursive SVAR specifications		
Model	Cycle description	Restrictions
Model 5	At impact the business cycle responds to the credit cycle.	$\zeta_0^* = \sigma_{\delta,\phi} = 0$
Model 6	At impact the credit cycle responds to the business cycle.	$\vartheta_0^* = \sigma_{\delta,\phi} = 0$

I estimate three alternative UC models by placing exclusion restrictions on the reduced-form VAR(2) of the system of state Eqs. (2). Model 2 sets the response of the credit cycle to lags of the business cycle, ζ_1 and ζ_2, to zero. The business cycle does not Granger cause the credit cycle under these restrictions, which are motivated by Borio et al. (2018). Next, Model 3 assumes Granger causality runs in the opposite direction by restricting $\vartheta_1 = \vartheta_2 = 0$. In this case, there is reduced-form predictability from lags of the business cycle to the credit cycle. The final model, Model 4, imposes zero restrictions on the off diagonals, $\zeta_1 = \zeta_2 = \vartheta_1 = \vartheta_2 = 0$, of the reduced-form VAR(2). The dynamics of the business cycle and credit cycle are separate in Model 4. The top panel of Table 1 summarizes Models 1, 2, 3, and 4.

2.5. Using recursive SVARs to generate business and credit cycles

Models 1, 2, 3, and 4 have reduced-form VARs that can be mapped into recursive structural VARs. The structural VAR is

$$\Theta_0 \begin{bmatrix} \delta_t \\ \phi_t \end{bmatrix} = \Theta_1 \begin{bmatrix} \delta_{t-1} \\ \phi_{t-1} \end{bmatrix} + \Theta_2 \begin{bmatrix} \delta_{t-2} \\ \phi_{t-2} \end{bmatrix} + B_c^* \varepsilon_{c,t}, \tag{5}$$

where $\varepsilon_{c,t} \sim N(0_{2\times 1}, I_{2\times 2}),\ B_c^* B_c^{*\prime} = \begin{bmatrix} \sigma_\delta^{*2} & 0 \\ 0 & \sigma_\phi^{*2} \end{bmatrix}$,

and $B_c^* = \Theta_0 B_c$ is the submatrix of B corresponding to δ_t and ϕ_t. The first step in mapping from the reduced-form VARs of Models 1, 2, 3, or 4 to the structural VAR of (5) involves pre-multiplying (5) by Θ_0^{-1}

$$\begin{bmatrix} \delta_t \\ \phi_t \end{bmatrix} = \Theta_0^{-1}\Theta_1 \begin{bmatrix} \delta_{t-1} \\ \phi_{t-1} \end{bmatrix} + \Theta_0^{-1}\Theta_2 \begin{bmatrix} \delta_{t-2} \\ \phi_{t-2} \end{bmatrix} + \Theta_0^{-1} B_c^* \varepsilon_{c,t},$$

where $\Theta_0^{-1} B_c^* \varepsilon_{c,t} \sim N(0_{2\times 1}, \Theta_0^{-1} B_c^* B_c^{*\prime} \Theta_0^{-1\prime})$. Next, the impact matrix, Θ_0, of the structural VAR is recovered using one of two recursive orderings of the business and credit cycles. In the first structural VAR, which is labeled Model 5, the credit cycle is structurally causally prior to the business cycle

$$\Theta_{0,CB} = \begin{bmatrix} 1 & -\vartheta_0^* \\ 0 & 1 \end{bmatrix}.$$

Take the upper Cholesky decomposition of the covariance matrix of the business and credit cycles of the reduced-form VAR, $\Theta_0^{-1} B_c^* B_c^{*\prime} \Theta_0^{-1\prime}$, which requires solving the bivariate system

$$\left[\Theta_{0,CB}^{-1} B_c^* B_c^{*\prime} \Theta_{0,CB}^{-1\prime}\right]^{1/2} = \begin{bmatrix} 1 & -\vartheta_0^* \\ 0 & 1 \end{bmatrix}^{-1} \begin{bmatrix} \sigma_\delta^* & 0 \\ 0 & \sigma_\phi^* \end{bmatrix}.$$

The structural VAR is found by pre-multiplying the lag coefficient matrices of the reduced-form VAR by $\Theta_{0,CB}$ to produce Model 5.

Model 6 reverses the structural ordering to place the business cycle before the credit cycle

$$\Theta_{0,BC} = \begin{bmatrix} 1 & 0 \\ -\zeta_0^* & 1 \end{bmatrix}.$$

A similar process recovers this impact matrix

$$\left[\Theta_{0,BC}^{-1} B_c^* B_c^{*\prime} \Theta_{0,BC}^{-1\prime}\right]^{1/2} = \begin{bmatrix} 1 & 0 \\ -\zeta_0^* & 1 \end{bmatrix}^{-1} \begin{bmatrix} \sigma_\delta^* & 0 \\ 0 & \sigma_\phi^* \end{bmatrix},$$

but in this case a lower Cholesky decomposition of the covariance matrix of the reduced-form VAR innovations is computed. The coefficient matrices of the structural VAR, Model 6, are recovered by pre-multiplying the reduced-form VAR by $\Theta_{0,BC}$.

3. Data

Data on consumption and income in the U.S. measures activity in the real sector. The financial sector is measured by data on credit supply and nonfinancial assets. The data are in constant dollars, per capita, logged and multiplied by 400.[2] The quarterly sample runs from 1960Q1 to 2018Q4.

3.1. The real sector

Consumption is equated to aggregate personal consumption expenditures on nondurable goods and services. Tests of the PIH most often measure consumption as its flow from nondurable goods and services. For example, at least since (Hall, 1978), consumer durable goods expenditures are excluded to avoid issues with imputing the value of the service flow from the stock of these goods. I use an ideal Fisher index to construct constant dollar nondurable goods and services consumption as discussed in Whelan (2002). Income is measured by real personal income excluding transfer payments.[3] This is consistent with the PIH from the household's perspective. Additionally, the use of real personal income excluding transfer payments, along with nondurable goods and services consumption, is standard in the empirical literature on the PIH. See for example, Hall (1978), Nelson (1987), and Kiley (2010).

3.2. The financial sector

Data for the financial sector comes from the Financial Accounts of the United States that is published by the Board of Governors of the Federal Reserve System. Credit supply is the sum of debt securities and loans of nonfinancial corporate businesses, households and nonprofit organizations, as well as loans of nonfinancial noncorporate businesses. This measure of credit is used by Borio (2014) and Drehmann et al. (2010) in their construction of the credit to GDP ratio. Aggregate nonfinancial assets of the private nonfinancial sector are held by nonfinancial corporate businesses, households and nonprofit organizations, and nonfinancial noncorporate businesses.[4]

[2] Details about the construction of the data are given in Appendix A.

[3] Consumption and income data are retrieved from FRED at the Federal Reserve Bank of St. Louis. In a robustness exercise reported in Appendix G, I reestimate the UC models with real GDP in place of real disposable income.

[4] This paper differs from existing literature by not including asset prices, such as housing, in the estimation of credit cycles. For example, Drehmann et al. (2012), Galati et al. (2016), Rünstler and Vlekke (2018), and Schüler et al. (2020) all show that the inclusion of house prices helps to identify periods of financial instability. However, the model of Brunnermeier and Sannikov (2014) implies the use of two quantity variables in the financial sector to get at a measure of leverage. Thus, credit and nonfinancial assets are used as discussed above.

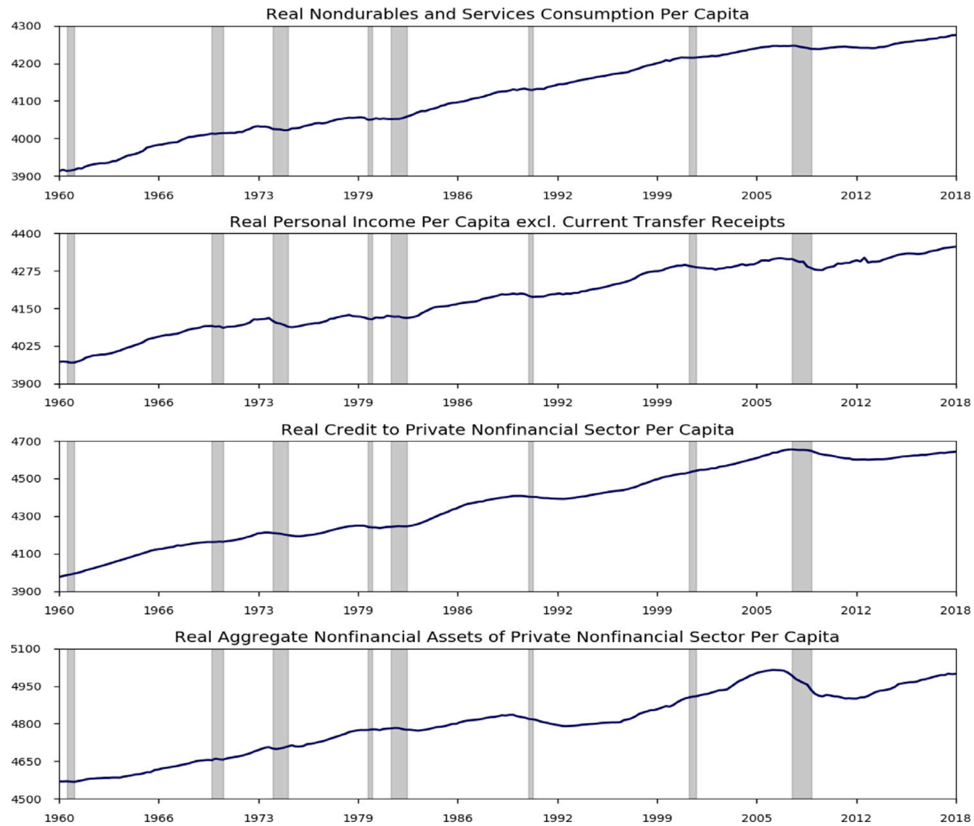

Fig. 1. Data in log levels, 1960Q1-2018Q4. Notes: The gray bars represent NBER recession dates. Details of data construction are found in Appendix A.

3.3. Describing the data

Figs. 1 and 2 plot the data in log levels and growth rates. Consumption and income appear to comove throughout the sample. Income is more volatile than consumption and business cycle movements are more pronounced. Consumption growth is below its sample mean and income declines during each NBER dated recession. Contractions in these series are most pronounced in the 1973–1975 and 2007–2009 recessions. Both recessions are of similar duration and severity in the real sector.

Credit supply and nonfinancial assets often contract during NBER dated recessions with the exception of the 2001 recession. Moreover, the financial series seem to have a prolonged period of negative growth on either side of the 1991 recession. This episode was followed by more than a decade of above average growth in credit supply and nonfinancial assets leading up to steep declines during the financial crisis. Credit supply growth remained well below its sample mean for several years following the most recent financial crisis.

4. Econometric methods

The innovations form of the Kalman filter is used to compute the log likelihood of Models 1, 2, 3, and 4, given initial state conditions, $X_{0|0}$, and an initial parameter vector, Γ_0.[5] The log likelihood is maximized via classical optimization to obtain estimates of the parameters and states of the UC models.

I adapt the bootstrap algorithm of Stoffer and Wall (2004) to produce the small sample distributions of model parameters and the states. Bootstrapped empirical distributions of the maximum likelihood (ML) estimates overcome problems created by reduced rank Hessian matrices and applying asymptotic theory in the presence of small sample sizes; see Angelini et al. (2021), Stoffer and Wall (2004), and Ansley and Newbold (1980). Another issue with using asymptotic theory is the autoregressive parameters are near the boundary of the parameter space when cyclical components are highly persistent; see Morley et al. (2003). The bootstrap algorithm first resamples with replacement the standardized errors from the Kalman filter of the ML estimates. These resampled standardized errors are used to back out a synthetic sample using the state space representation of a UC model. Next, the UC model is estimated on the bootstrap sample and the results are recorded. One thousand artificial samples are produced to create bootstrap distributions of UC model parameters, the covariance matrix of the parameters, and likelihood ratio statistics.[6]

Empirical distributions of likelihood ratio (LR) statistics are used to evaluate which UC model best fits the data. The LR tests provide evidence about whether the credit cycle Granger causes the business cycle. The likelihood of the UC model under the null corresponds to Model 1. The null is compared with Model 2, Model 3, and Model 4. Bootstrap methods described by Morley et al. (2016) produce the empirical distributions of the LR statistics. The LR statistics are computed

[5] A detailed discussion of the ML estimation and the innovations form of the Kalman filter is given in Appendix B. The initialization of the innovations form of the Kalman filter is discussed in Appendix B.2. I apply the bootstrap procedure of Stoffer and Wall (2004), which is described in Appendix C.

[6] Julia 1.3.1 is used to estimate the UC models and generate the bootstrap samples. Code is available upon request.

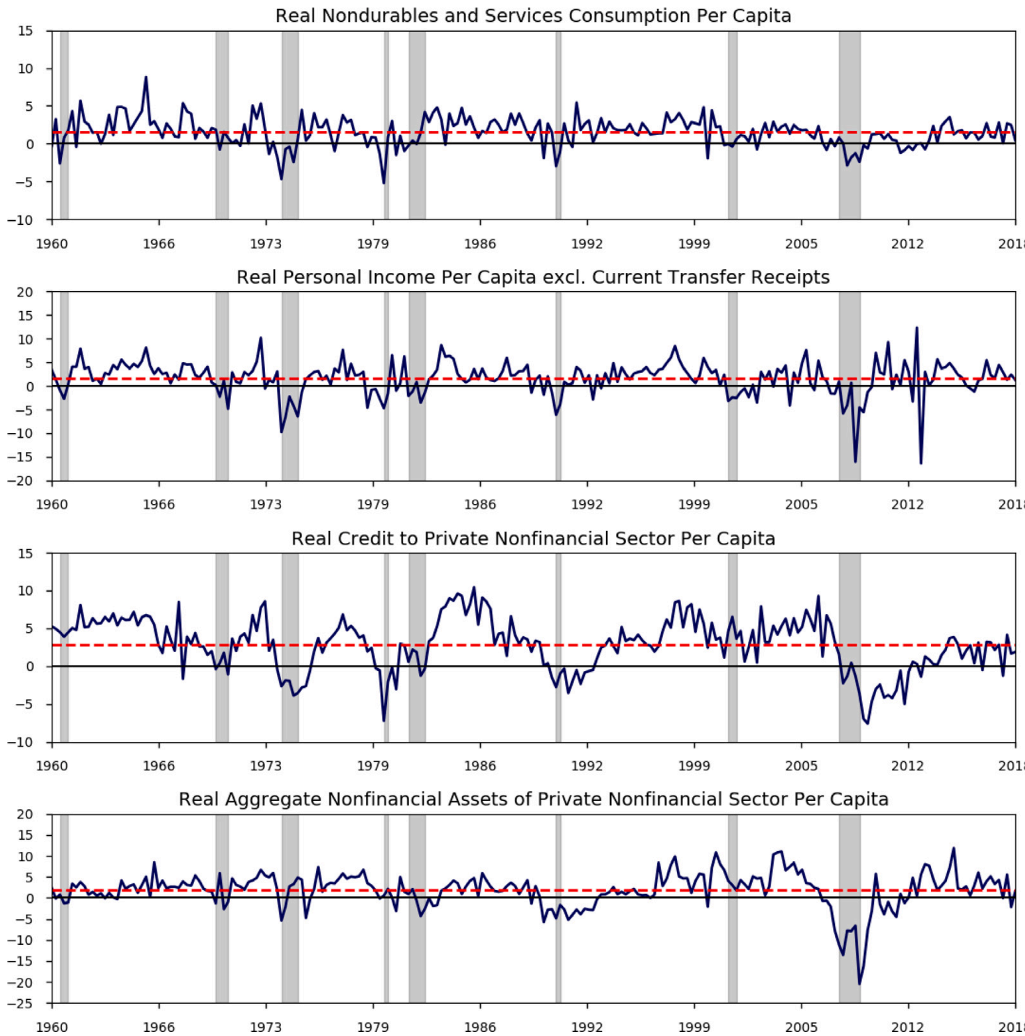

Fig. 2. Growth rates, 1960Q1-2018Q4. Notes: The dotted lines represent the mean of the growth rates over the sample period. Otherwise, see the notes to Fig. 1.

at the ML estimates of the alternative and null UC models

$$LR = -2(lh(\hat{\Gamma}_1) - lh(\hat{\Gamma}_i)), \quad i \in [2,3,4],$$

where lh denotes the UC model likelihood.

There is a five step algorithm to compute bootstrap p-values of the LR statistics. The steps are

i. generate 1000 bootstrap samples under the null of Model 1,
ii. estimate the UC models on the 1000 bootstrap samples,
iii. calculate 1000 bootstrap log likelihoods for the UC models,
iv. construct 1000 LR statistics for UC Models 2, 3, and 4 against the null of UC Model 1,
v. count the number of LR statistics greater than its sample counterpart for the three UC model comparisons.

The p-values equal the counts obtained in step (v) of the algorithm divided by 1000.

5. Results

Section 5.1 reviews estimates of Models 1, 2, 3, and 4. The fit of the UC models and the results of the bootstrap LR tests are in Section 5.2. Section 5.3 discusses the estimates of the trends and cycles across the sample period. I report the IRFs and FEVDs of Models 5 and 6 in Section 5.4. Section 5.5 explores the reduced form predictive content of the credit cycle for the business cycle. Finally, Section 5.6 tests whether my estimated credit cycle better predicts growth of the credit to GDP ratio h-quarters ahead compared with the Basel gap.

5.1. UC model parameter estimates

Table 2 reports estimates of the factor loadings, α, β, λ, and κ on the states. The cointegrating vector of consumption and income is approximately $[1, -1]$ according to the estimates of α. This supports the PIH. The estimates of κ indicate movements in consumption are dominated by the PI trend rather than business cycle fluctuations. Credit supply grows at a slower rate than nonfinancial assets because the point estimates of β are nearer a half than one. Similar to the relationship of consumption and the PI trend, estimates of λ show the supply of credit responds far more to changes in the level of the financial trend compared with the credit cycle. Estimates of the factor loadings are consistent across the UC models implying differences in the models are not reflected in the measurement equations.

Measurement error in income displays the greatest volatility in the measurement equations. Estimates of σ_{inc} are more than ten times larger than estimates of σ_{con} and two to three times the size of estimates of

Table 2
ML estimates of the UC model measurement equations, 1960Q1-2018Q4.

	Model 1	Model 2 $\zeta_1,\ \zeta_2 = 0$	Model 3 $\vartheta_1,\ \vartheta_2 = 0$	Model 4 $\vartheta_1,\ \vartheta_2,\ \zeta_1,\ \zeta_2 = 0$
Parameter	Estimate (s.e.)	Estimate (s.e.)	Estimate (s.e.)	Estimate (s.e.)
α	1.02 (<0.01)	1.02 (<0.01)	1.02 (<0.01)	1.02 (<0.01)
β	0.62 (<0.01)	0.62 (<0.01)	0.62 (<0.01)	0.62 (<0.01)
κ	0.21 (0.09)	0.21 (0.09)	0.22 (0.09)	0.22 (0.09)
λ	0.22 (0.07)	0.21 (0.07)	0.22 (0.07)	0.21 (0.07)
σ_{con}	0.15 (0.18)	0.15 (0.18)	0.15 (0.18)	0.15 (0.18)
σ_{inc}	1.63 (0.26)	1.63 (0.26)	1.67 (0.21)	1.67 (0.21)
σ_{nfc}	0.55 (0.23)	0.56 (0.23)	0.57 (0.22)	0.58 (0.21)
σ_{nfa}	0.69 (0.20)	0.71 (0.19)	0.67 (0.22)	0.69 (0.21)

Notes: Bootstrap standard errors are calculated as $\sqrt{\frac{\sum_{b=1}^{B}(\hat{\theta}_{ib}-\hat{\theta}_i)^2}{B-1}}1000$ and based on $B = 1000$ bootstrap samples.

σ_{nfa} and σ_{nfc}. Comparing the latter two standard deviations shows the volatility of the measurement errors of credit supply and nonfinancial assets have similar magnitudes.

Table 3 contains parameter estimates and associated bootstrap standard errors of the state equations of Models 1, 2, 3, and 4. Estimates of the drift in the PI trend, μ, are nearly identical across the models. The responses of the business cycle and credit cycle to their own lags, θ_i and γ_i respectively, for $i = 1,\ 2$, indicate that the cycles are highly persistent. Both pairs of parameters sum to close to one across all four models. This finding is further verified by the eigenvalues of the VAR(2). The eigenvalues of the VAR(2) in Model 1 are complex and indicate a high degree of persistence. A shock to the largest eigenvalue (0.912 ± 0.037i) has a half life of nearly two years. The largest eigenvalue of Model 2 is 0.938 while for Models 3 and 4 it is 0.954, which yield half-lives of about 3 years for Model 2 and almost 4 years for Models 3 and 4.

The off-diagonal elements of the VAR estimates, ϑ_1, ϑ_2, ζ_1, and ζ_2, capture the importance of lags in the credit cycle for the business cycle and lags of the business cycle for the credit cycle, respectively. These parameters are small and statistically insignificant for Models 1 through 3. This indicates there is little information contained in the business cycle for the credit cycle. The converse is also true.

Volatility of the shock innovation of the PI trend, σ_τ, is estimated to exceed that of the business cycle, σ_δ. The local linear trend of the financial sector produces estimates of the volatility of innovations to the slope of the financial trend, σ_ξ, that are greater than the estimate of the volatility of innovations to the financial trend level, σ_ψ. However, these components are less than half the size of the volatility of innovations to the credit cycle, σ_ϕ. The trend-cycle within sector correlations, $\rho_{\tau,\delta}$ and $\rho_{\psi,\phi}$, are negative but small and statistically insignificant. The correlation between cycles, $\rho_{\delta,\phi}$, is small across the models and statistically insignificant in Models 1 and 2, but has a t-ratio of about two in Models 3 and 4.

5.2. Fit of the UC models

The results of the bootstrap likelihood ratio tests are summarized in Table 4. Model 1 is assumed to be the null model and is compared to Models 2, 3, and 4 which are the alternative models. The null hypotheses fail to be rejected across the three tests. The data fits best to Model 1 with business and credit cycles that evolve jointly as a reduced-form VAR(2) relative to Models 2, 3, and 4. Thus, there is no evidence supporting Granger causality running from the credit cycle to the business cycle or the converse. This finding contradicts Borio et al. (2018). They present evidence of predictive causality running from the credit cycle to the business cycle. Placing exclusion restrictions on the business and credit cycles is at odds with the U.S. data. The rest of this paper focuses on the estimates produced by Model 1 as it is the model with the best fit to the data.

Table 3
ML estimate of UC model state equations, 1960Q1-2018Q4.

	Model 1	Model 2 $\zeta_1,\ \zeta_2 = 0$	Model 3 $\vartheta_1,\ \vartheta_2 = 0$	Model 4 $\vartheta_1,\ \vartheta_2,\ \zeta_1,\ \zeta_2 = 0$
Parameter	Estimate (s.e.)	Estimate (s.e.)	Estimate (s.e.)	Estimate (s.e.)
μ_τ	1.52 (0.12)	1.52 (0.12)	1.52 (0.12)	1.52 (0.12)
θ_1	1.62 (0.15)	1.62 (0.15)	1.68 (0.11)	1.68 (0.11)
θ_2	−0.66 (0.15)	−0.66 (0.15)	−0.71 (0.11)	−0.72 (0.11)
ϑ_1	0.07 (0.05)	0.07 (0.05)	–	–
ϑ_2	−0.08 (0.05)	−0.08 (0.05)	–	–
ζ_1	0.02 (0.11)	–	0.02 (0.11)	–
ζ_2	−0.01 (0.11)	–	−0.00 (0.11)	–
γ_1	1.71 (0.07)	1.73 (0.06)	1.69 (0.07)	1.71 (0.06)
γ_2	−0.72 (0.07)	−0.75 (0.06)	−0.70 (0.07)	−0.72 (0.06)
σ_τ	1.81 (0.26)	1.80 (0.26)	1.80 (0.34)	1.80 (0.31)
σ_ψ	1.18 (0.35)	1.15 (0.34)	1.14 (0.36)	1.12 (0.35)
σ_ξ	1.21 (0.14)	1.21 (0.14)	1.21 (0.14)	1.21 (0.14)
σ_δ	1.71 (0.64)	1.71 (0.63)	1.69 (0.62)	1.69 (0.60)
σ_ϕ	2.66 (0.36)	2.60 (0.34)	2.70 (0.37)	2.65 (0.34)
$\rho_{\tau,\delta}$	−0.02 (0.06)	−0.02 (0.06)	−0.01 (0.06)	−0.01 (0.06)
$\rho_{\psi,\phi}$	−0.15 (0.40)	−0.15 (0.48)	−0.15 (0.54)	−0.15 (0.69)
$\rho_{\delta,\phi}$	0.05 (0.04)	0.05 (0.04)	0.07 (0.04)	0.08 (0.04)

Notes: See the notes to Table 2.

Table 4
Bootstrap likelihood ratio test results.

	Model 1	Model 2 $\zeta_1,\ \zeta_2 = 0$	Model 3 $\vartheta_1,\ \vartheta_2 = 0$	Model 4 $\vartheta_1,\ \vartheta_2,\ \zeta_1,\ \zeta_2 = 0$
LogL (boot. se)	−2142.21 (35.78)	−2142.61 (35.82)	−2144.51 (35.75)	−2143.00 (11.28)
p-val	–	0.201	0.266	0.154

Notes: The test statistic is $LR = -2(lh(\hat{\Gamma}_1) - lh(\hat{\Gamma}_i)),\quad i \in [2,3,4]$, where Γ_i is the parameter vector for model i. The p-values are computed as the percentage of bootstrap estimates that have a larger test statistic than the true value of the test statistic.

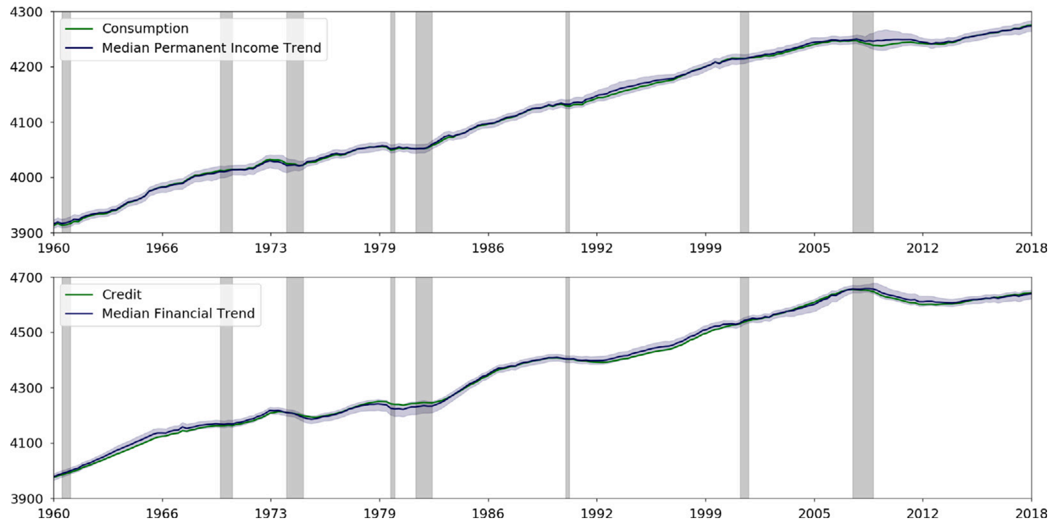

Fig. 3. Bootstrap estimates of the permanent income and financial trends, 1960Q1 to 2018Q4. Notes: The gray bars represent NBER recession dates. The blue shaded areas are the 90% sup-t uncertainty bands. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

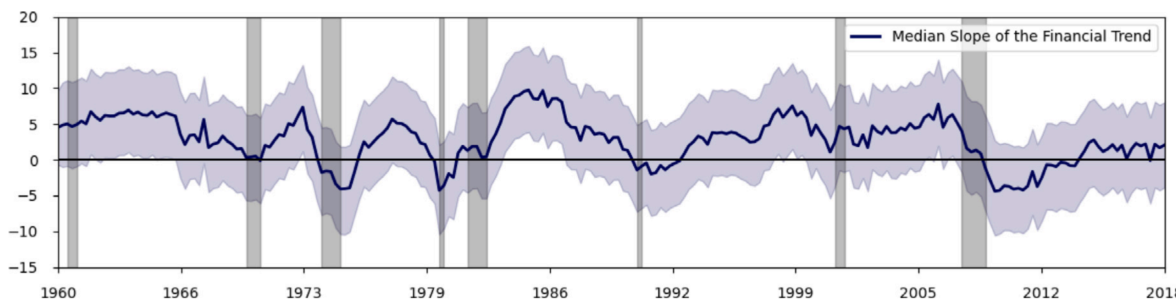

Fig. 4. Bootstrap estimates of the slope of the financial trend, 1960Q1 to 2018Q4. Notes: The blue shaded areas are the 68% sup-t uncertainty bands. Otherwise see notes to Fig. 3. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

5.3. Estimates of the trends and cycles

Figs. 3, 4, and 5 plot the median estimates of the bootstrap trends and cycles for the real and the financial sectors of Model 1 along with sup-t uncertainty bands of Olea and Plagborg-Møller (2018).[7] The sup-t uncertainty bands yield simultaneous coverage probability equal to the given confidence level. The significance level is 0.1 to achieve 90% uncertainty bands for plots of the PI trend and level of the financial trend. Plots of the slope of the financial trend and business and credit cycles are surrounded by 68% uncertainty bands implying a significance level of 0.32. Wider bands for the permanent components aid in visualization. The PI trend and financial trend are similar from 1960 until after the "double-dip" recession. Both trends feature pronounced downward movements around the 1973–1975 recession and the "double-dip" recession as seen in the top and bottom panels of Fig. 3. The PI trend differs from the financial trend in the subsequent period from 1983 to 2007. The PI trend grows steadily, while the financial trend exhibits large movements throughout the 1990s. Both trends contract during the 2007–2009 recession. During this period, movement in the PI trend is not as pronounced as the contractions of the 1973–1975 and "double-dip" recessions. However, there is substantial uncertainty surrounding the PI trend during these recessions. The financial trend has a sharp contraction from a peak in 2009 until 2013. The financial trend has not reached its pre-2007 level by the end of the sample in contrast to the PI trend.

There is also substantial uncertainty around the estimate of the slope of the financial trend. Fig. 4 shows the slope of the financial trend contracts during each NBER dated recession with the exception of the 1960–1961 and 2001 recessions. During the latter recession the slope actually increases. The most severe contractions in the slope occur during the 1973–1975 and 2007–2009 recessions.

The top and bottom panels of Fig. 5 display the business and credit cycles. The former cycle has troughs at or after NBER dates. The credit cycle features long swings. The first credit cycle peak lines up with the "double-dip" recession. After this however, the credit cycle does not match up with NBER dates. The credit cycle bottoms out in the mid 1990s and peaks for a second time in 2005, two years before the most recent financial crisis. The credit cycle troughs in 2010 following the 2007–2009 recession. The estimate of the slope of the financial trend appears to move with the business cycle. This removes some of the business cycle comovement and less persistent movements from the credit cycle.

The business and credit cycles differ both quantitatively and qualitatively over the time period. The volatility of the credit cycle is much larger than the business cycle. The bootstrap median standard deviation of the business cycle is 11.08 with 5% and 95% quantiles of 9.22 and 13.55. These values for the credit cycle are 33.74, 30.66, and 36.62 respectively. These observations are in line with Borio (2014).

The Basel gap, plotted in Fig. 5, is at odds with the estimated credit cycle. From 1960 until about 1983, the Basel gap is muted relative to the credit cycle. The Basel gap behaves much differently after 1983 with two long swings. Borio (2014) claims the shift in the behavior of the credit to GDP ratio in the mid-1980s reflects increasing financial liberalization and globalization which loosened financial constraints.

[7] Plots of the trends and cycles estimated using Models 2, 3, and 4 are found in Appendix I. These estimated trends and cycles resemble the plots in Figs. 3, 4, and 5.

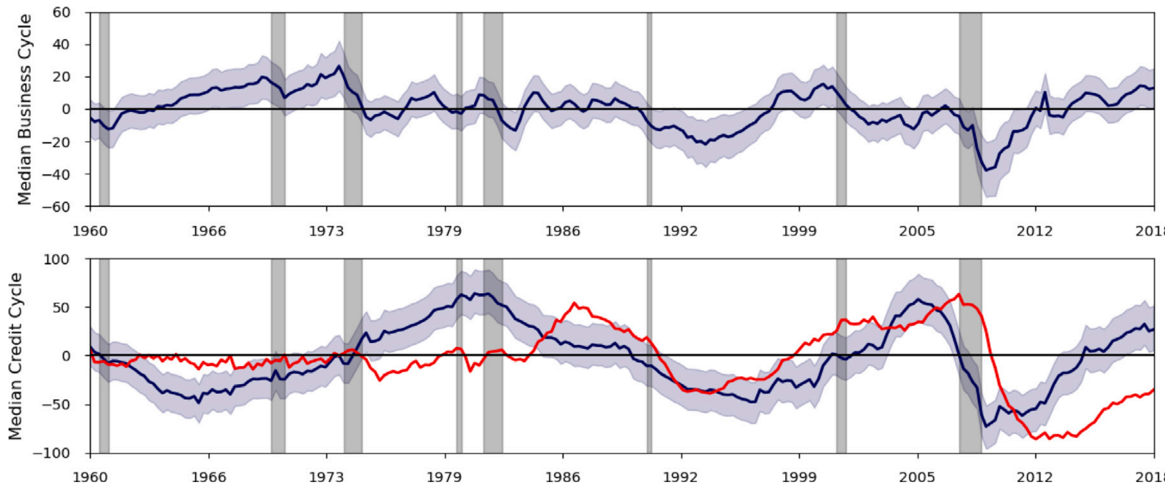

Fig. 5. Bootstrap estimates of the business and credit cycles, 1960Q1 to 2018Q4. Notes: The red line is the Basel gap scaled by 500 to help draw comparisons. The blue shaded areas are the 68% sup-t uncertainty bands. Otherwise see notes to Fig. 3. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

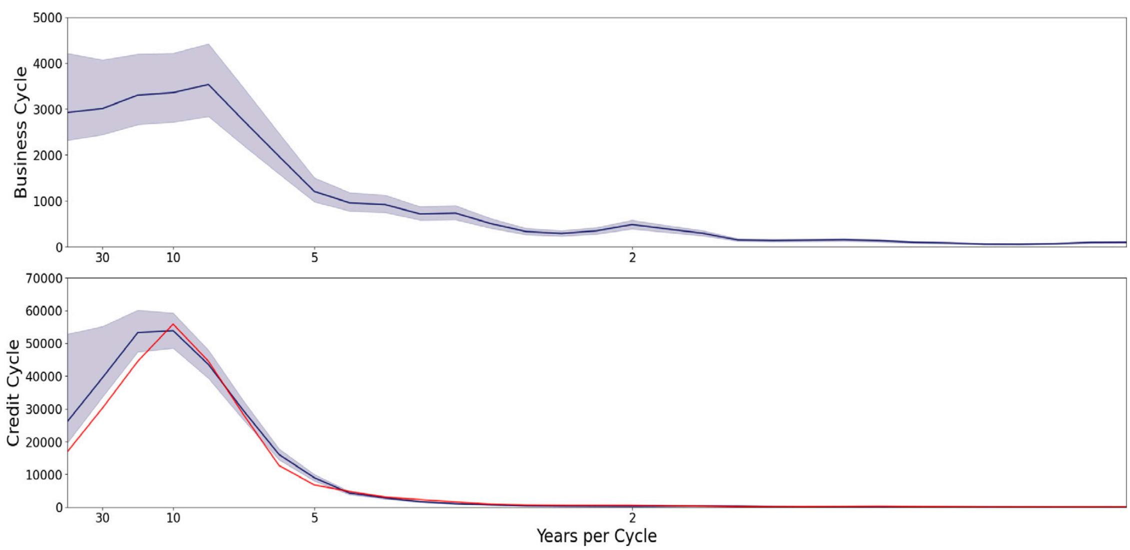

Fig. 6. Bootstrapped spectral densities of the business and credit cycles, 1960Q1 to 2018Q4. Notes: Plots display median bootstrap estimates of the spectral densities using a smoothed periodogram with a Bartlett window of length 7. The red line is the spectral density of the Basel gap scaled by 24 000 to help draw comparisons. The blue shaded areas are the 68% sup-t uncertainty bands. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

The first major peak in the Basel gap occurs in 1986 several years after the estimated credit cycle, which peaks during the "double-dip" recession. Both series decline and experience a protracted trough in the mid-1990s followed by a steady climb into the 2000s. The estimated credit cycle peaks in 2005 and its 68% uncertainty bands do not cover the peak in the Basel gap in 2007. Its trough occurs in 2012 while the estimated credit cycle troughs about three years earlier. Hence, my estimates indicate expansion in the U.S. financial markets ended two years or more before the start of that financial crisis and recession, but recovery was under way by the beginning of 2010.

The credit cycle is more persistent than the business cycle. The spectral densities of the business and credit cycles and Basel gap are plotted in the top and bottom panels of Fig. 6. The top panel shows the spectral density of the business cycle achieves maximum power at 7.5 years per cycle. In contrast, Morley et al. (2003) find the business cycle has a period of 2.5 years. This discrepancy results from the business and credit cycles being a reduced-form VAR(2). Rünstler and Vlekke (2018) also find that joint estimation of the business and credit cycles lengthens the period of the business cycle. The maximum power is 10 years per cycle for the estimated credit cycle and for the Basel gap. These results contrast with those of Drehmann et al. (2012) who find the length of their average credit cycle to be around 16 years.

5.4. Structural VAR results

Table 5 reports parameter estimates of the structural VARs, Model 5 and Model 6. The business cycle responds to the credit cycle on impact in Model 5. The impact response is reversed in Model 6. The business cycle responds negatively on impact to the credit cycle in Model 5, although the estimate of ϑ_0^* is statistically insignificant. In Model 6, the credit cycle responds negatively to the business cycle on impact, as shown by ζ_0^*. Once again, the estimated impact coefficient is statistically insignificant.

Estimates of the lag coefficients of the structural VAR(2)s are similar across Model 5 and Model 6. The own lag coefficients, θ_1^*, θ_2^*, γ_1^*, and γ_2^*, shown in Table 5 differ only marginally from the estimates of the own reduced-form lags of Table 3. Whether structural or reduced-form, these estimates always have large t-ratios (in absolute value). This is not true of the estimates of the off-diagonal lag coefficients, ϑ_i^* and ζ_i^* for $i = 1, 2$. These estimates are insignificant with t-ratios less than 2

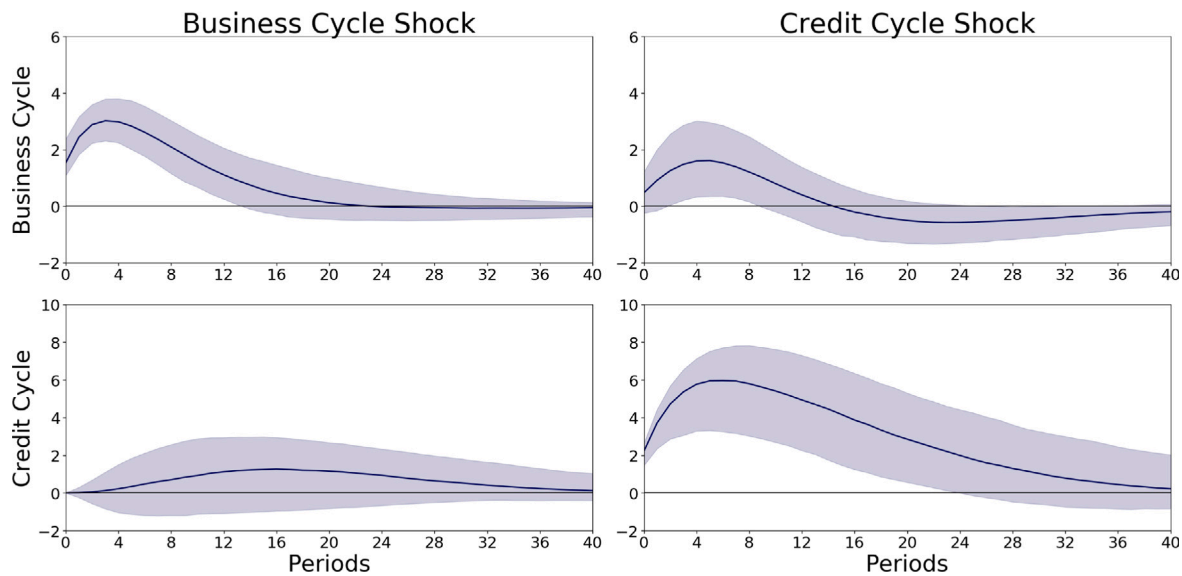

Fig. 7. IRFs of model 5. Notes: The blue line is the bootstrap median IRF. The blue shaded areas are 90% sup-t uncertainty bands. The shocks are one standard deviation shocks. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

Table 5
Estimates of structural VARs of the business and credit cycles, 1960Q1 to 2018Q4.

	Model 5 $\zeta_0^* = 0$	Model 6 $\vartheta_0^* = 0$
Parameter	Estimate (s.e.)	Estimate (s.e.)
θ_1^*	1.62 (0.15)	1.62 (0.15)
θ_2^*	−0.66 (0.15)	−0.66 (0.15)
ϑ_0^*	−0.21 (0.16)	–
ϑ_1^*	−0.29 (0.29)	0.07 (0.05)
ϑ_2^*	0.08 (0.14)	−0.08 (0.05)
ζ_0^*	–	−0.33 (0.28)
ζ_1^*	0.02 (0.11)	−0.50 (0.51)
ζ_2^*	−0.01 (0.11)	0.21 (0.25)
γ_1^*	1.71 (0.07)	1.69 (0.07)
γ_2^*	−0.72 (0.07)	−0.70 (0.07)
σ_δ	1.71 (0.64)	1.71 (0.64)
σ_ϕ	2.60 (0.34)	2.60 (0.34)

Notes: The table reports estimates of ζ_0^* and ϑ_0^* that are multiplied by negative one to be consistent with the construction of the SVAR impact matrices in Section 2.5. Otherwise, see the notes to Table 2.

(in absolute value). The inference is there is little support the business and credit cycles have a structural causal relationship in the short-run.

I compute IRFs to explore the structural responses of shocks to the business and credit cycles. Figs. 7 and 8 display median IRFs and sup-t uncertainty bands for Model 5 and Model 6 in response to one standard deviation business and credit cycle shocks. The only statistically significant and economically meaningful IRFs are with respect to own shocks, as shown by Figs. 7 and 8. The median IRF of the business cycle has a hump shape in response to its own shock, which peaks at 4 quarters. This IRF reverts to steady state in about four to five years. The credit cycle IRF also features a hump shape in response to its own shock, which peaks at 6 quarters. The median response takes between six to ten years to revert to zero. In response to a business cycle shock, the credit cycle exhibits little in the way of an economically interesting response in Models 5 and 6.

The business cycle features a hump shape in response to a credit cycle shock, which peaks around 6 quarters in Models 5 and 6. The responses have 90% uncertainty bands that are strictly positive only at the 4- to 8-quarter horizon in the top right panel of Fig. 7. Hence, Fig. 7 depicts the business cycle having statistically and economically meaningful responses to the credit cycle shock for one to two years, assuming this shock affects the business cycle at impact. When the direction of this structural impact causality is reversed, the IRF is muted and the 90% uncertainty bands cover zero quarter by quarter from impact to the 10-year horizon as depicted in the top right panel of Fig. 8. Comparing the IRFs of the business cycle to the credit cycle shock reveals the sensitivity of the results to the identification scheme.

The mean bootstrap FEVDs for Model 5 are reported in Table 6.[8] Remember that in Model 5, the credit cycle is assumed to structurally cause the business cycle at impact. The FEVD for the PI trend indicates that 92% of the variation is explained by its own shock across all horizons. Variation in the level of the financial trend is evenly split between its own shock and the credit cycle from impact to the 1-year horizon. However, beginning with the 1-year horizon, the shock to the slope of the financial trend comes to dominate movements in the financial trend. This dynamic only increases with the forecast horizon. Fluctuations in the slope of the financial trend are driven only by its own shock.

This is in contrast with the FEVDs of the business cycle. After one year, 75% of the variation in the business cycle is explained by its own shock, but this drops to 62% by the 10-year horizon. At this horizon, the credit cycle shock is responsible for about a quarter of the variation in the business cycle. The credit cycle is economically meaningful as a driver of business cycle fluctuations when the business cycle responds at impact to the credit cycle.

[8] I report the mean FEVDs to ensure the estimates sum to one at each horizon.

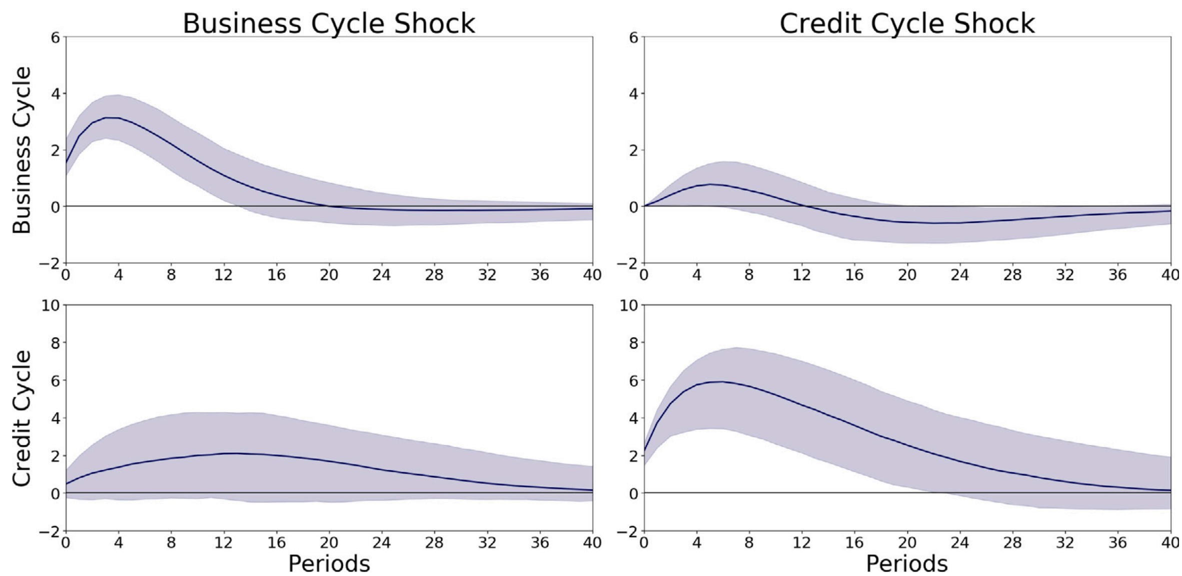

Fig. 8. IRFs of model 6. Notes: See notes to Fig. 7.

Table 6
FEVDs of model 5.

Permanent income trend

Horizon \ Shock	τ_t	ψ_t	ξ_t	δ_t	ϕ_t
0	0.92	0.00	0.00	0.08	0.00
1	0.92	0.00	0.00	0.08	0.00
2	0.92	0.00	0.00	0.08	0.00
4	0.92	0.00	0.00	0.08	0.00
8	0.92	0.00	0.00	0.08	0.00
16	0.92	0.00	0.00	0.08	0.00
24	0.92	0.00	0.00	0.08	0.00
32	0.92	0.00	0.00	0.08	0.00
40	0.92	0.00	0.00	0.08	0.00

Financial trend

Horizon \ Shock	τ_t	ψ_t	ξ_t	δ_t	ϕ_t
0	0.00	0.49	0.00	0.00	0.51
1	0.00	0.39	0.19	0.00	0.42
2	0.00	0.28	0.40	0.00	0.32
4	0.00	0.14	0.69	0.00	0.17
8	0.00	0.05	0.89	0.00	0.06
16	0.00	0.01	0.97	0.00	0.02
24	0.00	0.01	0.98	0.00	0.01
32	0.00	0.00	1.00	0.00	0.00
40	0.00	0.00	1.00	0.00	0.00

Slope of financial trend

Horizon \ Shock	τ_t	ψ_t	ξ_t	δ_t	ϕ_t
0	0.00	0.00	1.00	0.00	0.00
1	0.00	0.00	1.00	0.00	0.00
2	0.00	0.00	1.00	0.00	0.00
4	0.00	0.00	1.00	0.00	0.00
8	0.00	0.00	1.00	0.00	0.00
16	0.00	0.00	1.00	0.00	0.00
24	0.00	0.00	1.00	0.00	0.00
32	0.00	0.00	1.00	0.00	0.00
40	0.00	0.00	1.00	0.00	0.00

Business cycle

Horizon \ Shock	τ_t	ψ_t	ξ_t	δ_t	ϕ_t
0	0.08	0.00	0.00	0.80	0.12
1	0.08	0.00	0.00	0.78	0.14
2	0.08	0.00	0.00	0.77	0.15
4	0.07	0.01	0.00	0.74	0.18
8	0.07	0.02	0.00	0.70	0.21
16	0.07	0.02	0.00	0.69	0.22
24	0.07	0.03	0.00	0.66	0.24
32	0.07	0.04	0.00	0.63	0.26
40	0.07	0.04	0.00	0.63	0.26

Credit cycle

Horizon \ Shock	τ_t	ψ_t	ξ_t	δ_t	ϕ_t
0	0.00	0.30	0.00	0.00	0.70
1	0.00	0.30	0.00	0.00	0.70
2	0.00	0.30	0.00	0.00	0.70
4	0.00	0.30	0.00	0.01	0.69
8	0.00	0.29	0.00	0.02	0.69
16	0.00	0.28	0.00	0.04	0.68
24	0.01	0.26	0.00	0.06	0.67
32	0.01	0.26	0.00	0.07	0.66
40	0.01	0.26	0.00	0.07	0.66

Notes: Each table reports the bootstrap mean FEVD for one standard deviation shocks to the Permanent income trend (τ_t), the financial trend (ψ_t), financial trend drift (ξ_t), the business cycle (δ_t), and the credit cycle (ϕ_t).

The business cycle is not important for explaining fluctuations in the credit cycle under this identification. About two-thirds of the variation in the credit cycle comes from its own shock at all forecast horizons, while about one quarter comes from the level of the financial trend.

Table 7 reports the mean bootstrap FEVDs for Model 6 in which the credit cycle responds to the business cycle on impact. The FEVDs for the PI trend and the level and slope of the financial trend are similar to the results in Table 6 for Model 5. The credit cycle ceases

Table 7
FEVDs of model 6.

Permanent income trend					
Horizon \ Shock	τ_t	ψ_t	ξ_t	δ_t	ϕ_t
0	0.92	0.00	0.00	0.08	0.00
1	0.92	0.00	0.00	0.08	0.00
2	0.92	0.00	0.00	0.08	0.00
4	0.92	0.00	0.00	0.08	0.00
8	0.92	0.00	0.00	0.08	0.00
16	0.92	0.00	0.00	0.08	0.00
24	0.92	0.00	0.00	0.08	0.00
32	0.92	0.00	0.00	0.08	0.00
40	0.92	0.00	0.00	0.08	0.00

Financial trend					
Horizon \ Shock	τ_t	ψ_t	ξ_t	δ_t	ϕ_t
0	0.00	0.49	0.00	0.00	0.51
1	0.00	0.39	0.19	0.00	0.42
2	0.00	0.28	0.40	0.00	0.32
4	0.00	0.14	0.69	0.00	0.17
8	0.00	0.05	0.89	0.00	0.06
16	0.00	0.01	0.97	0.00	0.02
24	0.00	0.01	0.98	0.00	0.01
32	0.00	0.00	1.00	0.00	0.00
40	0.00	0.00	1.00	0.00	0.00

Slope of financial trend					
Horizon \ Shock	τ_t	ψ_t	ξ_t	δ_t	ϕ_t
0	0.00	0.00	1.00	0.00	0.00
1	0.00	0.00	1.00	0.00	0.00
2	0.00	0.00	1.00	0.00	0.00
4	0.00	0.00	1.00	0.00	0.00
8	0.00	0.00	1.00	0.00	0.00
16	0.00	0.00	1.00	0.00	0.00
24	0.00	0.00	1.00	0.00	0.00
32	0.00	0.00	1.00	0.00	0.00
40	0.00	0.00	1.00	0.00	0.00

Business cycle					
Horizon \ Shock	τ_t	ψ_t	ξ_t	δ_t	ϕ_t
0	0.09	0.00	0.00	0.91	0.00
1	0.09	0.00	0.00	0.91	0.00
2	0.08	0.01	0.00	0.90	0.01
4	0.08	0.01	0.00	0.88	0.03
8	0.08	0.02	0.00	0.84	0.06
16	0.08	0.03	0.00	0.82	0.07
24	0.08	0.04	0.00	0.77	0.11
32	0.07	0.05	0.00	0.75	0.13
40	0.07	0.05	0.00	0.75	0.13

Credit cycle					
Horizon \ Shock	τ_t	ψ_t	ξ_t	δ_t	ϕ_t
0	0.00	0.28	0.00	0.05	0.67
1	0.00	0.28	0.00	0.05	0.67
2	0.00	0.28	0.00	0.05	0.67
4	0.00	0.28	0.00	0.05	0.67
8	0.00	0.27	0.00	0.07	0.66
16	0.00	0.26	0.00	0.11	0.63
24	0.01	0.25	0.00	0.12	0.62
32	0.01	0.25	0.00	0.13	0.61
40	0.01	0.25	0.00	0.13	0.61

Notes: See notes to Table 6.

to be an important driver of business cycle fluctuations when causality runs from the business cycle to the credit cycle. Just under 90% of the business cycle variation comes from its own shock after one year. About three quarters of this variation comes from its own shock after 10 years and just over 10% comes from the credit cycle. The business cycle does not drive fluctuations in the credit cycle in Model 6. After 10 years over 60% of credit cycle variation comes from its own shocks and about 25% comes from the level of the financial trend.

5.5. The predictability of business and credit cycles

This section reexamines claims made by Schularick and Taylor (2012) and Borio et al. (2018). They, among others, report the credit cycle and Basel gap have short-term predictive power for the business cycle. Bootstrap t-statistics and p-values are computed to evaluate the significance of the credit cycle and the first difference of the PI trend for predicting the h-quarter ahead business cycle, $h \in [1, 2, 4, 8, 12, 16]$.[9] I also test the significance of the business cycle, the second difference of the level of the financial trend, and the first difference of the slope of the financial trend for predicting the credit cycle h-quarters ahead.[10]

Table 8 reports the regression equation considered and the bootstrap mean estimates of these regressions. The estimates of the first regression imply there is no predictive power in the credit cycle for the business cycle over the 1-year horizon. The estimated coefficient on the credit cycle, ϕ_t, for predicting the business cycle, δ_t, are all small and insignificant at the 5% level for 1 to 4 quarters ahead. These results are a challenge for Borio et al. (2018). They claim their estimated credit cycle is a significant predictor of recessions at the 1 year horizon. My results do, however, lend evidence to Borio et al. (2018)'s claim that the credit cycle is a significant predictor of the business cycle over 2- and 3-year horizons. The estimated coefficients on the credit cycle are negative at all horizons indicating that a credit cycle expansion predicts a business cycle contraction.

The second regression tests the implications of the Beveridge–Nelson decomposition. This decomposition implies that the growth rate of the trend is orthogonal to the cycle. As expected, the estimated coefficient on the first differences of the PI trend are negative across all horizons. However, these estimates are insignificant at the 5% and 10% level across all horizons.

The third regression examines the predictive content of the business cycle for the credit cycle. The estimated coefficients on the business cycle are positive across all horizons indicating greater transitory real economic activity anticipates temporary increases in credit activity. The estimates are significant at the 5% level.[11] In contrast, Section 5.4 provided evidence the business cycle does not structurally cause the

[9] The use of h-step ahead regressions to evaluate the impact of financial components is similar to the work of Hartwig et al. (2021) and Adrian et al. (2022).

[10] The first two lags of the dependent variable are included in the regressions to eliminate own predictability.

[11] As demonstrated by the robustness exercise in Appendix G, the estimated business cycle is not a significant reduced-form predictor of the credit cycle when income is measured by real GDP.

Table 8
Tests of business cycle and credit cycle predictive content, 1960Q1 to 2018Q4.

Regression:			$(cycle)_{t+h} = \alpha + \beta(predictor)_t + \gamma(L)(cycle)_t + e_t$					
Cycle	Predictor		Number of quarters ahead					
			1	2	4	8	12	16
δ_t	ϕ_t	β	−0.005	−0.013	−0.032	−0.088	−0.137	−0.159
		se	0.011	0.016	0.023	0.028	0.028	0.028
		t-stat	−0.451	−0.781	−1.415	−3.212	−4.862	−5.624
		p-val	0.329	0.223	0.085	0.001	0.000	0.000
δ_t	$\Delta\tau_t$	β	−0.359	−0.318	−0.146	−0.194	−0.153	−0.103
		se	0.204	0.287	0.412	0.522	0.564	0.596
		t-stat	−1.724	−1.064	−0.305	−0.340	−0.245	−0.152
		p-val	0.116	0.157	0.228	0.288	0.318	0.339
ϕ_t	δ_t	β	0.130	0.178	0.247	0.418	0.633	0.794
		se	0.060	0.084	0.124	0.195	0.242	0.274
		t-stat	2.180	2.122	2.000	2.145	2.612	2.906
		p-val	0.017	0.019	0.026	0.018	0.005	0.002
ϕ_t	$\Delta^2\psi_t$	β	0.133	0.061	0.528	0.387	0.281	0.083
		se	0.158	0.223	0.325	0.520	0.652	0.743
		t-stat	0.848	0.268	1.616	0.739	0.422	0.106
		p-val	0.216	0.390	0.056	0.232	0.338	0.454
ϕ_t	$\Delta\xi_t$	β	0.387	0.232	1.848	2.216	2.643	1.870
		se	0.525	0.743	1.072	1.705	2.139	2.444
		t-stat	0.768	0.329	1.731	1.289	1.219	0.750
		p-val	0.236	0.335	0.047	0.102	0.117	0.230

Notes: The coefficients, standard errors, and t-values are the mean values of the regressions from 1000 bootstrap resamples. The standard errors are Newey–West corrected. The term $\gamma(L)$ is a second order lag polynomial.

credit cycle. Additionally, there is some evidence the credit cycle structurally causes the business cycle over the 1- to 2-year horizon. These results serve as a caution against equating statistical predictability and structural causality.

The final two regressions assess the predictive content of the second difference of the level of the financial trend and the first difference of the slope of the financial trend for the credit cycle. The estimated coefficients on the second differences of the level of the financial trend are positive, but insignificant at the 5% level across all horizons. The estimated coefficients on the first difference of the slope of the financial trend are also positive across all horizons. However, the estimates are insignificant at the 5% level with the exception of the one year horizon.

5.6. Predictive regressions for the growth rate of credit to GDP

This section constructs bootstrapped Breusch–Godfrey tests to investigate the ability of the Basel gap, the estimated business and credit cycles, and the estimated slope of the financial trend to predict the growth rate of the credit to GDP ratio.[12] The Breusch–Godfrey test estimated here has two steps. The first step regresses the h-step ahead growth rate of the credit to GDP ratio on an intercept and predictor variables. Next, the residuals from the first step are regressed on its own lagged value and the explanatory variables of the first regression. The test statistic is the Lagrangian multiplier statistic that equals T times the R-squared of the second step regression, where T is the number of observations. The test statistic follows a chi-squared distribution with one degree of freedom.

The null hypothesis of the Breusch–Godfrey test is that the residuals of the first regression are serially uncorrelated. Serial correlation indicates predictability in the error terms. Hence, unaccounted for information exists in the dependent variable of the first-step regression. Nelson (2008) runs similar regressions to examine whether the HP-filtered measure of the output gap contributes to the ability of the

Table 9a
Predictive regressions for the growth rate of credit to GDP, 1960Q1 to 2018Q4.

Regression:		$\Delta\left(\frac{Credit}{GDP}\right)_{t+h} = \beta_0 + \beta_1(Basel\ Gap)_t + e_t$					
		Number of quarters ahead					
		1	2	4	8	12	16
β_1	coef	0.051	0.045	0.028	0.002	−0.016	−0.024
	se	0.011	0.012	0.012	0.013	0.013	0.014
	t-stat	4.461	3.801	2.261	0.122	−1.239	−1.770
	p-val	0.000	0.000	0.012	0.452	0.108	0.039
R^2	value	0.088	0.069	0.027	0.000	0.009	0.018
Breusch–Godfrey	value	5.037	10.002	14.027	15.781	15.775	15.946
	p-val	0.025	0.002	0.000	0.000	0.000	0.000

Notes: The null hypothesis of the Breusch–Godfrey test is that the regression errors are not serially correlated.

Table 9b
Predictive regressions for the growth rate of credit to GDP, 1960Q1 to 2018Q4.

Regression:		$\Delta\left(\frac{Credit}{GDP}\right)_{t+h} = \beta_0 + \beta_1(Basel\ Gap)_t + \beta_2\phi_t + e_t$					
		Number of quarters ahead					
		1	2	4	8	12	16
β_1	coef	0.036	0.029	0.010	−0.015	−0.025	−0.026
	se	0.012	0.012	0.013	0.013	0.014	0.015
	t-stat	3.075	2.425	0.798	−1.115	−1.781	−1.704
	p-val	0.001	0.008	0.213	0.133	0.038	0.045
β_2	coef	0.008	0.009	0.009	0.008	0.004	0.001
	se	0.002	0.002	0.002	0.003	0.003	0.003
	t-stat	3.625	3.642	3.798	3.082	1.531	0.274
	p-val	0.000	0.000	0.000	0.001	0.064	0.392
R^2	value	0.141	0.126	0.094	0.049	0.021	0.018
Breusch–Godfrey	value	2.773	5.503	8.385	11.552	14.524	15.849
	p-val	0.096	0.019	0.004	0.001	0.000	0.000

Notes: The coefficients, standard errors, and t-values are the mean values of the regressions from 1000 bootstrap resamples. The null hypothesis of the Breusch–Godfrey tests is that the regression errors are not serially correlated.

Beveridge–Nelson trend to predict output growth. The Breusch–Godfrey test is useful because the Basel gap is used to predict the state of the financial sector as measured by the credit to GDP ratio. However, the Basel gap is a hidden state retrieved from the residual of the HP-filtered credit to GDP ratio. If the Basel gap fails to predict the credit to GDP ratio then its predictive power is spurious in line with the findings of Schüler (2020). A lack of predictive power would indicate the Basel gap is not an appropriate early warning indicator for financial crises.[13]

Table 9a shows the h-quarter ahead growth rate of the credit to GDP ratio regressed on an intercept and the Basel gap, where $h \in [1, 2, 4, 8, 12, 16]$. The estimated coefficients on the Basel gap, β_1, in Table 9a are positive and significant at the 5% level over the first year. The coefficient approaches zero at the 8-quarter horizon before turning negative. The R^2 peaks at 8.8% at $h = 1$, is 6.9% at $h = 2$, and is under 3% at all other horizons. The Breusch–Godfrey test shows there is serial correlation in the residuals of this regression. The null of no serial correlation is rejected at the 5% level across all horizons indicating information in the dependent variable is left unexplained.

Table 9b adds the estimated credit cycle to the previous regression. The estimated coefficient on the Basel gap, β_1, is once again positive from the 1- to the 4-quarter ahead forecast horizons, but is insignificant at the 5% level beyond the 1-year ahead forecast. The estimate for β_1 turns negative at longer horizons, but has a bootstrapped p-value less than 4% at the 4-year forecast horizon. This implies the Basel gap predicts mean reversion in the credit to GDP ratio at longer horizons. Mean reversion suggests the Basel gap is forecasting financial stability

[12] Augmented Dickey Fuller tests reject the null of a unit root at the 1% level for the growth rate of the credit to GDP ratio. The null fails to be rejected for the log level of the credit to GDP ratio.

[13] See Donaldson (1992) and Canova (1994) for important work discussing the limitations of early warning indicators for financial crises.

Table 9c
Predictive regressions for the growth rate of credit to GDP, 1960Q1 to 2018Q4.

Regression:		$\Delta\left(\frac{Credit}{GDP}\right)_{t+h} = \beta_0 + \beta_1 (Basel\ Gap)_t + \beta_2 \phi_t + \beta_3 \delta_t + e_t$					
		Number of quarters ahead					
		1	2	4	8	12	16
β_1	coef	0.039	0.032	0.011	−0.015	−0.025	−0.026
	se	0.011	0.011	0.012	0.013	0.014	0.015
	t-stat	3.592	2.842	0.917	−1.110	−1.780	−1.721
	p-val	0.000	0.003	0.180	0.134	0.038	0.043
β_2	coef	0.006	0.007	0.008	0.008	0.004	0.001
	se	0.002	0.002	0.002	0.003	0.003	0.003
	t-stat	2.913	2.938	3.367	2.995	1.513	0.192
	p-val	0.002	0.002	0.000	0.002	0.066	0.424
β_3	coef	0.029	0.029	0.018	0.002	−0.000	0.004
	se	0.006	0.006	0.007	0.008	0.008	0.008
	t-stat	4.609	4.572	2.613	0.265	−0.015	0.562
	p-val	0.000	0.000	0.005	0.395	0.473	0.288
R^2	value	0.214	0.204	0.124	0.049	0.021	0.020
Breusch–Godfrey	value	0.145	1.755	5.574	11.525	14.520	15.704
	p-val	0.709	0.187	0.018	0.001	0.000	0.000

Notes: See notes to Table 9b.

in the longer run when the estimated credit cycle is taken into account. Thus, the Basel gap may not be suited to drawing conclusions about financial instabilities.

The bootstrap mean estimate of the coefficient on the credit cycle, β_2, is positive, but smaller in magnitude than β_1, across all horizons. These estimates are significant at the 5% level across the first eight quarters. The R^2 peaks at 14.1% for the 1-quarter ahead forecast. The Breusch–Godfrey test indicates that adding the credit cycle removes autocorrelation in the residuals only at the 1-quarter ahead forecast.

Table 9c adds the estimated business cycle to the regression in Table 9b. The coefficients on the Basel gap and the credit cycle, β_1 and β_2, are consistent with the estimates in Table 9b. The bootstrap mean estimate of the coefficient on the business cycle, β_3, is positive and significant at the 5% level from 1- to 4-quarter ahead forecasts. The coefficients are larger in magnitude than the coefficient on the credit cycle over these forecast horizons. At horizons longer than one year, β_3 is not significantly different from zero at the 5% level. The R^2 peaks at 21.4% at the 1-quarter ahead forecast, but falls to about 3% beyond a 2-year forecast horizon. The Breusch–Godfrey tests indicate the estimated business cycle improves the prediction of growth in the credit to GDP ratio after accounting for the Basel gap and the estimated credit cycle. The null hypothesis of no serial correlation in the residuals is rejected at better than the 18% level over 1- and 2-quarter ahead forecast horizons.

I also consider the ability of the estimated slope of the financial trend to predict growth in the credit to GDP ratio. Table 10 reports on bootstrapped regressions of this ratio on the estimated slope of the financial trend.[14] The bootstrap mean estimate of the coefficient on the slope of the financial trend, β_4, is positive from the 1- to the 12-quarter ahead forecast horizons, but is insignificant at the 5% level beyond the 3-year ahead forecast. This coefficient is larger in magnitude than those of the business and credit cycles in Table 9c in all but the 3-year horizon. The R^2 is above 20% from the 1- to 4-quarter horizon and peaks at 28.6% at the 2-quarter horizon. The R^2 falls below 5% at longer horizons.

The Breusch–Godfrey tests indicate the estimated financial trend slope has more predictive power for growth in the credit to GDP ratio than the other predictors considered. The null hypothesis of no serial correlation in the residuals is rejected at better than the 25% level

Table 10
Predictive regressions for the growth rate of credit to GDP, 1960Q1 to 2018Q4.

Regression:		$\Delta\left(\frac{Credit}{GDP}\right)_{t+h} = \beta_0 + \beta_4 \xi_t + e_t$					
		Number of quarters ahead					
		1	2	4	8	12	16
β_4	coef	0.177	0.189	0.160	0.077	0.012	−0.027
	se	0.023	0.023	0.026	0.034	0.036	0.036
	t-stat	7.712	8.304	6.157	2.241	0.336	−0.763
	p-val	0.000	0.000	0.000	0.016	0.369	0.224
R^2	value	0.248	0.286	0.207	0.049	0.002	0.006
Breusch–Godfrey	value	1.448	0.174	0.755	11.347	16.739	17.479
	p-val	0.267	0.744	0.469	0.001	0.000	0.000

Notes: See notes to Table 9a.

over 1- and 4-quarter ahead forecast horizons. Hence, the direction of the financial trend is important for predicting growth in the credit to GDP ratio. This suggests it is permanent shocks rather than transitory movements which matters for gauging the state of financial stability.

The ability of the slope of the financial trend to outperform the Basel gap in predicting growth in the credit to GDP ratio is due in part to the model specification. Note that the slope of the financial trend is the growth rate of its level and is estimated in the models. This slope is also a component of the HP filter as shown by Harvey and Jaeger (1993). The Basel gap is measured by subtracting the level of the HP-filtered trend from the observed series of the credit to GDP ratio. Therefore, the residuals, or Basel gap, contains information about the slope of the trend.

To further illustrate the importance of permanent shocks for gauging financial stability, I reestimate the regression of Table 10 on a rolling basis.[15] The slope of the financial trend is set to have a fixed window length of forty-eight quarters in the rolling regression. The purpose of this exercise is to determine whether the slope of the financial trend provided a signal of a permanent shift in the credit to GDP ratio.

Fig. 9 shows β_4 moves substantially lower in the two years prior to the 2007–2009 recession and financial crisis in the United States. A U-shaped trough is clearly visible spanning the period of 2005 to 2009 in the 1- and 2-quarter ahead regressions. The change in relationship is less pronounced in the 4-quarter ahead regression, but is still apparent. After the 2007–2009 recession the estimates of β_4 return to previous levels. A change in the relationship between the slope of the financial trend and the growth of the credit to GDP ratio signals a permanent shock to financial stability as measured by the credit to GDP ratio itself. These regressions indicate that the slope of the financial trend could have been used as a tool to detect a period of financial instability in real time.

6. Conclusion

This paper estimates UC models to examine the usefulness of macroprudential policy and present new estimates of the credit cycle. Income and consumption share a common Beveridge–Nelson trend as implied by the permanent income hypothesis. The macro-finance model of leverage in Brunnermeier and Sannikov (2014) is used to place parameter restrictions on credit supply and nonfinancial assets. The common permanent component of credit supply and nonfinancial assets is a local linear trend. The business and credit cycles form a VAR(2). Estimation of the UC models is done via classical optimization of the predictive likelihood of the Kalman filter on a quarterly U.S. sample from 1960 to 2018. The UC models are bootstrapped to construct the empirical

[14] Inclusion of the slope of the financial trend into the regression in Table 9c does not alter the results in Table 10. These results are available upon request.

[15] I am grateful to an anonymous referee who proposed the inclusion of additional support of this point.

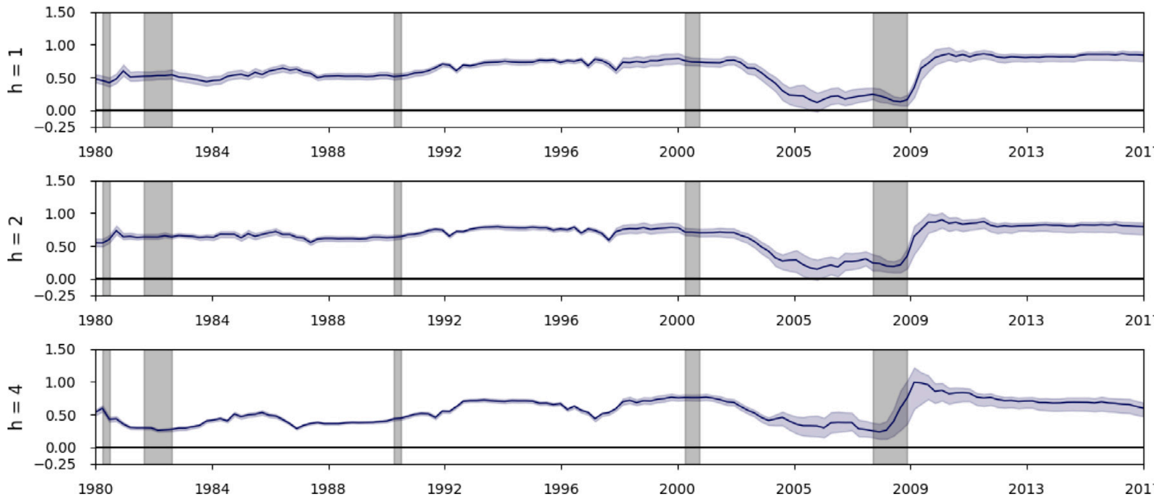

Fig. 9. Estimates of β_4 from rolling regressions, 1980Q1 to 2017Q4. Notes: The coefficient β_4 corresponds to the regression in Table 10 and h denotes the forecast horizon. The blue line is the bootstrap median value of the regression. The blue shaded areas are 90% sup-t uncertainty bands. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

sampling distributions of the model parameters, state variables, and test statistics.

There are five key contributions of this paper. First, my estimates support modeling the credit cycle jointly with the business cycle as a reduced-form VAR(2). Second, the estimated credit cycle features two peaks of similar magnitude, with the latter being two years prior to the financial crisis in contrast to the Basel gap. Third, recursive structural VARs lend support for causality running from the credit cycle to the business cycle over the 1- to 2-year horizon. Fourth, I find no evidence of reduced-form predictability of the credit cycle for the business cycle at the 1-, 2-, and 4-quarter horizons. Interestingly, the business cycle is a good predictor of the credit cycle from the 1-quarter to 4-year horizon. Fifth, the Basel gap is a poor predictor of the growth of the credit to GDP ratio at short, medium, and long forecast horizons. At 1- and 2-quarter horizons, the estimated credit and business cycles predict the growth rate of the credit to GDP ratio. However, the slope of the financial trend has forecasting power at the 1- to 4-quarter horizons for the growth of the credit to GDP ratio. Hence, my results caution against the use of the Basel gap as a signal of the underlying state of the financial markets. Evidence in this paper suggests policymakers should take permanent shocks to the financial sector into account when assessing financial stability.

Future work should focus on utilizing theories from the financial frictions literature to restrict the UC model. These theories can be used to address whether trends in the real and financial sectors are independent. If this assumption is not supported by the data, the implications for aggregate fluctuations should be of interest to economists and policymakers.

Data availability

The dataset is provided in the Data in Brief.

Appendix A. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.jfs.2023.101120.

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