Sustainable Financial Obligations and Crisis Cycles*

Mikael Juselius† and Moshe Kim‡

Abstract

The ability to distinguish between sustainable and excessive debt developments is crucial for making reliable assessments of the risks that aggregate credit pose to economic stability. By studying US private sector credit loss dynamics, we show that this distinction can be made based on a measure of the aggregate liquidity constraint, the financial obligations ratio. Specifically, when this variable exceeds an estimated critical threshold, the interaction between credit losses and the business cycle intensifies. This occurs 1-2 years before each recession in the sample, albeit unevenly between households and firms. Our results have implications for macroprudential policy and countercyclical capital-buffers.

Keywords: debt sustainability, credit losses, financial crises, leverage, financial obligations, regime-switching model, smooth transition regression.

JEL Classification: E32, E44, G01

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†Hanken School of Economics and HECER, e-mail: `mikael.juselius@hanken.fi`

‡Universitat Pompeu Fabra and University of Haifa, e-mail: `kim@econ.haifa.ac.il`

1 Introduction

The concern that private sector debt accumulations can become excessive, threatening both real and financial stability, has gained considerable momentum during the past decade. To assess the importance of such considerations empirically, one must be able to separate sustainable debt developments from excessive buildups. By studying US aggregate credit loss dynamics over the period 1985-2010, we show that the upper limit for sustainable debt developments is determined by the strength of the aggregate liquidity constraint, as measured by the financial obligations ratio. In particular, we find that both household and business sector financial obligations ratios act as regime switching variables. Once they exceed critical thresholds, the interaction between business cycle fluctuations and credit losses increases significantly. This occurs in either the household or the business sector 1-2 years prior to each economic downturn in our sample. The more severe recessions ensue when both sectors are simultaneously inflicted. In contrast to existing cross-sectional studies on individual episodes of financial distress, we do not find the amount of debt to income, or leverage, to be highly informative in this respect. These patterns suggest that liquidity constraints associated with excessive aggregate debt accumulations are likely to play a significant role in shaping business cycle movements.

The idea that credit cycles can be a source of real fluctuations is by now well established in a large body of theoretical work on financial frictions. For instance, Bernanke et al. (1999) show that feedback between firms' net worth and their borrowing opportunities can generate credit booms which result in increased investments. Similarly, by focusing on households, Kiyotaki and Moore (1997) demonstrate that increases in house prices raise the value of collaterals available to households, increasing their borrowing opportunities and thereby their consumption spending. In both cases, there is a financial accelerator effect which tends to reinforce the business cycle. More recent contributions along these lines include Kiyotaki and Gertler (2010), and references therein.

While the aforementioned literature is mainly concerned with the amplifying effect of credit on ordinary macroeconomic shocks, there is also a risk that aggregate debt can reach excessive and inefficient levels. For example, Lorenzoni (2008) and Miller and Stiglitz (2010) discuss how self-enforcing processes between net worth and borrowing can lead to asset price bubbles and excessive leverage under the assumptions that agents have limited commitment in financial contracts or dispersed beliefs. Because banks can have incentives to reduce their lending standards during upturns, the problem may be further exacerbated (Ruckes (2004) and Dell'Ariccia and Marquez (2006)). When aggregate debt reaches unsustainable levels, debt holders become highly vulnerable to any common negative shock which reduces their net worth, as it constrains their refinancing ability. In such situations, they may attempt to sell off assets and reduce spending to meet their debt obligations. Campello et al. (2010), for instance, document such alterations in behavior among financially constrained firms during the recent financial crisis. However, such actions can be contagious as they tend to reinforce the negative effects of the initial shock, triggering off a self-enforcing downward spiral which can lead to a severe recession or even a systemic financial crisis (e.g.,Gai et al. (2008)).

Theoretical predictions of this type have been lent considerable credibility by empirical studies that find close association between high aggregate debt to income ratios (leverage) and subsequent credit and output losses.[1] For example, King (1994) documents this type of relationship across countries in connection with the early 1990's recession. More recently, Mian and Sufi (2010) obtain similar results by exploiting US cross-county variation from the recent financial crisis. But, because these studies focus on cross-section variation from individual episodes of financial distress, they tend to overlook the persistent upward trend that has been present in US debt to income ratios for the past 25 year. If high aggregate leverage was one of the major factors behind the early 1990's recession, as suggested by King (1994), then how could even higher and increasing debt ratios be sustained during the two following decades?

This observation indicates that, when viewed over time, the connection between leverage and losses may not be as strong as the cross-sectional evidence suggests. To investigate this possibility we model US aggregate credit loss dynamics over the sample 1985Q1-2010Q2, as a function of leverage and various cyclical indicators. Focusing on credit losses instead of output losses allows us to assess the differential roles that business and household loans play in generating real and financial weakness (see e.g., Iacoviello (2005)).[2] We allow leverage to enter credit loss determination both linearly, in line with the literature on financial accelerators, as well as non-linearly, to capture altered behavior and contagion effects during episodes in which aggregate credit constraints become binding. In the latter case, leverage enters the empirical model as a regime switching variable which increases the interaction between credit losses and the business cycle once it exceeds an estimated critical threshold.

Applying this approach, we find evidence of significant nonlinearities in the credit loss data, associated with the episodes of severe financial distress in our sample. This seems consistent with theories that allow for excessive aggregate buildups of credit. However, we do not find any significant temporal relationship, linear or otherwise, between aggregate leverage and credit losses. The most likely explanation for this finding is that a large part of the time-series development in leverage over the sample can be attributed to sustainable changes in the long-run debt level, for example due to changes in the underlying economic environment. In contrast, because such long-run developments probably impinge on the cross-section in a uniform way, most of the cross-sectional variation will be due to possibly excessive short-run accumulations. If so, this would explain why the past studies find a seemingly close relationship between leverage and losses. Hence, to make progress, it seems crucial to be able to distinguish between *sustainable* and *excessive* debt developments already at the outset. This is recognized

[1] Several empirical studies also attempt to quantify the relative importance of the financial accelerator for output fluctuations. See for instance, Gertler and Lown (1999), Meier and Müller (2006), Gilchrist et al. (2009), and references therein.

[2] We also note that the temporal association between credit losses and output losses is very strong as can be seen by comparing panels (a) and (e) of Figure 1.

by Borio and Lowe (2002) and Borio and Drehmann (2009) who construct leading indicators of financial distress based on leverage and asset price gaps. However, these gaps are constructed using the Hodrick-Prescott filter rather than motivated by economic rationale and, thus, still run the risk of mistaking sustainable debt developments for excessive buildups.

A potential reason for the long-run growth trend in leverage is the concurrent decline in real interest rates, documented in Caballero et al. (2008), among others. Indeed, the optimal (sustainable) allocation of aggregate debt in a dynamic stochastic environment should vary with changes in the terms of credit (see e.g., Stein (2006)). For this reason we consider an alternative but related debt measure that implicitly incorporates such changes, namely the financial obligations ratio constructed by the Federal Reserve. Compared to leverage, the financial obligations ratio is more closely related to the strength of aggregate liquidity constraints (Hall (2011)) than to the notion of solidity.

Replacing leverage by the financial obligations ratio, we find that the latter significantly enters credit loss determination as a regime switching variable of the type described above. Hence, based on this variable we can adequately account for the nonlinear dynamics inherent in aggregate credit losses. In addition, we are able accurately estimate the critical threshold for the financial obligations ratio above which borrowers become highly vulnerable to aggregate economic conditions. We refer to this threshold as the maximum sustainable debt burden (MSDB).

By further distinguishing between total debt and real estate related debt in both the household and business sector, we gain important insights into how these different debt categories contribute to aggregate credit loss dynamics. For the household sector we find that the financial obligations ratio, specifically associated with real estate debt, exceeds an estimated MSDB threshold of 10.1% at two intervals over the sample period. The first interval is 1989Q2-1992Q1, i.e. MSDB is exceeded roughly one year prior to the recession in the early 1990's and returns to the sustainable region at the bottom of the recession. The second starts in 2005Q1, more than two years before the recent crisis, and continues to the end of the sample in 2010Q2, by which time the financial obligations ratio has not yet returned to the sustainable region. Both of these episodes are associated with massive credit losses and an unusually large number of bank failures, but differ with respect to the severity and length of the ensuing recession. This difference appears to be related to size with which the financial obligations ratio exceeded the MSDB estimate on each occasion.

For the business sector, we similarly find that major credit losses ensue when the associated financial obligations ratio crosses its MSDB estimate of 10.4% into the unsustainable region. This happens 1-2 years prior to each of the three US recessions in the sample but, as exemplified by the recession in the early 2000's, does not necessarily lead to large-scale bank failures. While the credit losses associated with excessive business loans seem less detrimental to financial stability than those associated with households' real estate loans, they may, nevertheless, exert a significant effect on the business cycle.

The observation that the financial obligations ratio in excess of its MSDB level precede economic downturns is likely to have important implications for how to design countercyclical capital standards for banks (Drehmann et al. (2010) and Repullo et al. (2010)) and implement more general macro prudential policies (e.g., Borio (2009)). For instance, the current practice of determining bank capital requirements, set fourth in the New Basel Capital Accord (Basel II), has been much criticized for its inherent tendency to amplify business cycle fluctuations by constraining bank lending in recessions (see e.g., Gordy and Howells (2006)). To obtain adequate assessments of banks' exposure toward *aggregate credit risk* sufficiently well in advance seems to be the major difficulty in this context. Our analysis suggests that credit risk assessment based on financial obligations ratios could lead to more countercyclical capital standards. Similarly, the financial obligations ratios, in particular those related real estate debt, may be useful for macro prudential policy as early warning indicators of such long-term debt accumulations which may eventually threaten financial stability.

Our results also impinge on the conduct of monetary policy. For instance, our analysis suggests that an interest rate increase, intended to curb inflationary pressure, is likely to be detrimental to financial stability in periods when aggregate debt is close to or above the sustainable level. This is because an interest rate increase directly raises the financial obligations of borrowers, which in turn makes credit losses both more likely and more severe. In such a situation monetary authorities should refrain from increasing the interest rate and, instead, choose policy measures directly aimed at reducing excessive debt, for example increasing mandatory collateral requirements.

The rest of the paper is organized as follows: Section 2 introduces the data, whereas Section 3 discusses methodology and statistical models. The results are presented in Section 4 and Section 5 concludes.

2 Data

This section introduces quarterly US time-series data of the key variables, spanning the sample 1985Q1-2010Q2. We first introduce credit loss rates and indicators of the business cycle, and discuss their temporal association graphically. Then, in Section 2.2, we present two different measures of aggregate debt and relate their dynamics to that of the credit loss rates. Detailed descriptions of the variables and their sources are provided in Appendix A.

2.1 Credit losses and business cycle indicators

As a measure of credit losses we use the net charge-off rate on loans held by all insured commercial US banks. We distinguish between losses on total loans (T), real estate loans (R), and business loans (B), denoted cl_t^T, cl_t^R, and cl_t^B, respectively. The loss rate on total loans, depicted in panel (a) of Figure 1, shows peaks at the low point of each of the three US recessions in the sample (as indicated by a standard output gap measure, $\tilde{y}_t$, depicted in panel e of the figure), with the most recent one being almost twice as severe as the previous ones. This pattern, however, is not preserved over different loan categories. For example, the loss rate on real estate loans (panel b) peaks only twice over the sample, first during the recession in the early 1990's and next during the recent financial crisis. As can be seen from panel (d) of the figure, both of these occasions are associated with large-scale bank failures. In contrast, the loss rate on business loans (panel c) displays peaks of roughly equal magnitude at each of the three recessions. In this sense, it resembles the term-spread, $\tilde{i}_t^S$, depicted in panel (g), more closely than the output gap. We also note that losses on business loans seem less strongly connected to bank failures, as exemplified by the early 2000's recession.

This ocular evidence suggests that there may be significant interactions between credit losses across different loan categories and the business cycle, potentially reinforcing each other. For instance, deep recessions and financial instability appear to be more closely associated with losses on real estate loans than losses on business loans, whereas the latter seems more related to ordinary business cycle fluctuations. The question is whether a suitable measure of the aggregate debt burden, either the conventional leverage or the financial obligations ratio that we propose in this paper, can predict when such interactions become pivotal.[3]

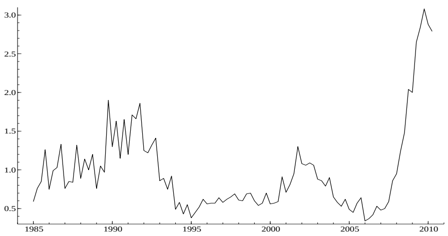
2.2 Leverage vs. financial obligations

Panels (a)-(d) in Figure 2 depict the household (H) and business (B) sector debt to income ratios, distinguishing between total (T) and real estate (R) debt, respectively. We use these loss ratios as a measure of leverage and denote them by l_t^{ij}, where $i = H$, B and $j = T$, R. By comparing panels (a) and (b), as well as panels (c) and (d), it appears that real estate loans comprise more than two thirds of total loans in the household sector, but less than 10% of total loans in the business sector. This points to potentially important disparities between the processes which generate excessive debt in the two sectors. For example, household sector debt is likely to have become excessive only in connection with the 1990's recession and the recent crisis. The loss pattern on business loans, on the other hand, suggests that debt in this sector may have been excessive prior to all three recessions in the sample.

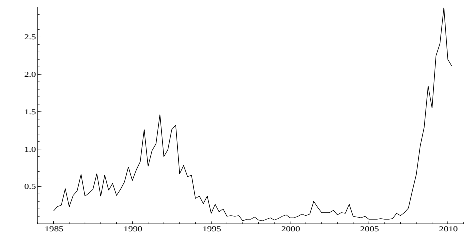
One potential problem with using the leverage variables for determining debt sustainability is their clear upward trends over the sample. This either implies that debt in the two sectors did not reach excessive levels until possibly just before the recent crisis or, alternatively, that the associated critical threshold must have been time-varying. The evidence in King (1994), for example, would argue against the former case, whereas estimation is problematic in the latter.

The likely reasons for the growth displayed by the debt to income ratios are changes in the terms of credit, as discussed in the introduction. For instance, both the federal funds rate and the long-term interest rate have been declining over the entire sample,

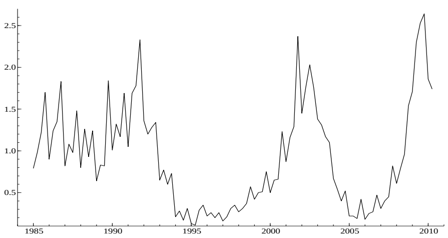
[3]In the empirical analysis of Section 4, we also control for a number of other variables including an indicator of the monetary policy stance, $\tilde{i}_t^T$, real house prices, p_t^R, the real exchange rate, q_t, the unemployment rate, u_t, and the inflation rate, π_t. See Appendix A for definitions.



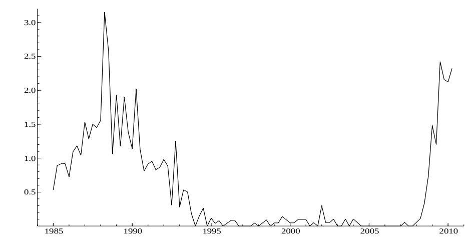
(a) Loss rate on total loans.



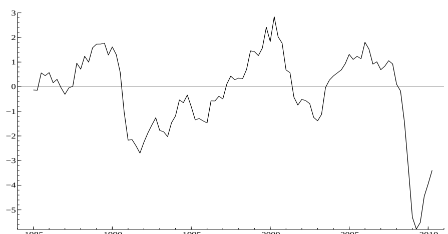
(b) Loss rate on real estate loans.



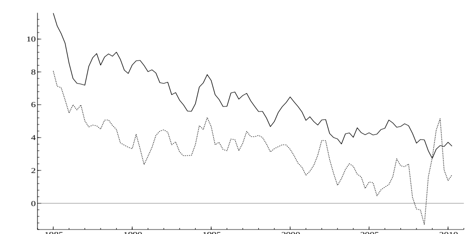
(c) Loss rate on business loans.



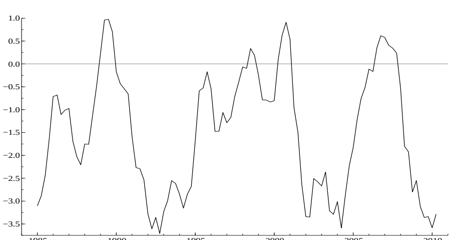
(d) Bank failure rate.



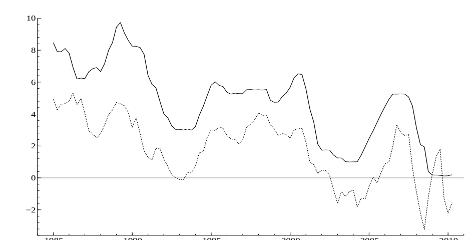
(e) Output gap



(f) Nominal (solid line) and real (dotted line) long-term government T-bill rate.

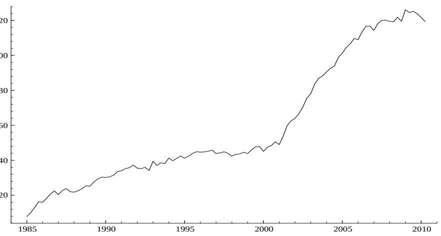


(g) Interest rate spread

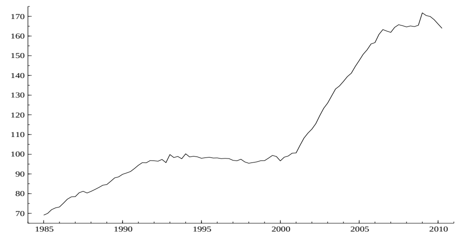


(h) Nominal (solid line) and real (dotted line) federal funds rate.

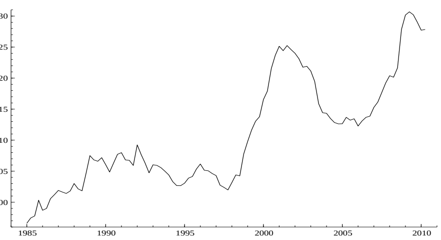
Figure 1: Credit loss rates and various indicators of financial, monetary, and real conditions in the United Sates. The real (ex-post) interest rates are constructed using the 4-quarter moving average inflation rate to facilitate the exposition.



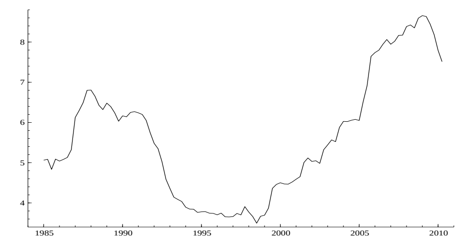
(a) Total leverage in the household sector.



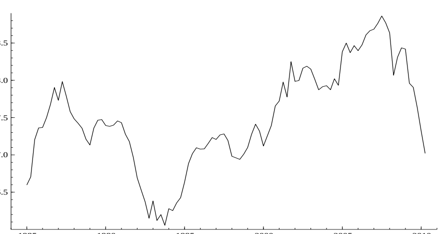
(b) Real estate leverage in the household sector.



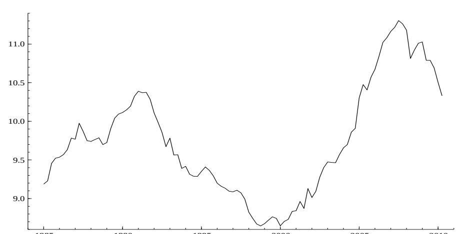
(c) Total leverage in the business sector.



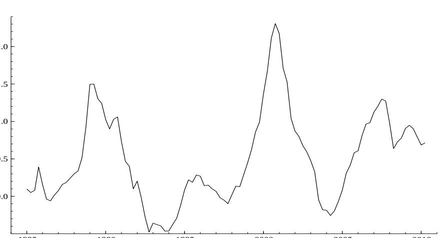
(d) Real estate leverage in the business sector.



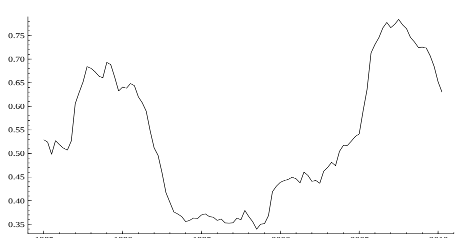
(e) Total financial obligations in the household sector.



(f) Real estate financial obligations in the household sector.



(g) Total financial obligations in the business sector.



(h) Real estate financial obligations in the business sector.

Figure 2: Indicators of leverage and financial obligations in the household and business sectors.

as is evident from panels (f) and (h) in Figure 1. Since the financial obligations ratio broadly consists of interest payments and amortizations, it explicitly accounts for such changes and can, hence, be used to address this issue. As the Federal Reserve only reports this measure for the household sector, we construct a corresponding measure for the business sector by using the federal funds rates as the relevant interest rate, a fixed maturity of 3 years,[4] and a linear amortization schedule. Panels (e)-(h) in Figure 2 depict the financial obligations ratios, denoted by f_t^{ij}, where i corresponds to the two sectors and j to the two debt categories. These ratios show less persistent growth and a stronger tendency to revert back to some benchmark value, compared to the leverage variables.

The differences in the dynamic behavior between the leverage variables and the financial obligations ratios indicate that much of the upward trend in the former is due to changes in the terms of credit. Hence, the financial obligations ratio is more likely to generate sensible estimates of the maximum sustainable debt burden than leverage.

3 Methodology

In this section, we present our empirical strategy and discuss statistical models which can be used for its implementation. We consider two alternative ways in which the aggregate debt variables can enter credit loss determination. The first approach is to model the debt variables, along with the credit loss rates and the other cyclical indicators, *linearly* in a vector auto-regressive (VAR) model, in line with existing empirical work on financial accelerators (e.g., Gertler and Lown (1999) and Gilchrist et al. (2009)). Because the economic models which underlie such accelerator effects typically exclude credit rationing (see e.g., Bernanke et al. (1999)), they seem more relevant as descriptions of credit market and business cycle interactions during normal (stable) times.

The second approach is to use the debt measures as transition variables in *nonlinear* regime-switching models for the credit loss rates. The idea is to capture increases in the interaction between credit losses and the business cycle which may arise if aggregate debt is allowed to reach excessive levels (see e.g., Miller and Stiglitz (2010)). The reason is that borrowers who are at the limits of their credit constraints may be forced to reduce their spending or sell off assets in order to meet their debt obligations in the wake of a negative shock. Campello et al. (2010), for example, document significant changes in the investment and employment decisions of credit constrained firms during the recent financial crisis. If the proportion of constrained borrowers is large, this type of behavior can easily reinforce the negative effects of the initial shock, thereby creating increased feedback between credit losses and the business cycle.

An advantage of the second modeling strategy is that it allows us to estimate a

[4]This value lies between the average maturities on firms' bank loans reported in Stohs and Mauer (1996) and Berger et al. (2005). We checked robustness of the results below by assuming 2 and 4 year maturities. The results did not change significantly and are available upon request.

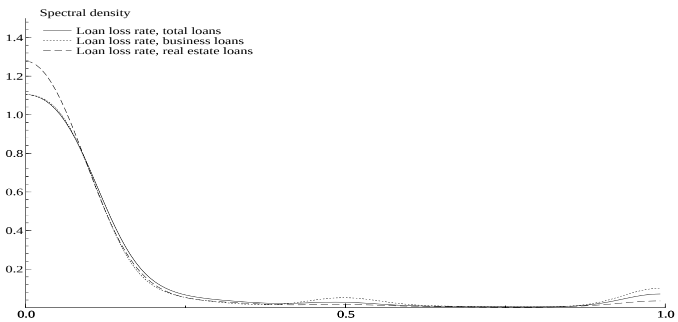


Figure 3: Spectral densities of the credit loss rates.

critical threshold for each debt variable above which it becomes excessive, provided that nonlinear transition-dynamics are present in the credit loss rates.[5] However, such dynamics can also induce the appearance of stochastic trending (Leybourne et al. (1998) and Nelson et al. (2001)) which may be difficult to distinguish from other sources of persistence, for example originating in some exogenous variables. This is problematic, as estimates may become biased if these two types of dynamics are confused with each other. To study this aspect, Figure 3 reports the spectral densities of the credit loss rates. As can be seen from the figure, all credit loss rates show significant variation at frequencies close to zero, consistent with unit-root persistence or, alternatively, cycles of longer duration than the available sample. We also find that our leverage variables, financial obligations ratios, and interest rates (see figures 1 and 2) all display similar stochastic trending.[6] Hence, each of the latter variables may conceivably be a source of persistence in the credit loss rates.

To overcome this difficulty, we initially restrict our attention to the pre-crisis sample 1985Q1-2006Q4, where regime shift dynamics are less likely to have played a dominant role in credit loss determination.[7] To identify potential sources of persistence associated with economic fundamentals, we model each of the credit loss rates jointly with the other persistent variables (both individually and in selected groups), using a cointegrated VAR model. We then test whether the latter variables are cointegrated and weakly exogenous with respect to the former. A variable that satisfies both of these criteria

[5]The precision with which the critical thresholds can be estimated depends more on the relative number of observations in each regime than the number of transitions between regimes. For instance, while our sample contains only two episodes of severe household sector financial distress, the number of observations associated with these events is 34, i.e. approximately one third of the entire sample.

[6]Standard unit-root and stationarity tests indicate that these variables, as well as the credit loss rates, display dynamics consistent with stochastic trends. The only exception is the financial obligations ratio on total business loans which is found to be stationary. We also note that the leverage measures exhibit significant linear trends over the sample. These results are available upon request.

[7]In fact, we do not find any significant non-linearities (at the 5% significance level) in the data for the 1985Q1-2006Q4 sample, using the linearity test in Choi and Saikkonen (2004). This does not, however, imply that such shifts are not present in the pre-crisis sample, but rather that the resulting dynamics are of a lesser magnitude and, hence, not likely to be confused with long-run movements in the credit loss rates.

can be considered a leading indicator of the long-run movements in the credit loss rates. Given that such leading indicators can be found, we next extend the analysis to the full sample, 1985Q1-2010Q2, and check whether they still can account for the persistent credit loss movements to a sufficient degree. If this is the case, we can conclude that the linear modeling approach is adequate. However, if this is not the case we use the leading indicators to remove the stochastic trends, s_t^j for $j = T$, R, B, which generate persistence in the credit loss rates during "normal" periods, and model the remaining variation by the regime-switching model.

3.1 Statistical models

A convenient way of capturing long-run comovement between the credit loss rates and other persistent variables, is the cointegrated VAR model

$$\Delta \boldsymbol{y}_t = \sum_{i=1}^{k-1} \Gamma_i \Delta \boldsymbol{y}_{t-i} + \Pi \boldsymbol{y}_{t-1} + \Phi \boldsymbol{d}_t + \boldsymbol{\varepsilon}_t \tag{1}$$

where $\boldsymbol{y}_t$ consists of the endogenous variables (including a credit loss rate), $\boldsymbol{d}_t$ is a vector of deterministic terms, $\boldsymbol{\varepsilon}_t \sim N_p(0, \Sigma)$, and k is the lag-length.

Cointegration in (1) can be tested by the likelihood ratio (LR) test for the rank of Π (Johansen (1996)). If the rank, r, is equal to the number of variables in the system, p, then $\boldsymbol{y}_t$ is stationary, i.e. $\boldsymbol{y}_t \sim I(0)$. If $0 < r < p$, then $\Pi = \alpha\beta'$, where α and β are two $(p \times r)$ matrices of full column rank and $\beta' \boldsymbol{y}_{t-1}$ describes the cointegration relationships. In this case $\boldsymbol{y}_t \sim I(1)$ and cointegrated with r cointegration vectors, β, and $p - r$ common stochastic trends, assuming that the "no $I(2)$ trends" condition $\left|\alpha'_\perp(I - \sum_{i=1}^{k-1} \Gamma_i)\beta_\perp\right| \neq 0$ is met, where $\perp$ denotes orthogonal complements. If $r = 0$, then $\boldsymbol{y}_t \sim I(1)$ and the process is not cointegrated. A testing sequence that ensures correct power and size starts from the null hypothesis of rank zero and then successively increases the rank by one until the first non-rejection.

When $0 < r < p$, it is possible to test the hypothesis that a variable, $y_{i,t}$ say, precedes the credit loss rate in question in the long-run. The test of this hypothesis is asymptotically χ^2, and amounts to imposing zero-restrictions on a row of α corresponding to $y_{i,t}$. If the null hypothesis cannot be rejected, $y_{i,t}$ is said to be weakly exogenous with respect to the long-run parameters of the model. An estimate of the stochastic trend, s_t, associated with $y_{i,t}$ can, for example, be obtained from the moving average representation of (1).

Given estimates of s_t^j for $j = T$, R, B, we can estimate the non-linear dynamics associated high levels of aggregate debt. We model this type of dynamics using a smooth transition regression (STR) model for the credit loss rates over the full sample. This model takes the form

$$\tilde{cl}_t^j = (1 - \varphi(\tau_t))(\mu_1 + \boldsymbol{\gamma}'_1 \boldsymbol{x}_t) + \varphi(\tau_t)(\mu_2 + \boldsymbol{\gamma}'_2 \boldsymbol{x}_t) + \boldsymbol{\psi}' \boldsymbol{d}_t + \upsilon_t \tag{2}$$

where $\tilde{cl}_t^j = cl_t^j - s_t^j$, $\boldsymbol{x}_t$ is a vector of explanatory variables, τ_t is a transition variable, $\boldsymbol{d}_t$ is a vector of deterministic terms, and υ_t is assumed to be a mean zero stationary disturbance term. In the empirical analysis (Section 4), $\boldsymbol{x}_t$ is selected from the three cyclical indicators $\tilde{i}_t^T$, $\tilde{i}_t^S$, and $\tilde{y}_t$, whereas τ_t is selected from a set which includes the leverage variables, l_t^{ij}, the financial obligations ratios, f_t^{ij}, and several control variables. The transition function $0 \leq \varphi(\tau_t) \leq 1$ determines the relative weights between regimes 1 and 2. We assume that this function takes the form

$$\varphi(\tau_t) = \frac{1}{1 + e^{-\kappa_1(\tau_t - \kappa_2)}}$$

giving symmetric weights around the threshold parameter, κ_2, where e is the natural exponent and $\varphi(\kappa_2) = 1/2$.[8] Both the explanatory variables and the transition variable are allowed to exhibit stochastic trends. This is convenient as all of the leverage measures and most of financial obligations ratios display dynamics consistent with unit-roots. We note that the stationarity assumption on the disturbance term implies that $\tilde{cl}_t^j$ and $\boldsymbol{x}_t$ are either linearily or non-linearily cointegrated. Thus, verifying this assumption ensures model consistency, as well as safeguards against spurious results, for example due to growth correlations over time.

We apply a linearity test by Choi and Saikkonen (2004) to identify the statistically significant transition variables. The test is based on a Taylor series approximation of (2), which under the null hypothesis of linearity will not contain any significant second (or higher) order polynomial terms. However, under the STR alternative, all significant higher order terms will involve the transition variable, τ_t. Hence, statistically valid transition variables can be detected by applying the test successively to each variable from the set of potential transition variables. Such information may be helpful in distinguishing between competing explanations for the recent crisis, such as lax monetary policy or excessive debt.

4 Results

This section reports the main empirical findings. Section 4.1 first investigates whether the observed persistence in the credit loss rates is due to exogenous factors or related to (transitory) regime shifts, or both. Next, Section 4.2 compares the ability of leverage and the financial obligations ratio for explaining shifts in credit loss dynamics. Section 4.3 reports the estimates associated with regime shift dynamics, and shows that they are informative about debt sustainability.

4.1 Linearity vs. regime shifts

To identify the sources of persistent movements in the credit loss rates over the pre-crisis sample 1985Q1-2006Q4, we estimate (1) for each of the three credit loss rates

[8] The signal extraction method outlined in Kaminsky and Reinhart (1999) also involves estimating critical thresholds and is, in this particular respect, similar in spirit to our approach.

Linear cointegration results								
	1985Q1-2006Q4				1985Q1-2010Q2			
$\boldsymbol{y}_t'$	$r=0$	$r \leq 1$	$\alpha_{cl}=0$	$\alpha_{i^M}=0$	$r=0$	$r \leq 1$	$\alpha_{cl}=0$	$\alpha_{i^M}=0$
$(cl_t^T,\, i_t^M)'$	**0.00**	0.38	**0.00**	0.42	0.96	0.98	–	–
$(cl_t^R,\, i_t^M)'$	**0.01**	0.79	**0.00**	0.13	0.95	0.94	–	–
$(cl_t^B,\, i_t^M)'$	**0.00**	0.19	**0.00**	0.54	0.27	0.29	–	–

Table 1: Linear cointegration results. Notes: The rows labeled "$r = 0$" and "$r \leq 1$" report the p-values of the LR tests for the rank of Π. The following two rows report the p-values from testing weak exogeneity for each of the variables in $\boldsymbol{x}_t$. Boldface values indicate significance at the 5% level.

combined with groups of variables consisting of at least one of the variables introduced in Section 2. Applying the LR test for cointegration rank, we find that none of the variables except the nominal federal funds rate are cointegrated with the credit loss rates.[9] This suggests, in particular, that the different debt measures cannot linearly account for the pronounced credit loss swings inherent in the data.

The left hand side of Table 1 reports the results of the LR test for the rank of Π and tests of weak exogeneity (conditional on $r = 1$) in estimates of (1) with $\boldsymbol{y}_t = (cl_t^j,\, i_t^M)'$, $j = T, B, R$, $k = 2$, a restricted constant, three centered seasonal dummies, and transitory impulse dummies to account for a few additive outliers in the credit loss rates (reported in Appendix A). As can be seen from the table $r = 0$ is rejected, whereas $r \leq 1$ cannot be rejected, in all three models. Furthermore, weak exogeneity is always rejected for the credit loss rates, but never rejected for the federal funds rate. This suggests that the declining interest rates during the past decades have reduced credit risks associated with the existing stock of loans in banks' loan portfolios, consistent with Altunbas et al. (2010).

We next investigate whether a linear combination between the federal funds rate and the credit loss rates continues to be cointegrating in the full sample, 1985Q1-2010Q2. As the results in the right hand side of Table 1 show, cointegration between the variables breaks down in this case. This is likely caused by a transitory but influential shift in the process that govern short-run credit losses, consistent with the nonlinear hypothesis in (2). We investigate this possibility using the linearity test of Choi and Saikkonen (2004). Prior to the estimations, we remove the long-run (stochastic) trend associated with the interest rate decline, s_t, from the credit loss rates, where the former is estimated by the Hodrick-Prescott filtered federal funds rate.[10] The filtered loss rates are denoted by $\tilde{cl}_t^j$,

[9]These results are omitted for brevity, but are available upon request. We also tried per capita GDP, the inflation rate, the unemployment rate, and the real exchange rate. None of these were found to be both cointegrated and weakly exogenous with respect to the credit loss rates.

[10]This is statistically justified if the federal funds rate is strongly exogenous. Exclusion restrictions on the Δcl_t^j terms in the equation for Δi_t^M in (1) produced marginal significance levels of 0.26, 0.03 and 0.37 for $j = T, R, B$, respectively. Hence, in conjunction with results on weak exogeneity, these results imply that the federal funds rate is strongly exogenous with respect to the credit loss rates (or close to in the case of cl_t^R). We also checked robustness with respect to this estimate of s_t, by

Tests of linearity vs. regime shifts											
1985Q1-2006Q2											
$\tilde{cl}_t^j \setminus \tau_t$	$\tilde{i}_t^T$	$\tilde{i}_t^S$	p_t^R	l_t^{HT}	l_t^{HR}	l_t^{BT}	l_t^{BR}	f_t^{HT}	f_t^{HR}	f_t^{BT}	f_t^{BR}
$\tilde{cl}_t^T$	0.244	0.170	0.918	0.828	0.719	0.535	0.419	0.963	0.406	0.780	0.570
$\tilde{cl}_t^R$	0.330	0.085	0.187	0.363	0.597	0.489	0.688	0.108	0.085	0.221	0.583
$\tilde{cl}_t^B$	0.559	0.582	0.249	0.370	0.408	0.072	0.256	0.132	0.929	0.141	0.420
1985Q1-2010Q2											
$\tilde{cl}_t^j \setminus \tau_t$	$\tilde{i}_t^T$	$\tilde{i}_t^S$	p_t^R	l_t^{HT}	l_t^{HR}	l_t^{BT}	l_t^{BR}	f_t^{HT}	f_t^{HR}	f_t^{BT}	f_t^{BR}
$\tilde{cl}_t^T$	0.819	**0.021**	**0.034**	**0.016**	**0.013**	**0.011**	**0.012**	0.181	**0.041**	0.411	**0.037**
$\tilde{cl}_t^R$	0.617	**0.015**	0.168	0.059	**0.042**	0.052	**0.021**	0.738	**0.018**	0.940	0.054
$\tilde{cl}_t^B$	0.784	0.338	0.068	**0.048**	**0.049**	**0.006**	**0.029**	0.058	0.151	**0.021**	0.064

Table 2: Tests of linearity against a STR alternative. Boldface values indicate rejection of the null hypothesis at the 5% significance level.

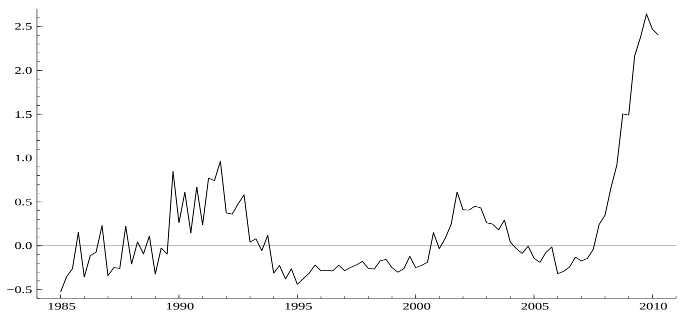
for $j = T$, R, B and depicted in Figure 4.

We test the null hypothesis of linearity against the STR model alternative in (2) and try different specifications for the determinants, $\boldsymbol{x}_t$, of short-run movements in the credit loss rates, and the transition variable, τ_t. In particular, we use the interest rate spread, $\tilde{i}_t^S$, and the output gap, $\tilde{y}_t$,[11] both individually and jointly, as explanatory variable(s), and successively try each of $\tilde{i}_t^T$, $\tilde{i}_t^S$, p_t^R, l_t^{ij}, and f_t^{ij} ($i = H$, B and $j = T$, R) as transition variable. We find that output gap movements, $\tilde{y}$, is neither significant in the first nor in the second regime in the model for the loss rate on business loans, $\tilde{cl}_t^B$, and is, hence, excluded from $\boldsymbol{x}_t$ in this equation. Both $\tilde{y}_t$ and $\tilde{i}_t^S$ produced significant results in the remaining models. Hence, we use $\boldsymbol{x}_t = (\tilde{i}_t^S, \tilde{y}_t)'$ in the models for the loss rate on total loans and real estate loans, $\tilde{cl}_t^T$ and $\tilde{cl}_t^R$, as well as $\boldsymbol{x}_t = \tilde{i}_t^S$ in the model of $\tilde{cl}_t^B$.

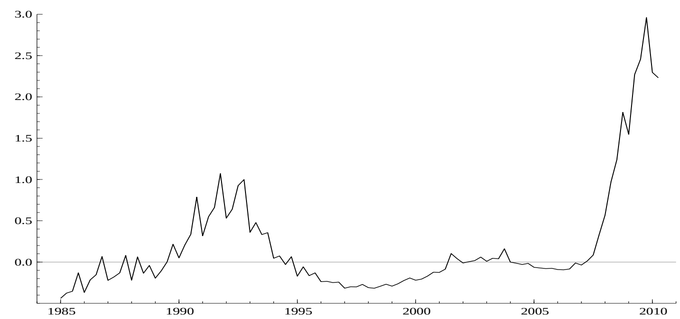
Given the indicated choices of $\boldsymbol{x}_t$, Table 2 reports the results of the linearity tests corresponding to each potential transition variable. For the pre-crisis period, the results in the upper part of the table show that the null hypothesis of linearity cannot be rejected in any of the models. However, turning to the lower part of Table 2, we see that the null hypothesis of linearity is rejected for several potential transition variables in the full sample. For instance, in the model for the loss rate on real estate loans, $\tilde{cl}_t^R$, there seems to be significant non-linearities associated with the interest rate spread, the household and business sector real estate debt to income ratios, and the household sector's real estate financial obligations ratio. In the model for the loss rate on business

estimating (2) with cl_t^j on the left hand side and i_t^M added to the right hand side. This did not change the results below to any significant degree.

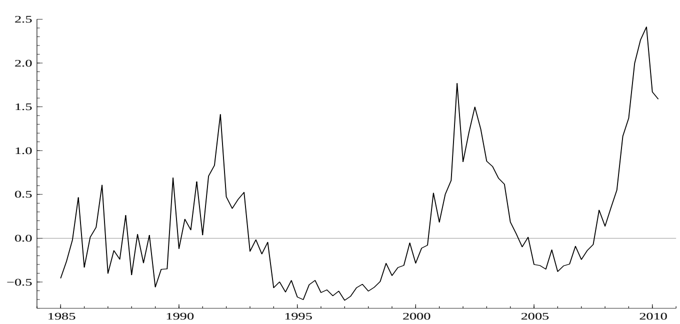
[11] We also tried the deviations from Taylor's rule, $\tilde{i}_t^T$, in $\boldsymbol{x}_t$, but this variable was not significant in any of the estimated regimes, and hence excluded from the analysis.



(a) Filtered Loss rate on total loans.



(b) Filtered loss rate on business loans.



(c) Filtered loss rate on real estate loans.

Figure 4: Indicators of financial distress with stochastic trend component removed.

loans, $\tilde{cl}_t^B$ on the other hand, all debt to income ratios and the financial obligations ratio in the business sector, are significant. The results of the model for the loss rate on total loans, $\tilde{cl}_t^T$ are, by and large, a combination of the results from the models of $\tilde{cl}_t^R$ and $\tilde{cl}_t^B$.

Summarizing, we find that the federal funds rate can be considered a leading indicator of long-run movements in the credit loss rates. While regime shifts do not play a very dominant role in the pre-crisis period, they are crucial for describing credit loss dynamics in the full sample, and in particular during the recent financial crisis.

4.2 Leverage vs. financial obligations

Next we estimate (2) for each the three credit loss rates, $\tilde{cl}_t^j$, with $\boldsymbol{x}_t$ as above, and τ_t successively equal to one of the transition variable candidates that has a significant entry in Table 2. When τ_t equals the interest rate spread, $\tilde{i}_t^S$, the real house price, p_t^R, or any of the leverage variables, l_t^{ij}, we find that either the estimated threshold parameter, κ_2, lies outside the range of the relevant transition variable or that the statistical fit of the model is poor, or both. More important, unit-roots cannot be rejected in the residuals of these models, implying that the underlying assumptions of the STR-model are not satisfied. Hence, these variables, and leverage in particular, cannot adequately account for the large and persistent fluctuations in the credit loss rates associated with the regime-shift dynamics.

In contrast, when any of the significant financial obligations ratios in Table 2 are used, we get stationary residuals, a good statistical fit, and a threshold parameter estimate which is in the range of the relevant transition variable. It can be seen from the table that the financial obligations ratios related to household real estate debt and total business debt, f_t^{HR} and f_t^{BT}, are the only statistically valid transition variables in the models for the loss rate on real estate loans and business loans, $\tilde{cl}_t^R$ and $\tilde{cl}_t^B$, respectively. We also find that the financial obligations ratios associated with real estate debt in both the household and business sector, f_t^{HR} and f_t^{BR}, produce sensible results in the model for the loss rate on total loans, $\tilde{cl}_t^T$. We choose the former financial obligations ratio as it produces a somewhat better fit and higher likelihood than the latter.

Based on these results we conclude that the leverage variables may not be able to signal an impending crisis with any sufficient precision. Financial obligations ratios, on the other hand, seem more relevant in this respect, as they can account for regime shift dynamics in the credit loss rates associated with episodes of severe financial distress.

4.3 Explaining credit losses

Table 3 reports the key parameter estimates of the STR-models. As can be seen from the table, both the estimated coefficients measuring the speed of transition between regimes, κ_1, and the estimated thresholds, κ_2, are positive, indicating that regime 2

STR estimates							
		Transition parameters		Regime 1		Regime 2	
$\tilde{cl}_t^i$	τ_t	κ_1	κ_2	$\gamma_{\tilde{i}^S}$	$\gamma_{\tilde{y}}$	$\gamma_{\tilde{i}^S}$	$\gamma_{\tilde{y}}$
$\tilde{cl}_t^T$	f_t^{HR}	**12.678** (5.630)	**10.192** (0.056)	−0.063 (0.034)	0.002 (0.045)	**−0.276** (0.094)	**−0.224** (0.051)
$\tilde{cl}_t^R$	f_t^{HR}	**3.609** (1.128)	**10.079** (0.106)	−0.023 (0.041)	−0.051 (0.038)	**−0.267** (0.099)	**−0.243** (0.049)
$\tilde{cl}_t^B$	f_t^{BT}	**2.318** (0.968)	**10.44** (0.199)	**−0.249** (0.085)	–	**−0.619** (0.119)	–

Table 3: Estimated transition parameters and regime coefficients from STR-models of the adjusted credit loss rates. Boldface values indicate significance at the 5% level (standard errors in parenthesis).

dominates for values *above* κ_2. Furthermore, the estimates of κ_1 indicate that speeds of transitions between regimes are rather fast in all cases. Each regime is characterized by the parameters $\gamma_{\tilde{i}^S}$ and $\gamma_{\tilde{y}}$, describing the effect of $\tilde{i}_t^S$ and $\tilde{y}_t$ on $\tilde{cl}_t^j$ in the relevant regime (except in the equation for $\tilde{cl}_t^B$ where only $\tilde{i}_t^S$ enter the regimes). The parameters in the first regime are generally negative but not significant, whereas in the second regime both parameters become negative and significant. It is notable that the effect on credit losses from a change in the output gap or the interest rate spread is much larger in the second regime. Therefore, the financial system becomes much more exposed to real economic fluctuations when the financial obligations ratios are above the estimated threshold values. Thus, the second regime describes unstable periods where even small negative shocks can lead to massive credit losses. In this sense, the threshold values, κ_2, can be viewed as estimates of the *maximum sustainable debt burden* (MSDB) with respect to a given credit category. Our estimates suggest that both total debt and real estate debt become unsustainable (i.e. susceptible to high loss rates) when the financial obligation ratio associated with households real estate loans exceed 10.19% and 10.08%, respectively. Similarly, business debt becomes unsustainable when the financial obligations ratio associated with total business loans exceeds 10.44%.

The upper panel of Figure 5 depicts the loss rate on real estate loans, and the lower panel depicts the financial obligations ratio related to household real estate debt along with a line demarking the corresponding MSDB estimate. The periods during which the second regime dominates are demarked by grey bars in the figure. As can be seen, there are only two unstable periods in the sample. The first begins in 1989Q2, roughly one year in advance of the recession in the early 1990's, and ends at its bottom. The second begins in 2005Q1, *over two years in advance of the recent crisis*, and has not yet ended by the last observation in our sample (2010Q2). Hence, armed with this MSDB estimate it might have been possible to foresee the recent crisis a full two years before its actual occurrence. In addition, the magnitude and duration by which the financial obligations ratio exceed the MSDB line seem to explain both the severity and length of the ensuing downturns. Indeed, this may explain why only the latter period developed into what is known as a full-blown financial crisis.

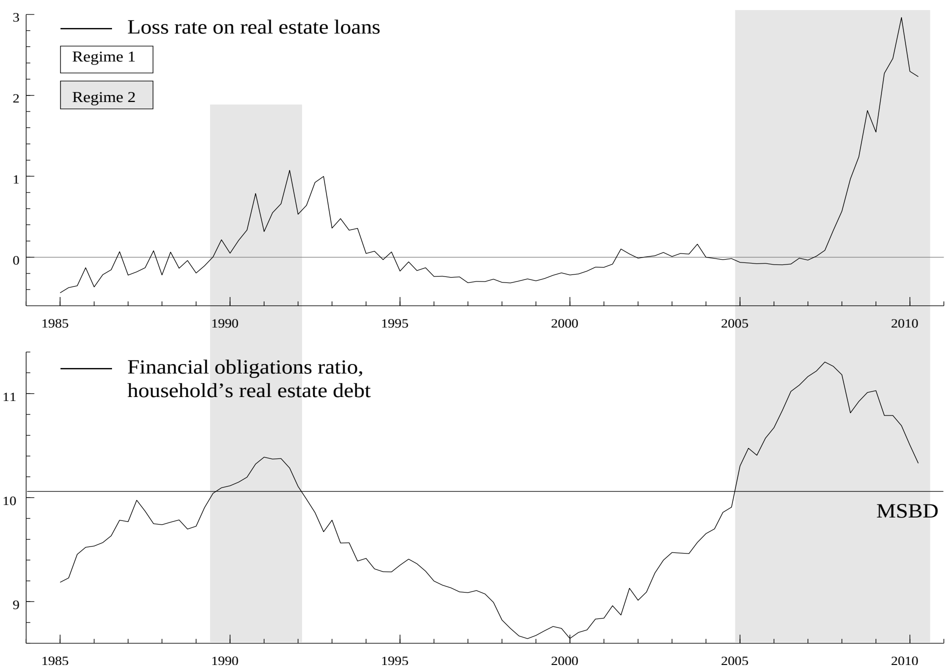


Figure 5: Transitions in the loss rate on real estate loans. The upper panel depicts the loss rate on real estate loans, whereas the lower panel depicts the financial obligations ratio associated with household's real estate debt and the corresponding MSDB estimate. Episodes when regime 2 dominate are demarked by grey bars.

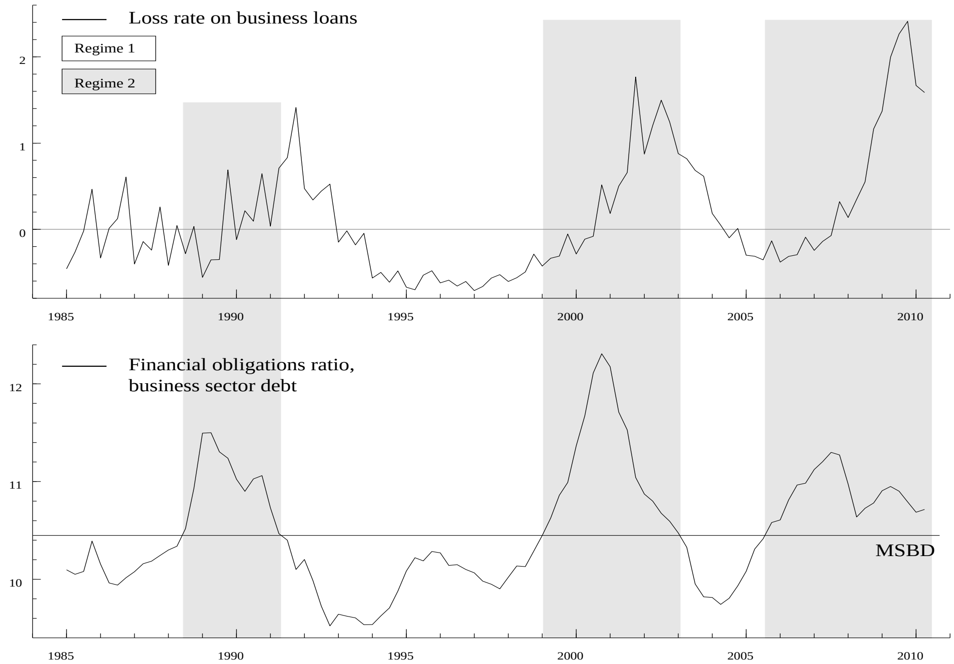


Figure 6: Transitions in the loss rate on business loans. The upper panel depicts the loss rate on business loans, whereas the lower panel depicts the financial obligations ratio associated with total business sector debt and the corresponding MSDB estimate. Episodes when regime 2 dominate are demarked by grey bars.

Similarly, Figure 6 depicts the loss rate on business loans and the corresponding financial obligations ratio. As can be seen form the figure, there are three unstable periods in our sample, each beginning between 1-2 years prior to one of the three known US recessions in the sample, and ending roughly at their low points. Prior to the 1990's recession, the MSDB of business loans is exceeded in 1988Q2, a full year earlier than the MSDB of households real estate loans. However, prior to the recent crisis the relative timing is reversed, i.e. the household sector MSDB was exceeded first. Finally, we note that it is possible to construct the business sector financial obligations ratio for earlier dates than those in our estimation sample. Hence, as a tentative test of the out-of-sample performance of the business sector MSDB, we checked whether it predicts the deep recession in the early 1980's.[12] We find that the financial obligations ratio crosses the MSDB line from below in 1980Q4, three quarters before the onset of the early 80's recession, and returns to the sustainable region at bottom of the recession. Since this pattern is in accordance with the within-sample results, it gives some additional support to our estimates.

[12]It is more difficult to conduct a similar test for the household sector, as the Federal Reserve does not record financial obligations ratios before 1985.

5 Conclusions

When do aggregate debt accumulations become excessive, compromising both real and financial stability? By studying US credit loss dynamics over the period 1985-2010, we show that it is the strength of the aggregate liquidity constraint, as measured by the financial obligations ratio, which determines the upper limit for sustainable debt developments. In contrast to previous studies which use cross-sectional data, we do not find the amount of debt to income, or leverage, to be particularly relevant in this respect. The reason for this finding seems to be that a large part of the growth trend in leverage during the past decades was in fact sustainable and due to a concurrent decline in the real interest rate. Because this trend likely has a uniform effect on the cross-section, most of the cross-sectional variation in leverage will be due to excessive buildups which, thereby, generate seemingly strong association with subsequent credit losses.

We find that the private sector financial obligations ratio displays a cyclical pattern, reaching unsustainable levels 1-2 years prior to each of the three US recessions in our sample. This pattern is, however, not identical among households and businesses. For instance, the household sector cycle seems to be approximately twice as long as the corresponding business sector cycle. Thus, the household sector financial obligations ratio only reached unsustainable levels prior to the deep recessions in the early 1990's and late 2000's, whereas the Business sector financial obligations ratio reached unsustainable level prior to each of the three recessions. These results suggest that the distinction between excessive financial obligations in the household and business sectors may be important for understanding why some recessions become deep and prolonged while others do not. They also indicate that the financial obligations ratio may be useful as an early warnings indicator.

While our empirical approach seems promising in the sense of successfully spotting buildups of excessive aggregate debt, several interesting avenues for future research remain to be explored. For instance, because different types of households are likely to differ with respect the tightness of their financial constraints (Hall (2011)), it might be worthwhile to decompose the financial obligations ratio according to such characteristics as age and income. This may significantly improve our ability to detect excessive debt accumulations, especially when population cohorts change along these dimensions. It is also conceivable that our framework can be extended to an analysis of public sector debt, which could potentially be very valuable in light of the ongoing US and European sovereign debt crisis. As a final remark, we note that the recurrent nature of excessive debt accumulations suggests that the underlying credit market behavior is systematic, which seems inconsistent with the basic assumptions of most theoretical models. Asset price models that incorporate imperfect knowledge and heterogeneous expectations (e.g., Frydman and Goldberg (2009) and Burnside et al. (2011)) are able to generate pervasive boom and busts as a consequence of the market's allocation of capital and, hence, seem more promising in this respect.

References

Altunbas, Y., Gambacorta, L., Marques-Ibanez, D., 2010. Does monetary policy affect bank risk-taking?, BIS Working Papers, No 298.

Berger, A., Espinosa-Vega, M., Frame, S., Miller, N., 2005. Debt maturity, risk, and asymmetric information. The Journal of Finance 60, 2895–2923.

Bernanke, B., Gertler, M., Gilchrist, S., 1999. The financial accelerator in a quantitative business cycle framework. In: Taylor, J., Woodford, M. (Eds.), Handbook of Macroeconomics, vol. 1. Amsterdam: North-Holland.

Borio, C., 2009. Implementing the macroprudential approach to financial regulation and supervision. Banque de France Financial Stability Review 13, 31–41.

Borio, C., Drehmann, M., 2009. Assessing the risk of banking crises - revisited, BIS Quarterly Review, March.

Borio, C., Lowe, P., 2002. Asset prices, financial and monetary stability: exploring the nexus, BIS Working Papers, no 114.

Burnside, C., Eichenbaum, M., Rebelo, S., 2011. Understanding booms and busts in housing markets, NBER Working Paper No. 16734.

Caballero, R., Farhi, E., Gourinchas, P., 2008. An equilibrium model of "global imbalances" and low interest rates. American Economic Review 98, 358–393.

Campello, M., Graham, J., Harvey, C., 2010. The real effects of financial constraints: Evidence from a financial crisis. Journal of Financial Economics 97, 470–487.

Choi, I., Saikkonen, P., 2004. Testing linearity in cointegrating smooth transition regressions. Econometrics Journal 7, 341–365.

Dell'Ariccia, G., Marquez, R., 2006. Lending booms and lending standards. The Journal of Finance 61, 2511–2546.

Drehmann, M., Borio, C., Gambacorta, L., Jiménez, G., Trucharte, C., 2010. Countercyclical capital buffers: exploring options, BIS Working Papers, no 317.

Frydman, R., Goldberg, M., 2009. Financial markets and the state: Price swings, risk, and the scope of regulation. Capitalism and Society 4, 1–43.

Gai, P., Kapadia, S., Millard, S., Perez, A., 2008. Financial innovation, macroeconomic stability and systemic crises. The Economic Journal 118, 401–426.

Gertler, M., Lown, C., 1999. The information in the high-yield bond spread for the business cycle: Evidence and some implications. Oxford Review of Economic Policy 15 (3), 132–150.

Gilchrist, S., Yankov, V., Zakrajšek, E., 2009. Credit market shocks and economic fluctuations: Evidence from corporate bond and stock markets. Journal of Monetary Economics 56, 471–493.

Gordy, M., Howells, B., 2006. Procyclicality in Basel II: Can we treat the disease without killing the patient? Journal of Financial Intermediation 15, 395–417.

Hall, R., 2011. The long slump, NBER Working Paper No. 16741.

Iacoviello, M., 2005. House prices, borrowing constraints, and monetary policy in the business cycle. American Economic Review 95, 739–764.

Johansen, S., 1996. Likelihood-Based Inference in Cointegrated Vector Auto-Regressive Models. Oxford: Oxford University Press.

Kaminsky, G., Reinhart, C., 1999. The twin crises: the causes of banking and balance-of-payments problems. American Economic Review 89, 473–500.

King, M., 1994. Debt deflation: Theory and evidence. European Economic Review 38, 419–455.

Kiyotaki, N., Gertler, M., 2010. Financial intermediation and credit policy in business cycle analysis. In: Friedman, B., Woodford, M. (Eds.), Handbook of Monetary Economics. Amsterdam: Elsevier.

Kiyotaki, N., Moore, J., 1997. Credit cycles. Journal of Political Economy 105, 211–248.

Leybourne, S., Newbold, P., Vougas, D., 1998. Unit roots and smooth transitions. Journal of time series analysis 19 (1), 83–97.

Lorenzoni, G., 2008. Inefficient credit booms. Review of Economic Studies 78, 809–833.

Meier, A., Müller, G., 2006. Fleshing out the monetary transmission mechanism: Output composition and the role of financial frictions. Journal of Money, Credit, and Banking 38 (8), 2099–2133.

Mian, A., Sufi, A., 2010. The great recession: Lessons from microeconomic data. American Economic Review 100, 1–10.

Miller, M., Stiglitz, J., 2010. Leverage and asset bubbles: Averting armageddon with chapter 11? The Economic Journal 120, 500–518.

Nelson, C., Piger, J., Zivot, E., 2001. Markov regime switching and unit-root tests. Journal of Business & Economic Statistics 19, 404–415.

Repullo, R., Saurina, J., Trucharte, C., 2010. Mitigating the pro-cyclicality of Basel II. Economic Policy 25, 659–702.

Ruckes, M., 2004. Bank competition and credit standards. The Review of Financial Studies 17, 1073–1102.

Stein, J., 2006. Stochastic Optimal Control, International Finance, and Debt Crises. Oxford: Oxford University Press.

Stohs, M., Mauer, D., 1996. The determinants of corporate debt maturity structure. The Journal of Business 69, 279–312.

Appendix A

Detailed definitions of the variables used in the analysis are provided in Table 4.

Data and definitions	
Variable:	Definition:
cl_t^j	Net charge-off rate on loans, all insured US commercial banks. $j = T$ (total loans), R (real estate loans), and B (business loans). Source: FRS (Bank Assets & Liabilities)
l_t^{ij}	Debt to income ratio (in %). $i = H$ (households'), B (Nonfarm nonfinancial corporate business). $j = T$ (total debt), R (real estate debt). Household income: total wages and salaries. Business income: Value added in non farm business. Sources: FRS (Flow of Funds Accounts) and BEA (National Economic Accounts).
f_t^{ij}	Financial obligations ratio. i and j are as above. For $i = H$ the series are taken from the FRS (Household Finance). For $i = B$ the definition is $l_t^{Bj} i_t^M/400 + l_t^{Bj}/12$.
p_t^R	House price index (all transactions) divided by CPI index. Sources: FHFA and BLS.
i_t^M	Effective federal fund rate (3-month average). Source: FRS (Interest Rates)
i_t^G	Yield on 10-year Treasury securities. Source: FRS (Interest Rates)
π_t	Consumer price inflation (4-quarter moving average). Source: BLS
u_t	Unemployment rate (seasonally unadjusted). Source: BLS
q_t	Real effective exchange rate (CPI weighted). Source: OECD
$\tilde{i}_t^S$	$i_t^M - i_t^G$
$\tilde{i}_t^T$	Deviations from a standard Taylor's rule, $\tilde{i}_t^T = i_t^M - 3.5 - 1.5(\pi_t - 2) - 0.5\tilde{y}_t$.
$\tilde{y}_t$	$100(\ln(Y_t/Y_t^*)$, where Y_t is real output and Y_t^* is potential output. Source: OECD.
y_t^L	GDP per capita. Source: BEA.

Sources: Federal Reserve System (FRS), Bureau of Economic Analysis (BEA), Bureau of Labor Statistics (BLS), OECD databases (OECD), Federal Housing Finance Agency (FHFA).

Table 4: Variable definitions and sources.

The underlying data are publicly available at the listed sources. To check robustness, we considered several alternative measures. For instance, we used the household debt service ratio (FRS) instead of f^{HT}, the Case-Shiller home price index (available from 1987Q1 onward) instead of p_t^R, deviations between real and Hodric-Prescott filtered GDP and the unemployment gap (congressional budget office definition) instead of $\tilde{y}_t$, and the difference between corporate BAA and AAA bonds instead of $\tilde{i}_t^S$. This did not produce significant changes to the results.

A few transitory impulse dummies were used in connection with the VAR estimates in Section 4.1. These dummies (labeled $DYYQ$) take the value 1 at date YYQ and -1 at the consecutive date, where YY and Q refer to the year and quarter digits, respectively. The model for $\boldsymbol{y}_t = (cl_t^T, i_t^M)'$ includes $D894$, the model for $\boldsymbol{y}_t = (cl_t^R, i_t^M)'$ includes $D904$, $D914$ and $D923$, and the model for $\boldsymbol{y}_t = (cl_t^R, i_t^M)'$ includes $D894$ and $D014$.