

# Sustainable Financial Obligations and Crisis Cycles\*

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## Abstract

The ability to distinguish between sustainable and excessive debt developments is crucial for securing economic stability. By studying US private sector credit loss dynamics, we show that this distinction can be made based on a measure of the incipient aggregate liquidity constraint, the financial obligations ratio. Specifically, as this variable rises, the interaction between credit losses and the business cycle increases, albeit with different intensity depending on whether the problems originate in the household or the business sector. This occurs 1-2 years before each recession in the sample. Our results have implications for macroprudential policy and countercyclical capital-buffers.

*Keywords:* debt sustainability; credit losses; financial crises; financial obligations; smooth transition regression; non-linear cointegration.

*JEL Classification:* E32, E44, G01

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# 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 incipient 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 move beyond critical levels, the interaction between business cycle fluctuations and credit losses starts to intensify. 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 affected simultaneously. 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 increasing liquidity problems associated with excessive aggregate debt accumulations can undermine both real and financial stability.

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 collateral 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'Araccia 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 a close association between high aggregate debt to income ratios (leverage) and subsequent credit and output losses.<sup>1</sup> 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 30 years. 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. The question remains, however: 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?

To make progress, it seems crucial to be able to distinguish between *sustainable* and *excessive* debt developments already at the outset. This is recognized by Borio and Lowe (2002) and Borio and Drehmann (2009) who construct early warning indicators of systemic banking crises based on leverage and asset price gaps. While the indicators perform well both in and out of sample, the gaps are, however, constructed using the Hodrick-Prescott filter rather than motivated by economic rationale. Thus, there is a risk of mistaking sustainable debt developments for excessive buildups. For example, if a credit boom lasts for a long time the filtered trend will eventually catch up, producing a gap which is close to zero or even negative. Similar problems can occur if the true underlying trend in debt-to-income suddenly changes. This suggests that the debt to income ratio should be detrended using economic rather than statistical criteria.

The most likely explanation for the upward trend in leverage during the recent decades is the concurrent decline in real interest rates, documented for example 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)). If this is the case, a more appropriate alternative measure for the burden imposed by private sector indebtedness is given by the financial obligations ratio constructed by the Federal Reserve (see Dynan et al. (2003)). Consisting of interest payments and repayments on debt divided by income, the financial obligations ratio captures the incipient aggregate liquidity constraints of borrowers (Hall (2011)). Rising financial obligations, for instance, indicate that borrowers have less leeway to smooth their consumption or make new investments, and are also more vulnerable to income and interest rate shocks. This may not be a problem as long as the

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<sup>1</sup>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.

business cycle is benign and banks' lending standards are soft. But when the business cycle turns, the liquidity constraints start to bind for more and more borrowers, forcing them in arrears and ultimately to default, thereby driving up banks' losses.

To investigate this possibility, we compare the ability of the financial obligations ratio for explaining US banking sector credit losses with that of the debt-to-income ratio. Focusing on credit losses instead of output losses also allows us to assess the differential roles that business and household loans play in generating real and financial weakness (see e.g., Iacoviello (2005)).<sup>2</sup> We allow the two debt measures 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, each debt measure is allowed to enter the empirical model as a regime switching variable which smoothly increases the interaction between credit losses and the business cycle once it exceeds an estimated critical threshold.

Applying this approach to quarterly US data from 1985Q1 to 2010Q2, 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. 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 to accurately estimate the parameters of the transition function which determines the weights given to the high and low credit loss regimes as a smooth function of the financial obligations ratio. We (loosely) refer to the half way point between regimes 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

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<sup>2</sup>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.

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 could be useful in designing capital standards for banks (Drehmann et al. (2010) and Repullo et al. (2010)) and for implementing more general macro prudential policies (e.g., Borio (2009)). For instance, 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 to 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.<sup>3</sup> Our results also suggest a channel through which monetary policy may affect financial stability under certain conditions. For instance, an interest rate increase, intended to curb inflationary pressure, can impinge on 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 can make credit losses both more likely and more severe.

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.

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<sup>3</sup>This conjecture has recently been corroborated in a subsequent paper by Drehmann and Juselius (2012), who construct debt service ratios, a more narrow counterpart to the financial obligations ratio, for 27 countries. They find that the debt service ratio produce more accurate early warning signals than other extant measures 1-2 years ahead of systemic banking crises, whereas the credit-to-GDP gap have superior performance at longer horizons.

## 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 (TL), real estate loans (RL), and business loans (BL), denoted  $loss_t^{TL}$ ,  $loss_t^{RL}$ , and  $loss_t^{BL}$ , 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,  $ygap_t = y_t - y_t^*$ , 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 more closely resembles the term-spread,  $term_t = fundr_t - govr_t$ , depicted in panel (g), where  $fundr_t$  is the federal funds rate and  $govr_t$  is the yield of 10-year treasury securities. 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.<sup>4</sup>

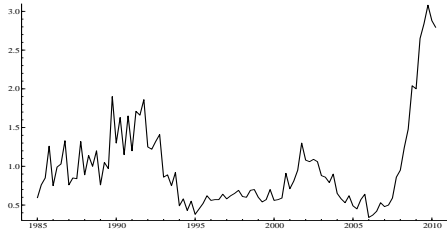
## 2.2 Leverage vs. financial obligations

Panels (a)-(d) in Figure 2 depict the household (H) and business (B) sector debt-to-income ratios, distinguishing between total and real estate loans (RL), respectively. We use these ratios as a measure of leverage and denote them by  $lev_t^{i,j}$ , where  $i = H, B$  and  $j = TL, RL$ . 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. Moreover, business sector leverage appears to be more volatile than household sector leverage. This points to potentially important disparities between the processes which generate excessive debt in the two sectors.

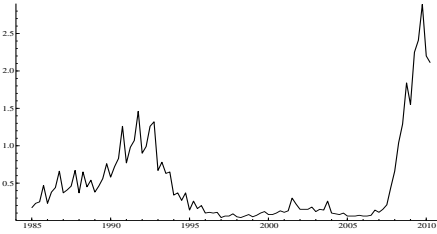
One potential problem with using the leverage variables for determining debt sus-

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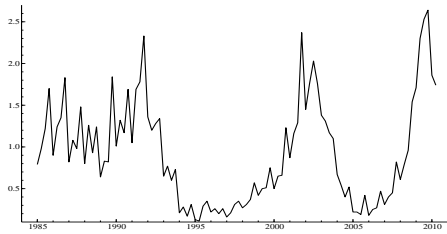
<sup>4</sup>In the empirical analysis, we also control for a number of other variables including real house prices, deviations from a standard Taylor's rule, the real exchange rate, the unemployment rate, and the inflation rate.



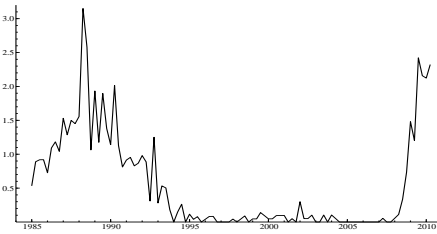
(a) Loss rate on total loans.



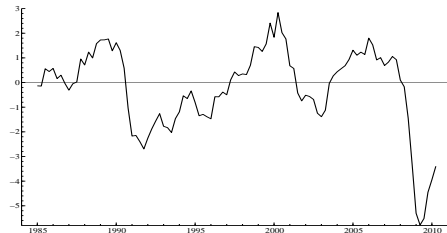
(b) Loss rate on real estate loans.



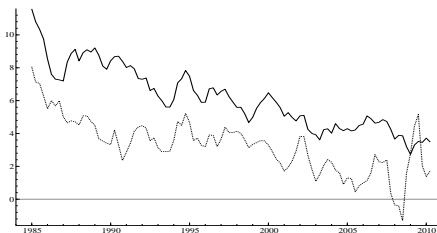
(c) Loss rate on business loans.



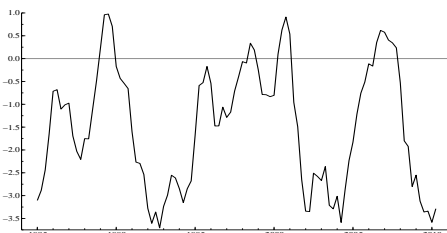
(d) Bank failure rate.



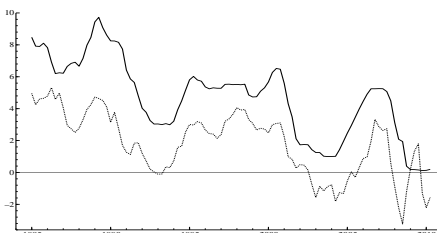
(e) Output gap.



(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 States. The real (ex-post) interest rates are constructed using the 4-quarter moving average inflation rate to facilitate the exposition.



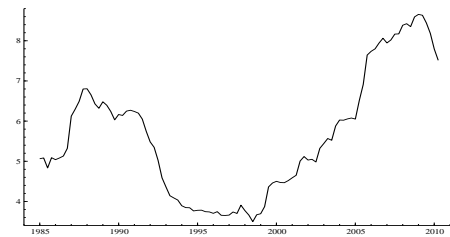
(a) Total leverage in the household sector.



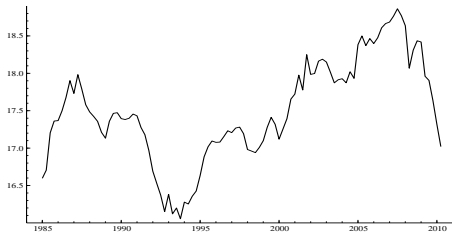
(b) Real estate leverage in the household sector.



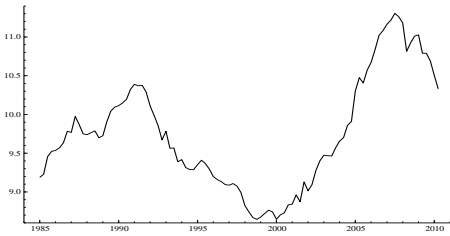
(c) Total leverage in the business sector.



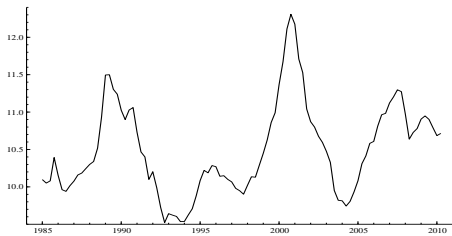
(d) Real estate leverage in the business sector.



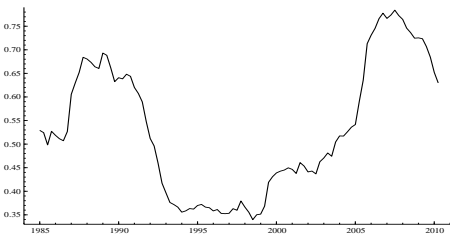
(e) Total financial obligations in the household sector.



(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.



tainability 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, 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,<sup>5</sup> and a linear amortization schedule. Panels (e)-(h) in Figure 2 depict the financial obligations ratios, denoted by  $for_t^{ij}$ , where  $i$  corresponds to the two sectors and  $j$  to the two loan 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 be informative about the limits to private sector indebtedness 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

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<sup>5</sup>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.

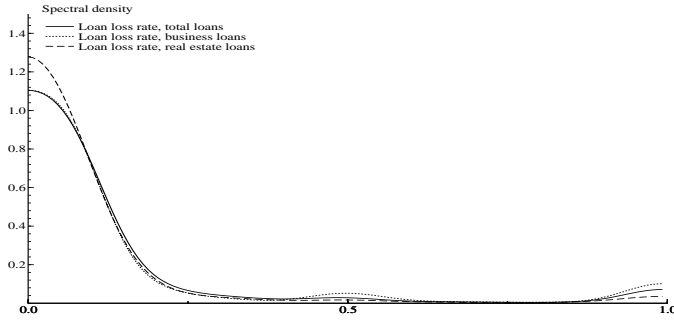


Figure 3: Spectral densities of the credit loss rates.

is that borrowers who are at the limits of their credit constraints may not be able to smooth their consumption or make optimal investments as they have to honor 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 loan defaults and the business cycle.

An advantage of the second modeling strategy is that it allows us to estimate a critical threshold for each debt variable above which it becomes excessive, provided that nonlinear transition-dynamics are present in the credit loss rates.<sup>6</sup> 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.<sup>7</sup> 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

<sup>6</sup>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.

<sup>7</sup>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.

role in credit loss determination.<sup>8</sup> 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 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,  $strend_t^h$  for  $h = TL, RL, BL$ , 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 co-movement between the credit loss rates and other persistent variables, is the cointegrated VAR model

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

where  $\mathbf{y}_t = (loss_t^h, ygap_t, term_t, fundr_t, debt_t)'$  for  $h = TL, RL, BL$ ,  $debt_t$  is successively one of the debt measures presented in Section 2.2, i.e.  $lev_t^{j,i}$  or  $for_t^{j,i}$  for  $j = H, B$  and  $i = TL, RL$ ,  $\mathbf{d}_t$  is a vector consisting of a constant and seasonal dummies (and possibly other dummies defined in the text),  $\boldsymbol{\varepsilon}_t \sim N_p(0, \Sigma)$ , and  $k$  is the lag-length. Note that having both  $term_t$  and  $fundr_t$  in  $\mathbf{y}_t$  is equivalent to having both  $fundr_t$  and  $gouv_t$  unrestricted in the system.

Cointegration in (1) can be tested by the likelihood ratio (LR) test for the rank of  $\Pi$  (Johansen (1996)). If the rank,  $r$ , is equal to the number of variables in the system,  $p$ , then  $\mathbf{y}_t$  is stationary, i.e.  $\mathbf{y}_t \sim I(0)$ . If  $0 < r < p$ , then  $\Pi = \alpha\beta'$ , where  $\alpha$  and  $\beta$  are two  $(p \times r)$  matrices of full column rank and  $\beta' \mathbf{y}_{t-1}$  describes the cointegration relationships. In this case  $\mathbf{y}_t \sim I(1)$  and cointegrated with  $r$  cointegration vectors,  $\beta$ , 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  $\mathbf{y}_t \sim I(1)$  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.

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<sup>8</sup>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.

When  $0 < r < p$ , it is possible to test the hypothesis that a variable,  $y_{i,t}$  say, precedes the credit loss rate in the long-run. The test of this hypothesis is asymptotically  $\chi^2$ , and amounts to imposing zero-restrictions on a row of  $\alpha$  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,  $strend_t^h$ , associated with  $loss_t^h$  can, for example, be obtained from the moving average representation of (1).

Anticipating results in Section 4.1, it turns out that there is a small but significant stochastic trend component in credit losses which is directly associated with the federal funds rate,  $fundr_t$ . This is consistent with Altunbas et al. (2010) who suggest that declining interest rates during the past decades have reduced credit risks associated with the existing stock of loans in banks' loan portfolios. Hence, we will remove this long-run influence on credit losses from the decline in the interest rate level before turning to estimating regime switch dynamics. We model this type of dynamics using a smooth transition regression (STR) model for the credit loss rates over the full sample. To keep the analysis tractable, we focus on a single-equation model for the variable of interest, i.e. the credit loss rate, rather than attempt to estimate a full-fledged multivariate STR model (see van Dijk et al. (2002)). In particular, the model takes the form

$$loss_t^h - strend_t^h = (1 - \varphi(debt_t))(\mu_1 + \boldsymbol{\gamma}'_1 \mathbf{x}_t) + \varphi(debt_t)(\mu_2 + \boldsymbol{\gamma}'_2 \mathbf{x}_t) + \boldsymbol{\psi}' \mathbf{d}_t + v_t \quad (2)$$

where,  $\mathbf{x}_t = (ygap_t, term_t, debt_t)'$  is a vector of potentially difference stationary explanatory variables,  $\mathbf{d}_t$  is a vector of deterministic terms define above, and  $v_t$  is assumed to be a mean zero stationary disturbance term. We note that the stationarity assumption on the disturbance term implies that  $loss_t^h$  and  $\mathbf{x}_t$  are either linearly or non-linearly cointegrated. Thus, verifying this assumption ensures model consistency, as well as safeguards against spurious results, for example due to growth correlations over time. Note also that  $fundr_t$  does not enter  $\mathbf{x}_t$  as its (long-term) influence on credit losses is accounted for by  $strend_t^h$  and its cyclical component is a part of  $term_t$ .<sup>9</sup>

Our primary interest lies in the transition function

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

which determines the relative weights between regimes 1 and 2, and has the properties  $0 \leq \varphi(debt_t) \leq 1$  and  $\varphi(\kappa_2) = 1/2$ . We use  $debt_t$  as the primary transition variable, i.e. we successively try one of the leverage or financial obligations ratios as arguments in  $\varphi(\cdot)$ .<sup>10</sup> Hence, for positive  $\kappa_1$  and  $\kappa_2$ , say, (2) captures gradual changes in the effect

<sup>9</sup>We also checked robustness by estimating (2) with  $loss_t^h$  on the left hand side and  $\gamma_0 i_t^M$  added to the right hand side. This did not change the results below to any significant degree.

<sup>10</sup>We also tried the other variables in  $\mathbf{x}_t$ , as well as real house prices. None, of these variables produced superior results in the sense discussed in Section 4.2.

(given by  $\varphi(\cdot)(\gamma_1 - \gamma_2)$ ) of the cyclical variables in  $\mathbf{x}_t$  on credit losses, as the debt variable increases. The halfway point between regimes, which we will loosely refer to as the maximum sustainable debt burden (MSDB), is determined by the  $\kappa_2$  and the speed of the transition is determined by  $\kappa_1$ .

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. 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) with  $\mathbf{y}_t = (loss_t^h, ygap_t, term_t, fundr_t, debt_t)'$  for  $h = TL, RL, BL$  and  $debt_t$  successively indicating one of the debt variables in Section 2.2. Applying the LR test for cointegration rank, we find that none of the variables except the nominal federal funds rate are *linearly* cointegrated with the credit loss rates.<sup>11</sup> In particular, this implies that neither the different leverage variables nor the different financial obligations ratios can linearly account for the pronounced swings inherent in credit losses over this period.

The left hand side of Table 1 reports the results of the LR test for the rank of  $\Pi$  and tests of weak exogeneity (conditional on  $r = 1$ ) in estimates of (1) with  $\mathbf{y}_t = (loss_t^h, fundr_t)'$ ,  $k = 2$ , 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

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<sup>11</sup>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.

Linear cointegration results				
1985Q1-2006Q4				
$\mathbf{y}'_t$	$r = 0$	$r \leq 1$	$\alpha_{loss} = 0$	$\alpha_{fundr} = 0$
$(loss_t^{TL}, fundr_t)'$	<b>0.00</b>	0.38	<b>0.00</b>	0.42
$(loss_t^{RL}, fundr_t)'$	<b>0.01</b>	0.79	<b>0.00</b>	0.13
$(loss_t^{BL}, fundr_t)'$	<b>0.00</b>	0.19	<b>0.00</b>	0.54
1985Q1-2010Q2				
$\mathbf{y}'_t$	$r = 0$	$r \leq 1$	$\alpha_{loss} = 0$	$\alpha_{fundr} = 0$
$(loss_t^{TL}, fundr_t)'$	0.96	0.98	–	–
$(loss_t^{RL}, fundr_t)'$	0.95	0.94	–	–
$(loss_t^{BL}, fundr_t)'$	0.27	0.29	–	–

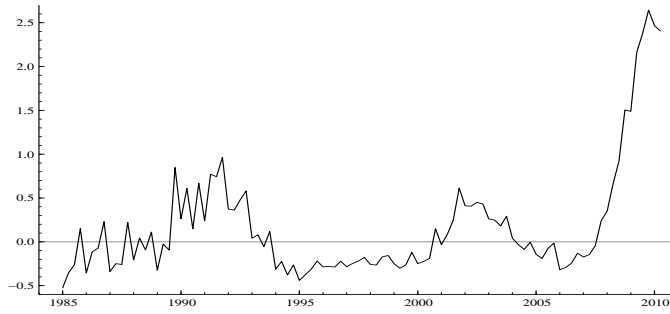
Table 1: Linear cointegration results. Notes: The rows labeled “ $r = 0$ ” and “ $r \leq 1$ ” report the  $p$ -values of the LR tests for the rank of  $\Pi$ . The following two rows report the  $p$ -values from testing weak exogeneity for both of the variables in  $\mathbf{y}_t$ . Boldface values indicate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

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).

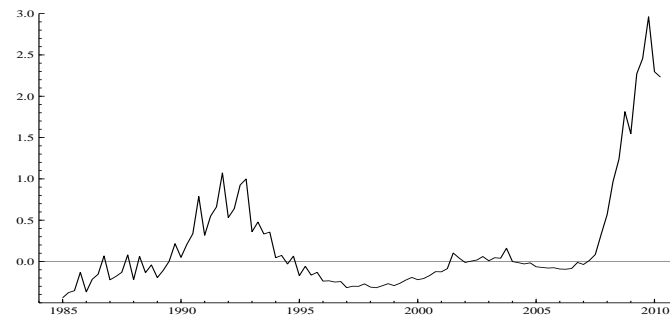
We next investigate whether a linear combination between the federal funds rate and the credit loss rates continues to be cointegrating in the full sample, 1985Q1-2010Q2. As the results in the right hand side of Table 1 show, cointegration between the variables breaks down in this case. This is likely 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 from the credit loss rates, where the former is estimated by the Hodrick-Prescott filtered federal funds rate.<sup>12</sup> The adjusted loss rates are depicted in Figure 4. Comparing these loss rates with the unadjusted ones in Figure 1, reveals that the effect of the detrending is relatively small. The main change is a relative reduction in the loss rates at the beginning of the sample compared to the rates at the end.

Having controlled for linear stochastic trends in the loss rates, we proceed to test the null hypothesis of linearity against the STR model alternative in (2). Initial modeling suggests that the debt variables (which successively enter through  $debt_t$ ) are neither significant in the first nor in the second regime. Similarly, the output gap,  $ygapt_t$ , is not significant in the model for the loss rate on business loans,  $loss_t^{BL}$ . To obtain more

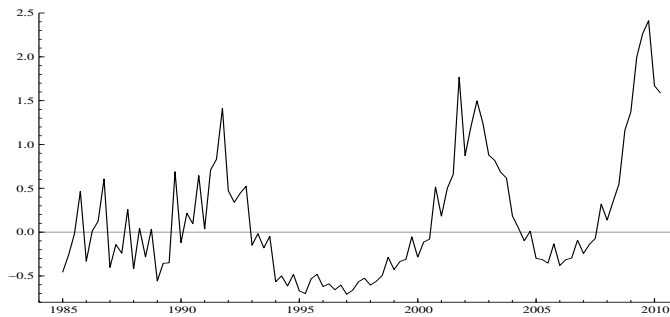
<sup>12</sup>This is statistically justified if the federal funds rate is strongly exogenous. Exclusion restrictions on the  $\Delta loss_{t-i}^h$  terms in the equation for  $\Delta fundr_{t-i}$  in (1) produced marginal significance levels of 0.26, 0.03 and 0.37 for  $h = TL, RL, BL$ , respectively. 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  $loss_t^{RL}$ ).



(a) Filtered Loss rate on total loans.



(b) Filtered loss rate on business loans.



(c) Filtered loss rate on real estate loans.

Figure 4: Credit loss rates with stochastic trend component removed.

Tests of linearity vs. regime shifts								
1985Q1-2006Q2								
	$lev_t^{H,TL}$	$lev_t^{H,RL}$	$lev_t^{B,TL}$	$lev_t^{B,RL}$	$for_t^{H,TL}$	$for_t^{H,RL}$	$for_t^{B,TL}$	$for_t^{B,RL}$
$loss_t^{TL}$	0.828	0.719	0.535	0.419	0.963	0.406	0.780	0.570
$loss_t^{RL}$	0.363	0.597	0.489	0.688	0.108	0.085	0.221	0.583
$loss_t^{BL}$	0.370	0.408	0.072	0.256	0.132	0.929	0.141	0.420
1985Q1-2010Q2								
	$lev_t^{H,TL}$	$lev_t^{H,RL}$	$lev_t^{B,TL}$	$lev_t^{B,RL}$	$for_t^{H,TL}$	$for_t^{H,RL}$	$for_t^{B,TL}$	$for_t^{B,RL}$
$loss_t^{TL}$	<b>0.016</b>	<b>0.013</b>	<b>0.011</b>	<b>0.012</b>	0.181	<b>0.041</b>	0.411	<b>0.037</b>
$loss_t^{RL}$	0.059	<b>0.042</b>	0.052	<b>0.021</b>	0.738	<b>0.018</b>	0.940	0.054
$loss_t^{BL}$	<b>0.048</b>	<b>0.049</b>	<b>0.006</b>	<b>0.029</b>	0.058	0.151	<b>0.021</b>	0.064

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

parsimonious specifications, we excluded the insignificant variables from the relevant equations. This has very little effect on the estimated regime switching dynamics, but improves the precision with respect to  $\gamma_1$  and  $\gamma_2$ . Hence, in the subsequent analysis we use  $\mathbf{x}_t = (term_t, ygap_t)'$  in the models for losses on total loans and real estate loans,  $loss_t^{TL}$  and  $loss_t^{RL}$ , as well as  $\mathbf{x}_t = term_t$  in the model for losses on  $loss_t^{BL}$ .

Given the indicated choices of  $\mathbf{x}_t$ , Table 2 reports the results of the linearity tests corresponding to each of the individual debt variables. 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,  $loss_t^{RL}$ , there seems to be significant non-linearities associated with household and business sector real estate debt-to-income, as well as the household sector's real estate financial obligations ratio. In the model for the loss rate on business loans,  $loss_t^{BL}$  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,  $loss_t^{TL}$  are, by and large, a combination of the results from the models of  $loss_t^{RL}$  and  $loss_t^{BL}$ .

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,  $loss_t^h$ , with  $\mathbf{x}_t$  as in the previous section, and  $debt_t$  in  $\varphi(\cdot)$  successively equal to one of the transition variable candidates that has a significant entry in Table 2. When the leverage variables,  $lev_t^{i,j}$ , are used



Unit-root and Stationarity tests								
Explained variable: $loss_t^{TL}$								
$debt_t$ :	$lev_t^{H,TL}$	$lev_t^{H,RL}$	$lev_t^{B,TL}$	$lev_t^{B,RL}$	$for_t^{H,TL}$	$for_t^{H,RL}$	$for_t^{B,TL}$	$for_t^{B,RL}$
<i>ADF</i> :	-1.99	-0.51	-2.08	-3.55***†	–	-4.84***	–	-3.49**
<i>KPSS</i> :	0.38*	1.11***	0.37*	0.09†	–	0.24	–	0.24
Explained variable: $loss_t^{RL}$								
$debt_t$ :	$lev_t^{H,TL}$	$lev_t^{H,RL}$	$lev_t^{B,TL}$	$lev_t^{B,RL}$	$for_t^{H,TL}$	$for_t^{H,RL}$	$for_t^{B,TL}$	$for_t^{B,RL}$
<i>ADF</i> :	–	-1.90	–	-2.41	–	-4.31***	–	–
<i>KPSS</i> :	–	0.63**	–	0.52**	–	0.12	–	–
Explained variable: $loss_t^{BL}$								
$debt_t$ :	$lev_t^{H,TL}$	$lev_t^{H,RL}$	$lev_t^{B,TL}$	$lev_t^{B,RL}$	$for_t^{H,TL}$	$for_t^{H,RL}$	$for_t^{B,TL}$	$for_t^{B,RL}$
<i>ADF</i> :	-2.36	-3.16**†	-2.58*	-2.57	–	–	-5.08***	–
<i>KPSS</i> :	0.37*	0.30†	0.84***	0.31	–	–	0.20	–

Table 3: Tests for non-linear cointegration. The null hypothesis of the Augmented Dickey-Fuller (ADF) test is that the residual from (2), with explained and transition variable as indicated in the columns, is a unit-root process. A constant and seasonal dummies were included, and lag-length was chosen based in the AIC information criterion. The 10%, 5%, and 1% critical values for this test are -2.58, -2.89, and -3.50, respectively. The null hypothesis of the Kwiatkowski–Phillips–Schmidt–Shin (KPSS) test is that the aforementioned residual is stationary. The bandwidth was set to 2 in each case. The 10%, 5%, and 1% critical values for this test are 0.35, 0.46, and 0.74, respectively. Rejections of the null hypothesis at the 10%, 5% and 1% significance levels are indicated by \*, \*\*, and \*\*\*, respectively. † Estimated values for  $\kappa_1$  and  $\kappa_2$  imply that regime 2 occurs outside the range of  $debt_t$ .

we find that the stationarity of the residual cannot be secured in most cases. This can be seen from Table 3 which reports (ADF) unit-root and (KPSS) stationarity tests for the residual. In only two cases,  $lev_t^{B,RL}$  in the equation for  $loss_t^{TL}$  and  $lev_t^{H,RL}$  in the equation for  $loss_t^{BL}$ , do the tests conclusively yield stationary residuals. In both of these cases, however, the estimated parameters of  $\varphi(\cdot)$  are such that regime 2 never occurs within the sample. In one case ( $lev_t^{B,RL}$  in the equation for  $loss_t^{BL}$ ), the tests yield inconclusive results. These results suggest that non-linear cointegration is generally rejected when the leverage variables are used, implying they cannot adequately account for the large and persistent fluctuations in the credit loss rates associated with the regime-shift dynamics.

In contrast, when the financial obligations ratios are used, both the ADF and the KPSS tests conclusively support the stationarity of the residuals as can be seen from Table 3. Moreover, in all of these cases the estimated parameters of  $\varphi(\cdot)$  yield regime transitions inside the range of the relevant financial obligations ratio. In the model for losses on total loans,  $loss_t^{TL}$  both the financial obligations ratios associated with real estate debt in the household and business sectors,  $for_t^{H,RL}$  and  $for_t^{B,RL}$ , have significant entries in Table 2. 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

STR estimates							
		Transition parameters		Regime 1		Regime 2	
Equ.	$debt_t$	$\kappa_1$	$\kappa_2$	$\gamma_{term}$	$\gamma_{ygap}$	$\gamma_{term}$	$\gamma_{ygap}$
$loss_t^{TL}$	$for_t^{H,RL}$	<b>12.678</b> (5.630)	<b>10.192</b> (0.056)	-0.063 (0.034)	0.002 (0.045)	<b>-0.276</b> (0.094)	<b>-0.224</b> (0.051)
$loss_t^{RL}$	$for_t^{H,RL}$	<b>3.609</b> (1.128)	<b>10.079</b> (0.106)	-0.023 (0.041)	-0.051 (0.038)	<b>-0.267</b> (0.099)	<b>-0.243</b> (0.049)
$loss_t^{BL}$	$for_t^{B,TL}$	<b>2.318</b> (0.968)	<b>10.44</b> (0.199)	<b>-0.249</b> (0.085)	-	<b>-0.619</b> (0.119)	-

Table 4: 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).

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 4 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,  $\kappa_1$ , and the estimated thresholds,  $\kappa_2$ , are positive, indicating that regime 2 dominates for values *above*  $\kappa_2$ . Furthermore, the estimates of  $\kappa_1$  indicate that speeds of transitions between regimes are rather fast in all cases. The two regimes are characterized by the parameters  $\gamma_{term}$  and  $\gamma_{ygap}$ , describing the effect of of the term spread,  $term_t$  and the output gap,  $ygap_t$ , on credit losses,  $loss_t^h$ , in each regime (except in the equation for  $loss_t^{BL}$  where only  $term_t$  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,  $\kappa_2$ , can loosely 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 results in Table 4 are robust to more general specifications of (2). For example, adding auto-regressive lags to the equation yields a well-specified model with approximately constant parameters that displays both quantitatively and qualitatively similar results. Moreover, the model also compares favorably to a simple Markov-Switching

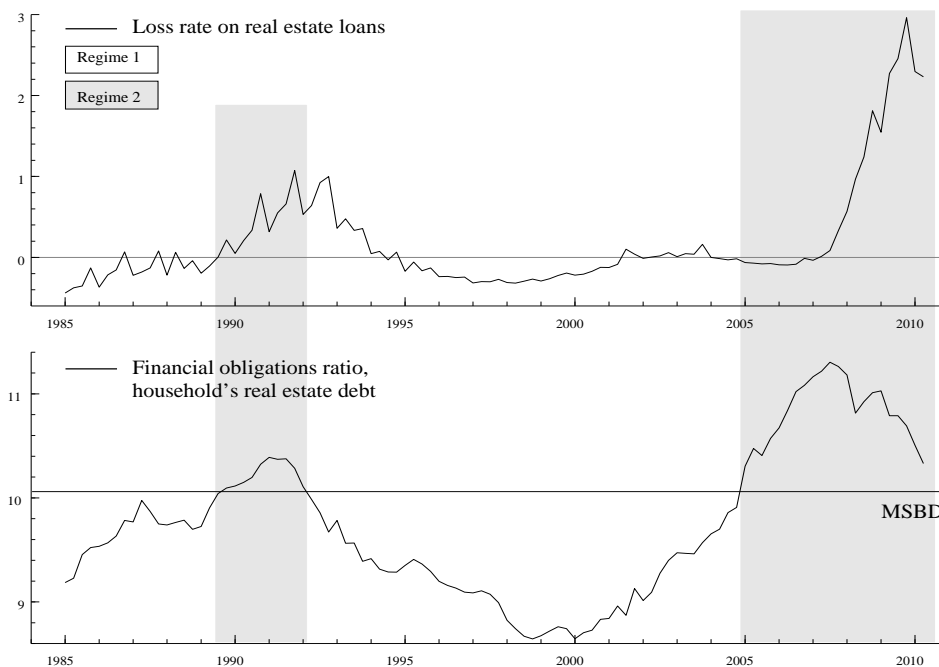


Figure 5: Transitions in the loss rate on real estate loans. The upper panel depicts the loss rate on real estate loans, whereas the lower panel depicts the financial obligations ratio associated with household's real estate debt and the corresponding MSDB estimate. Episodes when regime 2 dominates are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

specification of (2). This suggests that conditioning the transition dynamics on the financial obligations ratio is indeed beneficial for describing credit loss dynamics. The details of these robustness checks are reported in Appendix 5.

The relationship between the financial obligations ratio and the credit losses can also be presented graphically. 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, in retrospect this MSDB estimate would have signaled a significant increase in credit risk a full two years before the onset of the crisis. In addition, the magnitude and duration by which the financial obligations ratio exceeded 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.

Similarly, Figure 6 depicts the loss rate on business loans and the corresponding financial obligations ratio. As can be seen from the figure, there are three unstable

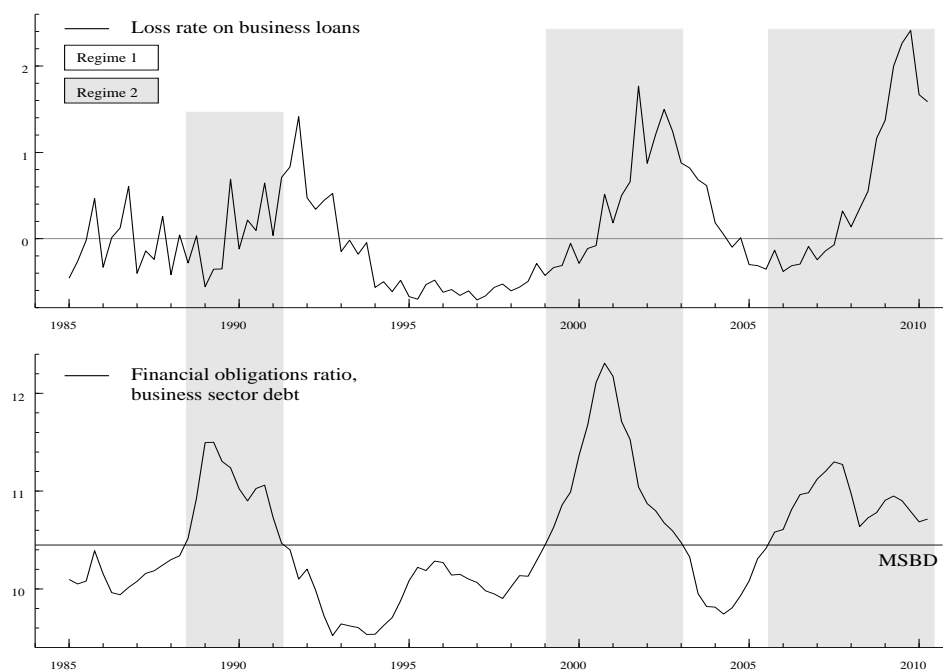


Figure 6: Transitions in the loss rate on business loans. The upper panel depicts the loss rate on business loans, whereas the lower panel depicts the financial obligations ratio associated with total business sector debt and the corresponding MSDB estimate. Episodes when regime 2 dominate are demarked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

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.<sup>13</sup> 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.

## 5 Conclusions

When do aggregate debt accumulations become excessive, compromising both macroeconomic 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 debt-to-income ratio, 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 levels 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.

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<sup>13</sup>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.

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 to 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.

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# Appendix A

Detailed definitions of the variables used in the analysis are provided in Table 5.

Data and definitions	
Variable:	Definition:
$loss_t^h$	Net charge-off rate on loans, all insured US commercial banks. $h = TL$ (total loans), $RL$ (real estate loans), and $BL$ (business loans). Source: FRS (Bank Assets & Liabilities)
$lev_t^{i,j}$	Debt-to-income ratio (in %). $i = H$ (households'), $B$ (Nonfarm nonfinancial corporate business). $j = TL$ (total loans), $RL$ (real estate loans). 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).
$for_t^{i,j}$	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 $l_t^{Bj} i_t^M / 400 + l_t^{Bj} / 12$ .
$fundr_t$	Effective federal fund rate (3-month average). Source: FRS (Interest Rates)
$govr_t$	Yield on 10-year Treasury securities. Source: FRS (Interest Rates)
$term_t$	$fundr_t - govr_t$
$ygap_t$	$100(y_t - y_t^*)$ , where $y_t$ is log real output and $y_t^*$ is the OECD production function based level of potential output. Source: OECD.

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

Table 5: 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  $for^{HT}$ , deviations between real and Hodric-Prescott filtered GDP and the unemployment gap (congressional budget office definition) instead of  $ygap_t$ , and the difference between corporate BAA and AAA bonds instead of  $term_t$ . 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  $\mathbf{y}_t = (loss_t^{TL}, fundr_t)'$  includes  $D894$ , the model for  $\mathbf{y}_t = (loss_t^{RL}, fundr_t)'$  includes  $D904$ ,  $D914$  and  $D923$ , and the model for  $\mathbf{y}_t = (loss_t^{BL}, fundr_t)'$  includes  $D894$  and  $D014$ .

# Appendix B

In this section we test robustness of the results reported in the main text with respect to alternative specifications. We begin by comparing the results in Table 4 with those obtained from a dynamic specification of (2). We also report the results from break-point Chow tests for these models. Finally, to assess the value added of the financial

obligations ratios for explaining regime-switching in credit loss rates, we compare the weights to Regime 2 from models in Table 4 with the ones obtained from a simple Markov-Switching (MS) dynamic regression specification of (2).

The results in Section 4.2 indicate that the STR models for the credit loss rates in conjunction with the financial obligations ratios can produce stationary residuals. These residuals are, however, severely auto-correlated and show other signs of misspecification as well. As this can affect both the precision and consistency of the estimates reported in Table 4, we re-estimate the STR models using a dynamic specification of the form

$$\widetilde{loss}_t^h = \sum_{i=1}^4 \rho_i \widetilde{loss}_{t-i}^h + (1 - \varphi(debt_t))(\mu_1 + \boldsymbol{\gamma}'_1 \mathbf{x}_t) + \varphi(debt_t)(\mu_2 + \boldsymbol{\gamma}'_2 \mathbf{x}_t) + \boldsymbol{\psi}' \mathbf{d}_t + v_t \quad (3)$$

where  $\widetilde{loss}_t^h = loss_t^h - strend_t^h$  for  $h = TL, RL, BL$ , and  $\mathbf{x}_t$  and  $\mathbf{d}_t$  are as in Section 4.3. Table 6 reports the estimates. As can be seen from the table, the estimated parameters of the transition function,  $\kappa_1$  and  $\kappa_2$ , are fairly close to the ones reported in Table 4. The biggest difference with respect to these parameters occurs in the model for losses on real estate loans, where  $\kappa_2$  increases from 10.08 to 10.92. While this increase is substantial, the speed of adjustment is now reduced from 3.61 to 2.50. This has the effect of widening the transition region, producing very similar regimes as before. At the same time, however, it becomes less appropriate to interpret  $\kappa_2$  as a maximum sustainable debt burden.

The effect of the explanatory variables, as given by  $\gamma_1$  and  $\gamma_2$ , cannot easily be compared to the estimates in Table 4. The reason is the contemporaneous effects in Table 6 will be reinforced by the auto regressive terms. The long run (steady state) effects are given by  $\gamma_j / 1 - \sum \rho_i$ . In the models for  $\widetilde{loss}_t^{TL}$ ,  $\widetilde{loss}_t^{RL}$ , and  $\widetilde{loss}_t^{BL}$ , the sums of auto-regressive coefficients are 0.88, 0.81, and 0.83, respectively, as can be seen from Table 6, giving long-run multipliers of 8.3, 5.3, and 5.9. This implies that the effects of the explanatory variables are larger than what is immediately apparent from the table. Overall, the same general pattern that was found in Table 4 seems to hold for the dynamic versions of the model: the effects in Regime 1 are smaller in magnitude and insignificant, whereas the effects in Regime 2 are large and often significant. Hence, we conclude that the patterns and results reported in the main text are broadly robust to dynamic extensions of the models.

Table 6 also report the results of several misspecification tests. It can be seen from the table that the residuals of the three models are reasonably well behaved. While there are still some signs of auto-correlation, in particular in the model for real estate losses, the effect on the results are nevertheless likely to be minor. Also, the normality assumption is rejected at the 5% significance level in all three models due to a few outliers. To investigate the parameter stability of the models, Figure 7 shows the results from recursive break-point Chow tests. Values above the black dotted line indicate rejection of parameter stability at the 1% significance level. As can be seen from the figure, all three models seem to display reasonable parameter stability.

Dynamic STR estimates			
Explained: $debt_t$	Model		
	$\widetilde{loss}_t^{TL}$ $for_t^{H,RL}$	$\widetilde{loss}_t^{RL}$ $for_t^{H,RL}$	$\widetilde{loss}_t^{BL}$ $for_t^{B,TL}$
Parameters			
$\rho_1$	<b>0.67</b> (0.10)	<b>0.50</b> (0.10)	<b>0.59</b> (0.11)
$\rho_2$	<b>0.47</b> (0.12)	0.21 (0.11)	<b>0.31</b> (0.13)
$\rho_3$	<b>-0.52</b> (0.12)	-0.19 (0.12)	-0.20 (0.12)
$\rho_4$	<b>0.26</b> (0.11)	<b>0.29</b> (0.11)	0.13 (0.12)
$\kappa_1$	29.80 (28.02)	<b>2.50</b> (1.28)	<b>3.37</b> (1.96)
$\kappa_2$	<b>10.34</b> (0.03)	<b>10.92</b> (0.62)	<b>10.72</b> (0.24)
$\gamma_{1,term}$	0.02 (0.02)	0.01 (0.02)	0.01 (0.05)
$\gamma_{1,ygap}$	0.00 (0.02)	0.01 (0.02)	-
$\gamma_{2,term}$	-0.02 (0.05)	-0.25 (0.22)	<b>-0.21</b> (0.10)
$\gamma_{2,ygap}$	<b>-0.08</b> (0.03)	-0.24 (0.23)	-
Misspecification			
AR	0.18	<b>0.01</b>	0.05
ARCH	0.97	0.16	0.15
Normality	<b>0.00</b>	<b>0.01</b>	<b>0.02</b>
$R^2$	0.96	0.97	0.90

Table 6: Estimated transition parameters and regime coefficients from dynamic versions of the STR models for the credit loss rates. Boldface values indicate significance at the 5% level (standard errors in parenthesis). The null hypothesis of no auto-correlation (AR) in up to five lags of the residual is tested by a Lagrange multiplier test. A similar test is conducted on the squared residuals to test for the null of no auto-regressive conditional heteroscedasticity (ARCH). The last row reports the adjusted coefficient of determination.

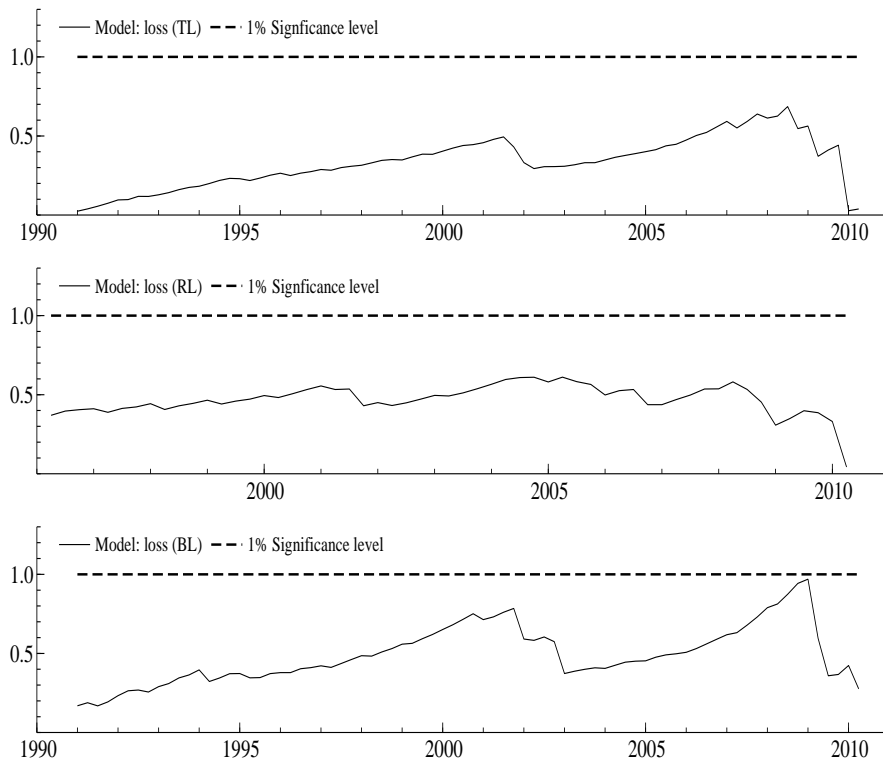


Figure 7: Parameter stability tests. The black solid lines depict recursive break-point Chow tests for the models in Table 6. Twenty quarters were used to initialize the recursions. Values above the dotted black line indicate rejection of parameter stability at the 1% significance level.

As a final assessment of the model, we compare the results in Table 4, which are based on the STR specification in (2), with an analogous MS model. In particular, the latter model has exactly the same explanatory variables and two regimes, but replaces the transition function,  $\varphi(\cdot)$ , with a unobserved random variable which follows a Markov chain. Hence, comparing the two models allows us to assess the benefits of having the financial obligations ratio as a specific transition variable: if the two models yield identical regimes, the value added of conditioning on this variable is limited. The estimates, of the MS-model (available upon request) are qualitatively in line with the ones for the STR model in Table 4, i.e. the effects of the cyclical variables are generally insignificant in Regime 1 and significantly negative in Regime 2. As a first statistical assessment of the MS model, we check if it produces stationary residuals for each of the three loss rates. The ADF-test statistics on the residuals of  $loss_t^{TL}$ ,  $loss_t^{RL}$ , and  $loss_t^{BL}$  are -2.66, -3.25, and -4.73, respectively. This implies that we cannot reject the unit-root hypothesis for the residuals of the equation for the loss rate on total loans. For the loss rate on real estate loans we reject this hypothesis at the 5%, but not on the 1% significance level, whereas the residual of the equation for losses on business loans is clearly stationary. In all three cases, however, the residual persistence of the STR model is less than that of the MS model.

Figure 8 depicts the weights to (or probabilities of) Regime 2 which are implied by the STR and MS models. While the two types of models yield transitions between regimes which are broadly reminiscent of each other, there are nevertheless several sharp differences as is clear from the figure. The most wide dispersion between the regimes is obtained with respect to the models for losses on total loans (upper panel). The regime classification of the MS model for this loss rate, does not seem to be entirely reasonable. In particular, the episodes in the “bad” regime which are associated with the crisis periods in the early 1990’s and late 2000’s are very long, for instance starting in the late 1999’s for the latter crisis. Moreover, the strength of Regime 2 declines just prior to the crisis. These results indicate that the MS model for losses on total loans may not be able to characterize the data adequately, which is also evidenced by the failure to reject the unit-root hypothesis for the residuals of this equation. Turning to the models for the two remaining loss rates, we see that the transition patterns are more closely aligned. However, there is a clear tendency for the STR regimes to increase and decline approximately one year before the MS regimes. The only exception to this pattern is during the early 90’s recession in the model for losses on real estate loans, where the MS transition moves more sharply around the crisis date than the one obtained from the STR model.

Taken together, these results point to substantial differences between the predictions of the two types of models. While the STR model is more demanding, as it requires successful specification of the transition variable, it nevertheless delivers significant pay-offs in terms of statistical fit, early warnings, and economic interpretation.

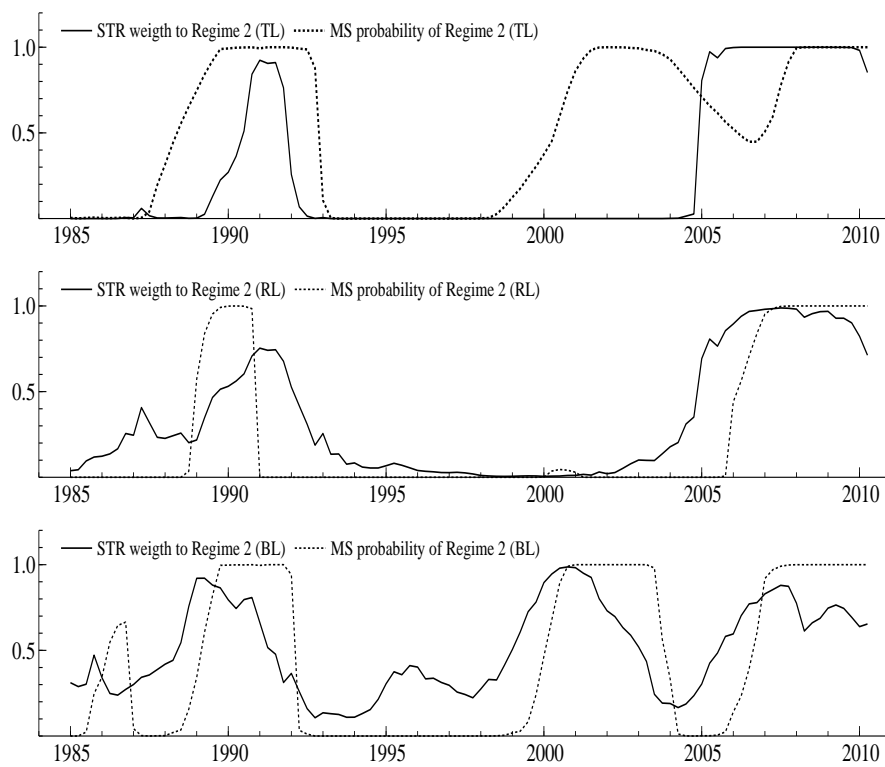


Figure 8: Estimated weights/probabilities to Regime 2 implied by the STR and the MS models.