**Mapping Heat in the U.S. Financial System**

David Aikman, Michael Kiley, Seung Jung Lee, Michael Palumbo,

and Missaka Warusawitharana[*,†]

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**Abstract**: We provide a framework for assessing the build-up of vulnerabilities to the U.S. financial system. We collect forty-four indicators of financial and balance-sheet conditions, cutting across measures of valuation pressures, nonfinancial borrowing, and financial-sector health. We place the data in economic categories, track their evolution, and develop an algorithmic approach to monitoring vulnerabilities that can complement the more judgmental approach of most official-sector organizations. Our approach picks up rising imbalances in the U.S. financial system through the mid-2000s, presaging the financial crisis. We also highlight several statistical properties of our approach: most importantly, our summary measures of system-wide vulnerabilities lead the credit-to-GDP gap (a key gauge in Basel III and related research) by a year or more. Thus, our framework may provide useful information for setting macroprudential policy tools such as the countercyclical capital buffer.

JEL classification: G01, G12, G21, G23, G28.

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[*] David Aikman: Bank of England, London, UK; Michael Kiley, Seung Jung Lee, Michael Palumbo, and Missaka Warusawitharana: Board of Governors of the Federal Reserve System, Washington, DC. This paper was written while David Aikman was visiting the Federal Reserve Board. The views expressed are those of the authors, and do not reflect those of the Federal Reserve Board, the Bank of England, or their staff.

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*The theory developed here argues that the structural characteristics of the financial system change during periods of prolonged expansion and economic boom and that these changes cumulate to decrease the domain of stability of the system. Thus, after an expansion has been in progress for some time, an event that is not unusual size or duration can trigger a sharp financial reaction.*

— *Hyman P. Minsky*

## 1. Introduction

The monitoring of risks to financial stability has become an issue of first-order importance for banking supervisors and monetary authorities around the world. Such efforts are crucial to mitigating threats to financial stability through macroprudential tools or other policy actions. In this analysis, we propose a method for summarizing the information in a wide array of indicators to highlight financial stability risks in the U.S. economy. Our framework is intended to capture the build-up of vulnerabilities in the financial system that can contribute to the amplification of economic and financial shocks.

Our analysis pulls together a wide range of indicators to inform an assessment of the extent of vulnerabilities in the financial system, reflecting the view that no single data series is appropriate for gauging the build-up of risks in a complex and evolving financial system. The indicators we choose for our analysis are drawn from an extensive literature (e.g., Cecchetti, 2008; BIS, 2010; Schularick and Taylor, 2012; Krishnamurthy and Vissing-Jorgenson, 2013; and Drehmann et al, 2014). Overall, we gather and synthesize data on forty-four indicators. Following the framework of Adrian, Covitz, and Liang (2013), we group these indicators into three broad classes of vulnerability: investor risk appetite in asset markets, nonfinancial sector imbalances, and financial sector vulnerabilities linked to leverage and maturity transformation.

In practical terms, we face challenges related to how to aggregate indicators along such varying dimensions of financial activity. Our approach is to define narrow sets of indicators (subsequently referred to as *components*) along well-defined economic concepts. Within the risk appetite category of vulnerabilities, the component measures we focus on include equity valuations, volatility, and pricing and lending standards in corporate credit markets, housing, and commercial real estate. For the nonfinancial sector (households and nonfinancial businesses) imbalances category, we consider the degree of borrowing and debt service burden associated with business credit, mortgage borrowing, and consumer credit, as well as the sector's net savings. Within the financial sector (banks and shadow banks) category of vulnerabilities, we consider the sector's leverage, maturity transformation, reliance on short-term funding, and size/interconnectedness.

We use data visualization tools to explore patterns in the data and inform subsequent statistical analysis.[3] Building on what we see an emerging interest in data visualization (for example, see IMF, 2014), we illustrate the use of "circular" or polar-coordinate charts – emphasizing a radar chart – to provide a detailed comparison across a few specific time periods. In addition, we use "ribbon" heat maps to examine the time-series variation in our components more comprehensively. These tools may be helpful in communicating financial stability conditions to a broad audience and facilitating the deliberation of countercyclical macroprudential tools by policymakers.

Our analysis provides a lens through which to view historical patterns of vulnerability in the U.S. financial system. Risk appetite was elevated in some areas in the late 1990s, most

[3] Schwabish (2014) provides a discussion of the value of data visualization tools in economics.

particularly in equity and business credit markets, but also, to some extent, in the housing market (Case, Quigley and Shiller 2005). But household borrowing was muted at that time, despite a low saving rate, and leverage in the financial sector was notably below levels that would prevail by the mid-2000s. By 2004, however, risk appetite was elevated everywhere except for equity markets, while mortgage-related imbalances were growing rapidly as was financial sector leverage and its reliance on short-term wholesale funding. This resulted in sizeable system-wide vulnerabilities that signaled substantial potential for the kind of amplification and transmission of shocks observed in the subsequent financial crisis.

This narrative, in which a broad range of vulnerabilities interacted in the U.S. economy prior to the recent financial crisis, is compelling on economic grounds – after all, it would be surprising if a single factor led to the most severe financial and economic crisis since the Great Depression. However, our narrative approach differs substantially from the regression/prediction approach in studies such as Bank of International Settlements (BIS, 2010), Schularick and Taylor (2012), and Krisnamurthy and Vissing-Jorgenson (2014). Each of these studies attempt to find regressors that predict crises using a binary probability model (e.g. the linear, logit, or probit probability models). Because crises are infrequent and data is hard to come by for many of the crises observed over the past century and a half, these studies focus on a small set of factors. Indeed, each considers different factors – with the BIS focusing on the level of bank capitalization, Schularick and Taylor (2012) focusing on borrowing by the nonfinancial sector (from banks), and Krisnamurthy and Vissing-Jorgenson (2014) emphasizing short-term wholesale funding. Each of these factors is plausibly important – but not all can be demonstrated to be important using a regression approach when crises are infrequent.

Nonetheless, we consider a number of statistical properties of the data and their value in forecasting the credit cycle. We obtain the following results. First, alternative methods of summarizing our data, such as equally-weighted aggregates or principal component analysis, provide a broadly similar view of fluctuations in the vulnerabilities we analyze. Second, we find that the investor risk appetite components tends to lead the movements in credit, leverage, and maturity transformation captured in our assessments of vulnerabilities in the nonfinancial and financial sectors, providing an important motivation for including that information in a monitoring framework for the financial system. Third, vector autoregression analyses indicate that our measures of vulnerability "Granger-cause" the credit-to-GDP gap, a measure of the build-up of financial vulnerability that is widely used both in the academic literature and in policy applications (e.g., see Borio and Lowe, 2002, and Basel Committee on Banking Supervision, 2010). This finding indicates that our framework may provide useful information for guiding macroprudential policy tools, such as the countercyclical capital buffer (see Hanson et al, 2011). Fourth, taking a real-time perspective, we find that, while our approach would have signaled heightened vulnerabilities in the mid-2000s, it would have also signaled elevated risks during the late 1990s. Whether the identification of elevated vulnerabilities during the late 1990s is a feature (or a bug) of our approach is not obvious: the period included significant financial strains that led to important interventions by U.S. policymakers, including the collapse of Long Term Capital Management and several international crises (see Carlson, Lewis and Nelson, 2014). But events were clearly of a more limited nature than those that led to the global financial crisis.

Turning to current conditions, our framework indicates that vulnerabilities in the financial system have remained subdued even five years after the financial crisis. Although risk appetite is currently elevated, our measures of vulnerabilities in the financial sector (and in residential mortgage debt) remain at or near historically low levels. That said, an important limitation of our approach is that it does not capture *structural* weaknesses in the financial system such as the potential run-risk associated with money market funds or other confidence-sensitive funding, or the high degree of interconnectedness among the largest, most complex financial institutions.

The remainder of the paper is divided into eight sections. We first discuss how our approach relates to the existing literature. Next, we present the data we analyze, and categorize these data in a manner that informs our subsequent work. We then examine the time series behavior of our vulnerability measures, in real time and ex post. The next section compares our measures with some prominent indicators emphasized in the literature, such as the credit-to-GDP gap. The penultimate section outlines how the vulnerability measures provided could be used for informing countercyclical capital buffer decisions. A final section concludes.

## 2. Existing literature and practices at official sector institutions

### 2.1 Literature

The global financial crisis has led to a large amount of research on the channels through which "shocks" can be rapidly transmitted through the financial system and the merits of various indicators to measure the build-up of financial stability risks. This work builds on an earlier literature on early warning indicators for banking and currency crises, developed in large part in the aftermath of the emerging market crises of the 1990s.[4] In contrast to that literature, which focused on predicting the timing of crises, recent work has placed greater emphasis on identifying the build-up of vulnerabilities, or the tendency for the financial system to amplify

[4] See Kaminsky et al (1998) for a survey of the work on early warning indicators.

shocks rather than absorb them. We organize our discussion around the indicators that have been found to have information content as reliable and timely warning signals of financial instability.

The view that credit booms lie at the heart of financial crises is a central component of the work of both Minsky (1972) and Kindleberger (1978) (see also Mendoza, 2010 and Reinhart and Rogoff, 2010). More recently, various authors have found that indicators of excess credit growth have some power in providing advance signals of financial crises. In a series of recent papers, economists at the BIS, building upon earlier work by Borio and Lowe (2002, 2004), have explored the credit-to-GDP gap as a predictor of financial crises across countries. They find that the signal from this indicator is high, whether used on a stand-alone basis (Drehmann et al, 2010) or in combination with measures of asset price gaps (Drehmann et al, 2012). These findings are corroborated by Schularick and Taylor (2012), who find lagged credit growth to be a highly significant predictor of financial crises using data spanning over a century for several advanced economies. Relatedly, Dell'Ariccia et al (2012) find that one-third of credit booms have been followed by crises and three-fifths followed by prolonged periods of weak economic growth.

Another strand of the literature argues that the funding of credit booms is a key determinant of the financial fragility they create. One dimension of this is the extent to which financial institutions finance the credit extension by taking on more leverage – see Diamond and Rajan (2001), who show that low capital levels could be associated with increased fragility, and Adrian and Shin (2010), who emphasize the procyclical nature of leverage at financial institutions. Other authors emphasize the importance of the degree of maturity and liquidity transformation underpinning the extension of credit. For example, Hahm et al (2013) find the ratio of "non-core" to "core" liabilities to be a robust predictor of crises. Relatedly, Krishnamurthy and Vissing-Jorgensen (2013) find that the probability of a financial crisis in the

United States rises with the quantity of short-term debt issued by the financial sector. And Brunnermeier and Oehmke (2013) show that short maturity of debt contracts may exacerbate rollover risk and increase vulnerabilities in the financial sector. Finally, Gorton and Metrick (2012) catalog developments in the repo market – a key source of short-term funding for the largest, most complex firms that proved to be quite fragile prior to and during the recent financial crisis.

Yet another line of research emphasizes the role of inflated asset prices ("bubbles") in generating financial market vulnerabilities. Boom-bust cycles in real estate prices, both residential and commercial, are viewed by many economists as key sources of financial fragility (see Cecchetti, 2008, and Reinhart and Rogoff, 2010). Others have suggested there may be complementary information in bond risk premiums (Stein, 2013). According to this view, when risk premiums are unusually low there is a greater probability of an upward spike, which may be associated with significant adverse economic effects. Finally, it has been argued that low volatility may spur risk taking, with the potential for a destabilizing unraveling when volatility spikes (Brunnermeier and Sannikov, 2014, and Adrian and Brunnermeier, 2014).

Finally, it should be noted that our focus on indicators that highlight the build-up of cyclical vulnerabilities in the financial system is quite distinct from another recent strand of the literature, which seeks to measure interconnectedness, or the potential for adverse spillovers to occur across financial institutions. Examples of this approach include the CoVaR measure developed by Adrian and Brunnermeier (2014), the SRISK measure developed by Acharya et al (2012), and the DIP measure developed by Huang et al (2009). These measure combine market and balance sheet data to provide a perspective on the cross-sectional distribution of systemic risks posed by financial institutions. These measures tend to provide accurate signals in stressed market conditions such as the fall of 2008 and winter of 2009, but tend to portray a more benign outlook when markets are liquid and confidence is high. By contrast, the measures we develop recognize the tendency for systemic risks to be building during such quiescent market conditions.

### 2.2 Practices at official sector institutions

Table 1 summarizes the use of indicators by selected official sector institutions. The first two rows of the table (the International Monetary Fund (IMF) and the Office of Financial Research (OFR)) report practices at institutions focused on monitoring risks to financial stability, and the third row (the Bank of England) details practices at an institution with the explicit purpose of informing policy decisions. These practices are broadly reflective of those at many other official sector institutions.[5]

**Table 1: Selected Use of Macroprudential Indicators by Official Sector Institutions**

| Institution | Purpose | Number of indicators | Visualization devices |
|---|---|---|---|
| International Monetary Fund[(1)] | • Indicators used for monitoring financial stability risks in the Global Financial Stability Report | • 33 indicators, reflecting a balance of economic, market-based, and survey-based information | • 6 composite indicators of risks and conditions shown in a radar chart |
| Office of Financial Research[(2)] | • Indicators used to analyze threats to financial stability in the OFR's Annual Report | • Large number of indicators – specific indicators not provided | • Heat map presentation of risk categories |
| Bank of England[(3)] | • Inform decisions on sectoral capital requirements and the countercyclical capital buffer | • 25 indicators for countercyclical capital buffer; 22 indicators for sectoral capital requirements | • Indicators published in a table alongside reference values |

Notes: (1) See Annex 1.1 of the Global Financial Stability Report, IMF (2010) and Dattels et al (2010) for a description of the methodology underlying the Global Financial Stability Map; (2) see Office of Financial Research (2013), page 11; (3) see Bank of England (2014), tables C and D on pages 40-43.

[5] We provide a table reviewing a broader set of practices in an appendix.

All three institutions employ a large number of indicators, suggesting there are benefits to combining information across a range of metrics, and two out of the three use visualization techniques such as heat maps or spider charts to summarize this information. These institutions tend to stop short, in their public pronouncements at least, of synthesizing information into an overall assessment of system-wide vulnerabilities or risk.

## 3. Categorizing and aggregating indicators

### 3.1 Indicators

As highlighted in the introduction, we pull together data on forty-four indicators.[6] Even this large data set is small relative to the diverse and continually-evolving forces influencing financial stability that are highlighted in Eichner, Kohn, and Palumbo (2010) and Adrian, Covitz, and Liang (2013). Nonetheless, this large number of indicators is not simple to summarize, as evidenced, for example, by looking at charts of their evolution: we present the time series of all indicators in the appendix. One natural approach for condensing the information in our data set would be a statistical dimension-reduction method such as principal component analysis. Principal components analysis has the advantage of familiarity to many economists, but it can be hard to explain the motivations for such (statistical) weighting in a policy context. Moreover, this approach does not ensure consistency with prior views regarding the economic mechanisms that may be important. For this reason, we organize the indicators into three broad categories – risk appetite, nonfinancial imbalances, and financial sector vulnerability – and then use simple rules-of-thumb to further define subcategories, or components, within these broad areas. This approach also has the benefit of helping to avoid over-weighting areas of the economy for which

[6] We view the inclusion of too many indicators as potentially counterproductive: a large number of indicators may lower the signal value of the resulting aggregate(s) when the additional data add noise instead of signal.

data are easily available, such as equity valuations. We will compare our approach to principal components later.

Figure 1 presents a schematic summarizing how the forty-four indicators are parsed into fourteen components within the three broad categories of risk appetite, nonfinancial imbalances, and financial-sector vulnerabilities. Tables A1 to A3 in the appendix present greater detail on these indicators.

**Risk appetite/asset valuations:** Our risk appetite category consists of five components: housing; commercial real estate; business credit; equity markets; and volatility. For housing, we judge valuation pressures via the price-to-rent ratio (relative to a 10-year moving average[7]), the change in lending standards from the Senior Loan Officer Opinion Survey (SLOOS) and FICO scores for mortgages sold to Government-Sponsored Enterprises (GSEs). One limitation of the SLOOS is that it measures changes in lending standards rather than levels, which may be more desirable for our purposes. In commercial real estate, we consider prices (relative to a 10-year moving average) and the change in lending standards from the SLOOS. For both classes of real estate, the inclusion of price measures reflects the idea that elevated real estate prices may leave borrowers or lenders exposed to strains should prices fall, consistent with the importance of real estate prices in some studies predicting financial crises (e.g., Cecchetti, 2008). The inclusion of lending standards proxies for the idea that the underlying riskiness of loans and the overall stance of credit availability may be important sources of vulnerability.

[7] Our decision to remove the trend in this and several other series described in the text reflects our intention to focus on *cyclical* fluctuations in vulnerabilities. But it means that, implicitly, we are treated trend changes in those indicators as representing benign developments in the context of financial system vulnerabilities.

Within business credit, we look at spreads on high-yield and Baa-rated bonds over Treasury yields, issuance of high-yield bonds and leveraged loans, and the change in lending standards for commercial and industrial loans from the SLOOS. The motivation for inclusion of standards is much the same as that above in the real estate categories, while the inclusion of spreads and the volume of issuance in riskier debt categories reflects the finding that low spreads and riskier issuance may forecast future defaults (e.g., Greenwood and Hanson, 2013), which could spill over into broader financial strains. For equity markets, we use the ratio of forward earnings to prices for the S&P500, and this ratio minus the real 10-year Treasury yield (that is, the yield minus long-term inflation expectations), a crude measure of the equity premium. For expected price volatility, we use logs of the VIX and of a CDS index for the investment-grade corporate sector. Our treatment of these indicators reflects the view that low volatility may spur leverage, leaving borrowers and investors vulnerable to a shift in market conditions (Brunnermeier and Sannikov, 2014, and Adrian and Brunnermeier, 2014).

**Nonfinancial imbalances:** Our nonfinancial imbalances index consists of four components: home mortgage debt; consumer debt; nonfinancial business debt; and savings. For the home mortgages component, we include the ratio of aggregate mortgage debt to GDP (relative to its 10-year moving average), and a measure of the debt service ratio on home mortgages. We supplement these indicators with measures of home mortgage debt owed by riskier borrowers, and the incidence of rapid borrowing among such households: this activity is likely to generate higher credit risk and is consistent with aggressive lending practices (Mayer, Pence, and Sherlund, 2009, and Mian and Sufi, 2009). Another indicator we track is the incidence of "piggy-back" mortgages accompanying new loan originations, which signals the kind of very high loan-to-value ratio borrowing that proved fragile over the U.S. financial crisis.

The micro-data used to construct the latter indicators extend back only to 1999 (Lee and van der Klaauw, 2010).

We employ an analogous set of indicators in the consumer debt component, including: the ratio of consumer credit to GDP (relative to its 10-year moving average); the ratio of debt service payments on consumer debt to disposal personal income; consumer debt owed by riskier borrowers; and the incidence of very rapid borrowing by such borrowers.

For nonfinancial businesses, we include the growth rate of sector debt (in real terms) as this provides an overall view of the risks posed by the sector. We also examine the net leverage of speculative-grade firms and unrated firms with debt, as higher leverage among these riskier firms may indicate increased vulnerability of the sector. In addition, we capture the ability of the sector to finance its debt obligations through the amount of debt outstanding relative to sector income (relative to a 10-year moving average), and through interest expenses as a percentage of cash flow. Finally, we use the share of bond issuance accounted for by firms with very low credit ratings to examine the extent to which the riskiest firms are obtaining debt finance.

For the savings component, we examine the savings of the household and business sectors, respectively, net of capital formation. A low level for net savings may capture whether households and businesses have overextended themselves, and are thus vulnerable to a shock. Low private sector net savings is generally associated with a pick-up in nonfinancial borrowing and leverage, and is akin to the inclusion of current account imbalances in gauges of vulnerability in an international context (e.g., Reinhart and Reinhart, 2009). We focus on private sector savings, but acknowledge that this may limit the ability of our approach to identify strains that may emerge if confidence in the U.S. fiscal situation were to shift significantly.

**Financial sector vulnerabilities:** We classify vulnerabilities within the financial sector into five components: bank leverage, nonbank leverage, maturity mismatch, reliance on short-term wholesale funding and size/interconnectedness.

We combine various measures of leverage in our analysis. For bank leverage, we combine the total risk-based capital ratio at commercial banks, and the tangible equity to tangible assets ratio and tier 1 common ratio at bank holding companies. We measure nonbank leverage by broker-dealers' leverage ratio, a measure of financing provided by broker-dealers to the rest of the financial system, which provides a proxy measure of hedge funds' balance sheet leverage, and non-agency securitization issuance divided by GDP.

Maturity mismatch indicators include the loan-to-deposit ratio at bank holding companies, the maturity gap between commercial banks' assets and liabilities, and a very broad measure of net short-term wholesale funding (relative to a 10-year moving average) at nonbanks. In the short-term wholesale funding component, we include data on bank holding companies' short-term funding and the gross short-term wholesale funding of nonbank financial institutions (relative to a 10-year moving average). In addition, we include a measure of "runnable" liabilities in the financial system (both at banks and nonbanks), which includes fed funds and repurchase agreements, commercial paper, uninsured deposits, variable rate demand obligations, securities lending, and money market mutual funds (relative to a 10-year moving average).

For size and interconnectedness, we examine the ratio of total liabilities of the U.S. financial sector to GDP (relative to a 10-year moving average), the total assets of the top five bank holding companies relative to total banking system assets, and an indicator of asset illiquidity as defined in Duarte and Eisenbach (2013).

### 3.2 A first look at the data

We present a number of cuts of the data, using different visualization approaches, to inform our overall assessment and statistical analysis. Our first summary looks at fourteen components of overall vulnerability in the financial system, defined as follows:

1. Define fourteen components capturing risk appetite, nonfinancial sector imbalances and financial sector vulnerability, as in Figure 1. For example, equity valuations is a component of the risk appetite category. Denote each component by $k$.

2. Identify indicators that provide quantitative information on each component. We denote the indicators within each component $k$ by $X(l,k,t)$, where $l$ denotes the specific indicator, (e.g., the P/E ratio is one indicator within the equity valuations component) and $t$ denotes a point in time.

3. For each indicator $X(l,k,t)$, we subtract the mean and divide by the standard deviation, where the latter statistics are computed using data from 1990Q1 to 2014Q4, or the full sample for indicators with shorter histories. Denote the standardized indicator by $\tilde{X}(l,k,t)$. We choose a 25-year window rather than something longer because of the major structural changes that have occurred in the financial system in recent decades; in our view these changes limit somewhat the value of earlier data as a reference point for gauging current vulnerabilities. We explore the implications of taking a one-sided, real-time standardization of the data in Section 5.

4. Each component index, $V(k,t)$, is generated as the simple unweighted average of the standardized indicators for that component:

(1) $$V(k,t) = \frac{1}{L}\sum_{l}\tilde{X}(l,k,t).$$

One point to note is that the starting dates of the various indicators used in the study differ (see appendix Tables A1-A3). This enables us to incorporate additional indicators as more data become available, covering a wider range of vulnerabilities since the late 1990s.

5. We estimate the distribution of each component using a non-parametric kernel estimator (Figure 2). The quarterly observation for each component is then transformed onto the (0, 1) interval based on its quantile in its historical distribution.

With these component indices in hand, we next examine the data to detect patterns to analyze further. Our first approach uses a version of a radar chart (see, for instance, the IMF's Global Financial Stability Report, 2014) where the fourteen components of systemic vulnerability trace out the vertices of a polygon. Radar charts such as this are well suited to comparing levels of vulnerability across a few points in time. They have the property that the area within the polygon can be both sensitive to the ordering of components and increasing in components' squared values; for some readers, this may potentially hinder interpretation, by over-emphasizing some observations or configurations. To address this issue, we also present a "coxcomb" or polar area chart, where the radii are *square roots* of the component measures, ensuring that the total area of the polygon varies linearly with their average values. We also present a "sun-burst" chart, which combines elements of both the radar and coxcomb charts: component values are shown as the vertices of a polygon whose area is a linear (affine) function of the average of those components. While these latter two charts, in a sense, provide a truer representation of the data, they are arguably less visually intuitive (Tufte, 1992).

Figure 3 displays a radar plot of the fourteen components underlying our aggregate index. The upper panel presents a comparison of conditions as of mid-2004 with those at end-

2006; the lower panel compares current conditions with those in mid-2011. The outer polygon (colored in black) represents the maximum value of each component over our sample, representing an extremely vulnerable financial system; the center polygon (colored in grey) represents the minimum, in which case the system would appear exceptionally resilient to shocks.

The radar plot in the upper panel of Figure 3 shows a widespread elevation of vulnerabilities across the components we consider in the years before the financial crisis. Looking more closely across these time periods, we observe that conditions in the risk appetite category, in particular real estate markets, were especially elevated in mid-2004 (red line). However, by the end of 2006 (blue line), our measures show a marked further build-up in vulnerabilities in the financial sector, driven by a notable pick up in maturity mismatch and reliance on short-term wholesale funding. Although risk appetite in real estate markets had eased somewhat by late-2006, household mortgage debt continued to increase rapidly, including loans with riskier attributes, reflecting an extended period of rising prices and weak lending standards. While indicators of risk appetite for business credit, such as narrow credit spreads and robust issuance of risky debt, pointed to elevated vulnerability in this period, this was partially mitigated by generally healthy conditions of nonfinancial businesses.

The lower panel of Figure 3 reflects the large retrenchment in vulnerabilities in both the nonfinancial and financial sectors that occurred following the financial crisis. Strikingly, leverage, maturity transformation, and reliance on short-term funding are now at or close to their respective minima since 1990. That is not to say that these measures are necessarily in the vicinity of their social optima: Admati and Helwig (2013), for instance, have argued that there are significant net benefits to be had from material further increases in banks' regulatory capital requirements.  While financial sector vulnerabilities appear historically subdued, investor preferences for risk have risen to levels comparable to those seen in the lead-up to the financial crisis.  Given the role that risk appetite plays as a leading indicator in our system (as we demonstrate in Section 4.3), this suggests the possibility of a broad-based increase in vulnerability over the next few years.

The coxcomb chart in the upper panel of Figure 4 presents component values for 2011Q3 (red) and 2014Q4 (blue) using the *area* rather than *length* of each slice.  This requires that the radial axes of the chart correspond to the square roots of the components.  We use the following color scheme to help compare across the two sets of components: the purple shaded area reflects equivalent levels of vulnerabilities across the two periods, and the red (blue) area represents the difference between the components when the 2011Q3 (2014Q4) component values are higher. There are some subtle differences in the visual impression created by this chart and the radar chart.  In particular, the area implied by the radar chart's 2014Q4 polygon is noticeably larger than the 2011Q3 polygon, while that is not the case in the coxcomb chart.  Moreover, the level of financial sector vulnerability (the upper-right region) implied by the coxcomb chart in 2011Q3 appears more elevated than in the radar chart.  Nevertheless, the overall impression created by these two charts is similar.

For completeness, we also present a "sun-burst" chart in the lower panel of Figure 4. This novel chart avoids a pitfall of the coxcomb by presenting component values along each axis without transformation, as in the radar chart.  But in contrast with the radar, the total area covered by the polygon in the sunburst corresponds to the average of the components (plus a constant corresponding to the area of the inner polygon), thus preserving the linearity property of the coxcomb chart.  For ease of comparison, we apply the same coloring scheme to this figure as for the coxcomb chart. Despite the potential advantages of the sunburst chart, the presence of the central polygon makes it difficult to gauge the relative sizes of the combination of vulnerabilities presented in the chart. This is because the affine function ($A + \sum X$) is dominated by the constant term ($A$), making the sum hard to perceive. The radar and coxcomb charts avoid this visual problem, as a constant term is not central to the assessment of area in either case.

In general, we view all three visualization tools as potentially helpful communication devices, whose utility may vary with the underlying data being presented. But while these charts are well suited to providing a cross-sectional comparison of large number of components across a few points in time, they cannot be used to present broader trends over time. As a result, we consider ways to further reduce the dimensionality of the data and introduce alternative visualization tools in the next section.

## 4. A time-series perspective and aggregation to an overall index

### 4.1 Approaches to aggregation

A central challenge to presenting a single summary statistic of vulnerability is the relatively unstructured approach we take: in the absence of a specific theory regarding how asset valuations, nonfinancial borrowing, and leverage and maturity transformation by the financial system interact to generate the vulnerability of the economy to financial stress, there is no clear direction to combining the indicators we consider into an overall assessment.

As a result, we consider a number of approaches. Each of the approaches we consider falls within the simple class of constant-elasticity-of-substitution aggregators of the following type:

(2) $$V(t) = \left[\sum_{k=1}^{N} w(k)\big(V(k,t)\big)^{r}\right]^{\frac{1}{r}}$$

In this expression, $w(k)$ represents the weight on component $k$ (the weights sum to one) and $1/(1-r)$ is the elasticity of substitution across components. This method of combining components is very restrictive: for example, it precludes lead/lag relationships, hierarchical relationships, and differential elasticities of substitution with respect to some components. Nonetheless, it nests several cases of interest:

- **Arithmetic average**: Setting $r$ equal to one and $w(k)$ to $1/N$, the aggregate is the average of the fourteen components presented in the radar charts. This approach is simple and has been found to be a robust method of reducing data in some forecasting applications (e.g., Stock and Watson, 2004). The arithmetic average does not depend on the distribution of components about the mean: for example, it does not matter if all fourteen series entering the average equal one-half, or if their average is one-half but individual values are widely dispersed. In economic terms, this would be consistent with an infinite elasticity of substitution across components. While the actual vulnerability of the financial system might depend on which specific components are elevated at any point in time (e.g., it probably matters whether equity prices or the degree of financial sector leverage is taking elevated values), this seems a useful benchmark.
- **Geometric average**: Setting $r$ equal to zero and $w(k)$ to $1/N$ results in an aggregate equal to the geometric average of the fourteen components. This simple alternative aggregator is one that places significant weight on interactions among component values. For example, dispersion in indicators lowers the geometric average relative to the arithmetic mean as a consequence of Jensen’s inequality. In a financial stability context, this may be useful, in

that one might view financial vulnerabilities to be more pronounced when many components are elevated at the same time.

- **Root mean square**: Setting $r$ equal to two and $w(k)$ to $1/N$ results in an aggregate measure equal to the root mean square of the fourteen components. This option has several features that make it a useful case to consider for the sake of robustness. First it implies an elasticity of substitution of minus one, and hence is the natural complement to the unitary-elasticity case given by the geometric mean. In economic terms, the root mean square captures the fact that elevations in a few components may be sufficient to generate financial instability even if the other components are low. The root mean square is also closely related to the area of the polygon defined within a radar chart, as in Figure 2.
- **Principal components**: Setting *r* equal to one and the elements of $w(k)$ to the eigenvector associated with the largest eigenvalue of the correlation matrix of the fourteen components results in an aggregate measure equal to the first principal component of the normalized matrix of the fourteen components. While arithmetic means, geometric means, and the root mean square of the components treat interactions among the data differently in a fixed manner, principal components summarize the co-movement in the data by exploiting correlations across the indicators – that is, data that have historically tended to move together get weighted in similar ways. Because this method is widely used in economics, including in analyses of financial stability (e.g., Stock and Watson, 1999, and Sarlin, 2014), we consider this approach in addition to those above.[8]

[8] We place each of these aggregate indexes on the (0, 1) interval using the kernel density/quantile procedure described above in step 5.

As this discussion makes clear, these alternative ways of aggregating the data are not linked to a particular view of the economic mechanisms at work – but may provide some idea with respect to the importance of accounting for interactions among the data in future analyses.

Figure 5 presents the time-series aggregates of the components obtained by each of these approaches. Along some dimensions, the results demonstrate that these approaches, for the most part, yield similar results. This similarity reflects the fact that there are important correlations across all of the components we consider. However, there are also important differences. For example, the root mean square measure picks up notably in 2014, reflecting the widespread increase in the risk appetite components apparent in the radar chart (Figure 3) and the effect of Jensen's inequality we highlighted above.

In addition, the principal components approach yields a result very roughly similar to the arithmetic average because it places weights on each component that are not too far away from the average. This can be seen in the lower panel, where the principal component weights are presented in a bar chart. Despite this broad similarity over the full sample, principal component weightings are sensitive to the sample period considered: for example, the weights placed on the fourteen components using data through 2006Q4 are quite different to their full-sample counterparts (as also shown in the bar chart).

Taking the broad similarities of the different approaches and the sensitivity of the principal components weights to sample period into account, we focus our subsequent analysis on the overall index given by the arithmetic average.

For completeness, we also explored a number of alternatives for normalizing our indices. These included using a Normal cumulative distribution function (CDF) to place the component and aggregate indices on the (0, 1) interval, scaling components relative to just their minimum and maximum values (rather than their entire empirical distributions), and using ranks to provide an ordinal rather than cardinal representation of the indices. While these alternatives do influence the dynamic profiles of some component indices – the risk/volatility and business credit components within the risk appetite category in particular – the effects on the aggregate index are negligible, as Figure 6 shows.

### 4.2 Heat maps

Before turning to the formal statistical analysis, we use heat maps, comparable to the presentation in OFR (2013), to report the full time series of our aggregate and component indices. [9] To generate our heat maps, we assign a color for each quarterly observation of our components or overall index. Values near zero appear "cool" (deep blue), indicating subdued vulnerabilities, while values near one appear "hot" (dark red), indicating acute vulnerabilities. To illustrate this correspondence between values and colors, Figure 7 presents the time-series evolution of our overall index generated by averaging across the fourteen component indices, in a line chart (top panel) and a heat map (bottom panel).

The heat map adds particular value when used to present the historical evolution and movement across a large number of time series, each of which appears as a "ribbon". Figure 8 presents the evolution of the overall index of vulnerability (top panel) and all fourteen of the underlying components, grouped into the categories of risk appetite/valuation pressure (the top

[9] See Flood et al (2014) for a discussion of the benefits and challenges of data visualization tools in a financial stability context.

block), nonfinancial imbalances (the middle block) and financial sector vulnerability (the bottom block).

The figure demonstrates that, in the early 1990s, overall vulnerabilities in the system were muted as the financial sector was recuperating from the strains that followed the savings and loans crisis. Thereafter, vulnerabilities rose steadily from the mid-to-late 1990s until 2000, albeit with a brief respite in 1998 following the collapse of Long Term Capital Management. This rise was driven by a fairly broad increase in vulnerabilities across components, as equity valuations rose sharply, savings fell and the size of the financial sector rose. Vulnerabilities in the nonfinancial and financial sectors remained elevated. From 2003 onwards, the aggregate index rose sharply, reflecting a widespread increase in risk appetite (all components except for equity valuations) and a further increase in the vulnerability of the financial sector. Strains continued to rise through the mid-2000s, as real estate markets became exuberant and leverage and maturity transformation in the financial system increased, setting the stage for the recent financial crisis.

Conditions began to reverse in the third quarter of 2007, around the time of the collapse of two subprime hedge funds at Bear Stearns and the panic in the asset-backed commercial paper market (see Gorton, 2010). Our approach captures these developments through a sharp drop in the components within the risk appetite category, which thereafter continued to fall dramatically throughout the Great Recession. By the first quarter of 2008, credit conditions in the nonfinancial sector began to tighten significantly, as illustrated by cooler colors within this category of the heat map. However, our approach indicates that vulnerabilities in the financial sector remained elevated through the early stages of the financial crisis. Vulnerability in the financial sector began to fall in 2008Q4, as the financial system began to recapitalize following the collapse of Lehman Brothers in September 2008. By this time, our aggregate index of vulnerability reached a hitherto historical low, even though the financial system was, of course, still in crisis and depressed levels of asset prices and financial intermediation likely still provided a significant drag on real economic activity.

In the years following the financial crisis, a rise in some components within the risk appetite category has been offset by further falls in the level of vulnerabilities in the financial sector and a small decline in nonfinancial sector imbalances. Indeed, a material increase in some risk appetite components has brought this region of our heat map to colors similar to those around 2004.

This time profile suggests our collection of indicators (and the associate aggregate index) may function as a leading indicator of stress in the financial system. In particular, many components of vulnerability were extremely elevated in the years leading up to the financial crisis (from 2003 to 2007) and fell sharply at its onset. This contrasts with traditional financial stress indicators, which provide a contemporaneous view of the state of the financial system (see Section 6.2 for a further discussion). As such, our aggregate index may provide helpful information for the application of macroprudential tools such as the countercyclical capital buffer. One notable point is that an approach based on our aggregate index would imply that one may want to switch-off cyclical tools such as the countercyclical capital buffer at the onset of a crisis. In comparison, an approach mechanically tied to a slower-moving variable such as the credit-to-GDP gap may not imply such a reaction. Our statistical analysis will compare these approaches more rigorously.

### 4.3 Lead-lag relationship between the categories

The components exhibit clear correlations within the heat map. In order to further understand this, we construct category indices by averaging across components within our three categories. In Figure 9, we plot the cross-correlation of each category index with leads and lags of the overall index. The peak of the cross-correlation function with respect to risk appetite (top panel) occurs at a lead of 3-to-5 quarters – that is, risk appetite tends to lead the overall index by about a year. In contrast, financial sector vulnerability (bottom panel) tends to lag the overall index by a few quarters.

In Table 2, we examine the statistical relationships between these categories more formally using Granger causality tests. We find that the risk appetite category Granger-causes both the nonfinancial imbalances category and the financial vulnerability category – that is, it provides significant incremental forecasting power for these series. But neither of the two latter categories Granger-cause risk appetite. We also find that nonfinancial sector imbalances Granger-cause the financial sector vulnerability category, but not the reverse. These relationships corroborate the simple lead-lag relationships shown in Figure 8.

To the best of our knowledge, these lead-lag relationships have not been documented in the existing literature.[10] We provide the following tentative interpretation. The credit cycle is triggered initially by an increase in investor willingness to bear risk, which is reflected in higher asset prices and a relaxation of lending standards. Households and businesses respond to these developments by taking on more debt, further supporting asset prices. While financial institutions are initially able to accommodate this credit expansion, as the boom continues, their

[10] It is of course possible that these lead-lag relationships are a feature of the time period we examine, rather than being a general feature of credit cycles.

balance sheets become stretched and vulnerabilities increase. This interpretation corresponds with Adrian and Shin (2010), who argue that increases in asset prices lead financial institutions to increase their leverage.

**Table 2: Pair-wise Granger causality tests on category indices**

| Null hypothesis: | Test statistic: |
|---|---|
| Risk appetite *does not cause* nonfinancial sector imbalances | 29.30$^{***}$ (0.00) |
| Risk appetite *does not cause* financial sector vulnerability sector imbalances | 11.85$^{***}$ (0.01) |
| Nonfinancial sector imbalances *does not cause* risk appetite | 6.88$^{*}$ (0.08) |
| Nonfinancial sector imbalances *does not cause* financial sector vulnerability | 3.54 (0.32) |
| Financial sector vulnerability *does not cause* risk appetite | 5.87 (0.12) |
| Financial sector vulnerability *does not cause* nonfinancial sector imbalances | 2.34 (0.51) |

Notes: The table reports *F*-statistics for Granger causality tests and associated *p*-values (in parentheses) from a vector autoregression with 3 lags containing the three category indices, risk appetite, nonfinancial sector imbalances and financial sector vulnerability. $^{***}$, $^{**}$ and $^{*}$ indicate statistical significance at the 1, 5 and 10 percent levels, respectively.

## 5. Challenges for measurement in real time

So far, we have analyzed vulnerability indices constructed using means and standard deviations of the full sample of data to standardize indicators and carry out the aggregation. This provides a retrospective viewpoint on the evolution of vulnerabilities. It addresses the question: given what we now know, how overheated were asset valuations, say, back in the mid-2000s. An alternate approach, which would provide a more accurate impression of how this monitoring system might have performed in real time, would base the time *t* assessment on information available only up to time *t*. In this section, we examine how our results change when we take such a real-time perspective of the data.[11]

The top panel of Figure 10 presents pseudo-real-time versions of the aggregate of the fourteen factors we consider, analogous to the top panel of Figure 7. The figure was constructed by using a 25-year rolling window to calculate means, standard deviations and ranges, allowing for missing data in some components prior to 1990. The blue line plots the aggregate index from the perspective of 2002Q3; the red line plots the index from the perspective of 2005Q4; and the black line plots the 2014Q4 (current) vintage. The 2002Q3 vintage indicates that the level of vulnerabilities reached new highs in 2000, at the height of the internet bubble, and had receded somewhat thereafter. By contrast, the 2005Q4 vintage indicates that vulnerabilities had risen dramatically to reach a new historical high. This finding indicates that this aggregate, even considered in real time, may have provided early warning about the build-up of vulnerabilities that led to the financial crisis.

The bottom panel of Figure 10 presents a summary of the full set of pseudo-real-time estimates (1990 to the present) for our overall index by plotting the range of values that would have been constructed in real time. There is considerable variation in the quarterly readings based on different vintages of data. In particular, our methods point to heightened vulnerability in the mid-2000s for almost every vintage of data, but also highly-elevated vulnerabilities for most of the period from mid-1997 through 2000. While the 1997-to-2000 period did include bouts of significant turbulence – including the Asia and Russian crises, the collapse of Long-

[11] This comparison to a real-time analysis is subject to two important caveats. First, our choice of indicators is made with the benefit of hindsight and our framework is based on recent work such as Adrian, Covitz, and Liang (2013); presumably different choices would have been made in real time. Second, the data we use are current vintage, and in some cases have undergone various revisions. As such, our analysis is best described as "pseudo-real-time".

term Capital Management, and the internet stock-market bubble – these events did not have the broader adverse domestic implications of the recent financial crisis.[12] In that sense, our quantitative measures may have overstated the actual vulnerabilities in the U.S. financial system at that point in time.

## 6. Comparison to other approaches

It is also useful to compare our approach to two others emphasized in recent research – the credit-to-GDP ratio, and financial conditions indices.

### 6.1 Credit-to-GDP gap

The credit-to-GDP gap, defined as the ratio of private nonfinancial sector credit to GDP less its estimated trend, plays an important role as a guide variable in the Basel 3 process for setting countercyclical capital buffers – see Basel Committee on Banking Supervision (2010) and also Bank of England (2014). More generally, it has been considered a useful indicator of the build-up of financial imbalances – see Drehmann and Tsatsaronis (2014) and, for a differing view, Edge and Meisenzahl (2011).

The overall index of vulnerability is positively correlated with estimates of the credit-to-GDP gap and over the past 25 years.[13] But, as Figure 11 shows, these series have quite different dynamic profiles, whether viewed from a full-sample perspective or in pseudo real time. The differences are particular stark in the 1990s, during which time the index climbs more or less

[12] Challenges posed by real-time assessments of cyclical fluctuations are by no means unique to our approach or application. For example, real-time assessments of economic slack differ notably from such estimates made with the benefit of hindsight (e.g., Orphanides and van Norden, 2002, and Edge and Rudd, 2012). This concern has also been emphasized in the literature on the credit-to-GDP gap (e.g., Edge and Meisenzahl, 2011).

[13] We measure the credit-to-GDP gap by applying a Hodrick-Prescott filter to the log of the ratio of nonfinancial credit to GDP with a smoothing parameter of 400,000, as is the convention in the literature.

monotonically, whereas the estimated credit-to-GDP gap remains subdued. The differences are also pronounced in the periods before and after the financial crisis. The aggregate picks up strongly in the early 2000s, reaching a series high in 2007, at which point it collapses. By contrast, the credit gap begins to increase only in 2005, and reaches its peak in 2009Q1, before declining persistently.

The impression that the credit-to-GDP gap lags our measure(s) is confirmed by examining cross-correlation functions, shown in Figures 12 and 13 (full sample and pseudo real time, respectively). The top panel presents the correlation between our index and leads and lags of the credit gap. Evidently, our overall index leads the credit gap by about two years: that is, the *current* value of our measure has a strong positive correlation with *future* values of the credit-to-GDP gap. This leading indicator property of our index is not solely a function of the fact that it loads positively on to asset prices. To see this, the subsequent panels of Figures 12 and 13 present cross-correlation functions between our three category indices – risk appetite, nonfinancial imbalances and financial sector vulnerability – and the credit-to-GDP gap. While the risk appetite category (second panel) tends to lead the credit gap by about three years, the nonfinancial sector imbalances (third panel) and financial sector vulnerability (fourth panel) categories also tend to lead significantly, albeit by one-to-two years.

We also considered a more formal regression analysis. We examined a number of vector autoregressions (VARs) containing the credit-to-GDP gap and our aggregate index, with controls for other factors including the rate of change in real GDP, house prices, and corporate bond spreads. We also considered VARs with the level of nonfinancial credit (divided by the price index for GDP), the level of real GDP and the aggregate vulnerability index, along with house prices, corporate bond spreads and a time trend – this alternative does not involve any detrending with the Hodrick-Prescott filter. In both the stationary and non-stationary VARs, we also examined the impact of replacing the aggregate vulnerability index with our three category indices.

Figures 14 and 15 present impulse responses of the credit-to-GDP gap and the level of credit to a one standard deviation shock of the aggregate index (full sample and pseudo-real-time estimates, respectively). The upper panel of Figure 14 indicates that a one standard deviation increase in the aggregate index is associated with a persistent increase in the credit-to-GDP gap, peaking around 1.2 percentage points higher after 25 quarters, following a small decline in the first year. A similar response is observed in the level of credit, which increases to around 1.8 percent above its baseline after 20 quarters. Figures 16 and 17 present analogous sets of impulse responses for the credit-to-GDP gap and level of credit following shocks to the risk appetite, nonfinancial sector imbalances and financial sector vulnerability category indices (full sample and pseudo-real-time estimates, respectively). The results indicate that "news" in our risk appetite category index leads to persistent changes in the forecasts for credit and the credit-to-GDP gap.

The vector autoregressions (VARs) also reveal that our overall index Granger-causes credit and the credit-to-GDP gap. This can be seen in Tables 3 and 4, which report chi-squared test statistics and *p*-values (in parentheses) from a series of block exogeneity tests (full sample and pseudo-real-time estimates, respectively). In many cases, even with additional controls, the *p*-values for the exclusion of the overall index from the equation with credit or the credit-to-GDP gap are well below 0.05, although our results are noticeably less strong in the VARs with the credit-to-GDP gap and our indices both measured in pseudo real time. The block exogeneity tests also indicate that the risk appetite category index has some predictive power. That said, the

**Table 3: Granger causality/block exogeneity tests, full sample**

(a)

| | VAR specification: | | | |
|---|---|---|---|---|
| | Aggregate index and credit-to-GDP gap | Plus GDP growth | Plus house price growth | Plus bond spread |
| Null hypothesis: | | | | |
| Aggregate index *does not cause* credit-to-GDP gap | 25.64*** (0.00) | 7.24* (0.06) | 7.08* (0.07) | 6.51* (0.09) |

(b)

| | 3 category indices and credit-to-GDP gap | Plus GDP growth | Plus house price growth | Plus bond spread |
|---|---|---|---|---|
| Null hypothesis: | | | | |
| Risk appetite category index *does not cause* credit-to-GDP gap | 10.65** (0.01) | 8.52** (0.04) | 3.94 (0.27) | 1.42 (0.70) |
| Nonfinancial sector imbalances category index *does not cause* credit-to-GDP gap | 5.76 (0.12) | 5.64 (0.13) | 5.71 (0.13) | 6.74* (0.08) |
| Financial sector vulnerability category index *does not cause* credit-to-GDP gap | 2.10 (0.55) | 0.63 (0.89) | 1.07 (0.79) | 0.73 (0.87) |
| Three category indices jointly *do not cause* credit-to-GDP gap | 38.37*** (0.00) | 19.86** (0.02) | 17.58** (0.04) | 13.25 (0.15) |

(c)

| | Aggregate index, level of credit, time trend | Plus level of GDP | Plus house price level | Plus bond spread |
|---|---|---|---|---|
| Null hypothesis: | | | | |
| Aggregate index *does not cause* level of credit | 37.00*** (0.00) | 19.16*** (0.00) | 9.52** (0.02) | 6.18 (0.10) |

(d)

| | 3 category indices, level of credit, time trend | Plus level of GDP | Plus house price level | Plus bond spread |
|---|---|---|---|---|
| Null hypothesis: | | | | |
| Risk appetite category index *does not cause* level of credit | 25.00*** (0.00) | 20.41*** (0.00) | 6.19 (0.10) | 1.57 (0.67) |
| Nonfinancial sector imbalances category index *does not cause* level of credit | 5.66 (0.13) | 1.26 (0.74) | 1.69 (0.64) | 2.04 (0.56) |
| Financial sector vulnerability category index *does not cause* level of credit | 6.34* (0.10) | 3.90 (0.27) | 5.99 (0.11) | 4.55 (0.21) |
| Three category indices jointly *do not cause* level of credit | 35.57*** (0.00) | 27.81*** (0.00) | 21.27** (0.01) | 14.96* (0.09) |

Note: The table reports $\chi^2$ test statistics for block-exogeneity tests and associated *p*-values (in parentheses) from a set of vector autoregressions with 3 lags. Panels (a) and (b) use VARs with the credit-to-GDP gap and our aggregate and category indices respectively (plus controls); panels (c) and (d) use VARs with the (log) level of credit, our aggregate and category indices respectively, and time trends (plus controls). All series are full sample estimates. ***, ** and * indicate statistical significance at the 1, 5 and 10 percent levels, respectively.

**Table 4: Granger causality/block exogeneity tests, pseudo real time**

| | | VAR specification: | | | |
|---|---|---|---|---|---|
| | | Aggregate index and credit-to-GDP gap | Plus GDP growth | Plus house price growth | Plus bond spread |
| (a) | Null hypothesis: | | | | |
| | Aggregate index *does not cause* credit-to-GDP gap | 11.24** (0.01) | 1.97 (0.58) | 1.13 (0.77) | 2.06 (0.56) |

| | | | | | |
|---|---|---|---|---|---|
| | | 3 category indices and credit-to-GDP gap | Plus GDP growth | Plus house price growth | Plus bond spread |
| | Null hypothesis: | | | | |
| | Risk appetite category index *does not cause* credit-to-GDP gap | 2.92 (0.40) | 1.85 (0.60) | 1.48 (0.69) | 0.12 (0.99) |
| (b) | Nonfinancial sector imbalances category index *does not cause* credit-to-GDP gap | 7.68* (0.05) | 9.02** (0.03) | 6.72* (0.08) | 7.62* (0.05) |
| | Financial sector vulnerability category index *does not cause* credit-to-GDP gap | 3.18 (0.37) | 3.31 (0.35) | 0.65 (0.89) | 2.70 (0.44) |
| | Three category indices jointly *do not cause* credit-to-GDP gap | 26.21*** (0.00) | 13.98 (0.12) | 9.87 (0.36) | 11.08 (0.27) |

| | | | | | |
|---|---|---|---|---|---|
| | | Aggregate index, level of credit, time trend | Plus level of GDP | Plus house price level | Plus bond spread |
| (c) | Null hypothesis: | | | | |
| | Aggregate index *does not cause* level of credit | 36.46*** (0.00) | 19.68*** (0.00) | 10.44** (0.02) | 7.66* (0.05) |

| | | | | | |
|---|---|---|---|---|---|
| | | 3 category indices, level of credit, time trend | Plus level of GDP | Plus house price level | Plus bond spread |
| | Null hypothesis: | | | | |
| | Risk appetite category index *does not cause* level of credit | 22.59*** (0.00) | 15.96*** (0.00) | 5.99 (0.11) | 2.03 (0.57) |
| (d) | Nonfinancial sector imbalances category index *does not cause* level of credit | 7.39* (0.06) | 4.97 (0.17) | 4.97 (0.17) | 5.42 (0.14) |
| | Financial sector vulnerability category index *does not cause* level of credit | 2.45 (0.48) | 1.45 (0.70) | 1.34 (0.72) | 2.13 (0.55) |
| | Three category indices jointly *do not cause* level of credit | 36.74*** (0.00) | 27.12*** (0.00) | 18.93** (0.03) | 16.33* (0.06) |

Note: The table reports $\chi^2$ test statistics for block-exogeneity tests and associated *p*-values (in parentheses) from a set of vector autoregressions with 3 lags. Panels (a) and (b) use VARs with the credit-to-GDP gap and our aggregate and category indices respectively (plus controls); panels (c) and (d) use VARs with the level of credit, our aggregate and category indices respectively, and time trends (plus controls). All series are pseudo-real-time estimates. ***, ** and * indicate statistical significance at the 1, 5 and 10 percent levels, respectively.

results are strongly supportive of there being value-added to aggregating categories into the overall index. Indeed, an exclusion test for the combination of risk appetite, nonfinancial sector imbalances and financial sector vulnerability categories strongly suggests that these indices jointly provide information relevant for the evolution of the credit cycle, with *p*-values below 0.05 across most specifications.

Taken together, these findings suggest that our approach may provide a somewhat earlier signal than that provided by the credit-to-GDP gap. In particular, this property suggests that our measures may be well suited for informing macroprudential actions, such as increasing the countercyclical capital buffer, which require a lengthy lead-in period to become fully effective.

**6.2 Financial conditions indexes**

Another strand of the literature uses financial markets data to construct financial stress indices. These indices are primarily meant to pick up contemporaneous instability in the financial system (see the surveys by Kliesen, Owyang, and Vermann, 2012, and Aramonte, Rosen, and Schindler, 2013). In contrast, our approach focuses on identifying the build-up of vulnerability that could lead to future instability.

We examine the correlation between the financial conditions index used in Nelson and Perli (2007), a well-known effort that predates the crisis, and our aggregate vulnerability and risk appetite indices. The upper panel of Figure 18 compares our aggregate index with the Nelson and Perli (2007) financial stress index; the lower panel compares the latter with our risk appetite index. The series tend to move opposite directions, reflecting a raw correlation of -0.20 between the Nelson-Perli index and our aggregate index. This negative correlation increases to -0.69 when comparing the stress index to our risk appetite index. The main factor driving this negative co-movement is that our risk appetite index, which is meant to capture investor willingness to bear risk, is elevated when volatility and credit spreads are low; in comparison, financial stress indices would be elevated when volatility and credit spreads are high.

The average of the equity market, volatility, and corporate debt components within the risk appetite category is even more negatively correlated (-0.87) with the Nelson-Perli index than the overall category index; however, the real-estate portions of the risk appetite index are less negatively correlated (-0.29). We view the inclusion of measures of conditions in real estate markets as important given the importance of this sector in previous financial crises (Cecchetti, 2008), and note that this component of the risk appetite index was quite elevated in the mid-2000s, as seen in Figure 18.

## 7. Practical application: policy rules for the countercyclical capital buffer

As a final exercise, we outline how the vulnerability measures proposed in this paper could be put to practical use as "guide variables" in an operational regime for the countercyclical capital buffer (CCyB).[14] The leading-indicator nature of our measures makes them particularly well-suited for this purpose, given the potentially significant lags involved in applying this tool (e.g. banks will have one year to comply with decisions to tighten the CCyB).

We examine two illustrative policy rules derived from our vulnerability indexes. The first is based on the aggregate vulnerability index. We define this policy rule as a simple piece-wise linear function of the current value of this aggregate index, $V_t$:

$$CCYB_t = 0 \quad \text{if } V_t < V^L$$

[14] While some degree of discretion is likely to be desirable in a CCyB regime, simple policy rules such as these could have a role to play to help inform policymakers' decisions.

$$= 2.5 \cdot \left(\frac{V_t - V^L}{V^H - V^L}\right) \quad \text{if } V^L \leq V_t \leq V^H$$

$$= 2.5 \quad \text{if } V_t > V^H$$

We calibrate the lower threshold, $V^L$, at the 65th percentile of the historical distribution of $V_t$ and the upper threshold, $V^H$, at the 85th percentile. If this distribution is stationary, we would expect the buffer to be "switched on" around one-third of the time under this rule, and for it to be at its 2.5 percent maximum around fifteen percent of the time.

The second policy rule is a step-function of the fourteen component indexes, $V_t^k$. The rule switches on at 50 basis points when three of these vulnerability components cross their 80th percentile—this threshold corresponds to the "red zone" in Figure 8. The rule then notches up a further 50 basis points with each additional component that exceeds this threshold, until the 2.5 percent maximum buffer is reached when seven or more components exceed the threshold. Relative to the first rule, this "component intensity score" rule allows for more limited substitutability across the vulnerability components, in the sense that components with "low" readings do not offset the effects of those in the red zone.

Figure 19 presents a time series plot of these rules (blue solid lines) alongside the implied effective buffer that banks would be required to meet (black dashed lines). For simplicity, the figure (unrealistically) ignores the possibility of any feedback from the setting of the countercyclical capital buffer to the vulnerability indexes themselves. The rules have quite similar time series profiles over our sample period, 1990-present. Both generate sizeable capital buffers during the dot-com bubble of the late 1990s, before releasing these buffers in full in the early 2000s. By the mid-2000s, the rules signal a need to raise the countercyclical capital buffer once more: both switch on in 2003Q2 and reach their 2.5 percent maximum buffer in 2004Q4, implying that banks would have had the full capital buffer in place to absorb the heightened losses associated with the financial crisis. Thereafter, the aggregate vulnerability index rule begins to turn off in 2007Q4, reaching 0 percent in 2008Q2, while the component intensity score rule begins to turn off somewhat later, reaching 0 percent in 2009Q1.

## 8. Conclusion

We draw on a large literature on the factors that contribute to the build-up of vulnerabilities within the financial sector to develop a framework for assessing vulnerability of the U.S. financial system. We collect data on a broad range of indicators, standardize them, and group them into fourteen components, drawn from three broad categories: investor risk appetite, nonfinancial imbalances and financial sector vulnerability. The data reveal the extent to which vulnerabilities in the U.S. financial system had built to an acute level prior to the financial crisis. Our measures of system-wide vulnerability are shown to lead the credit cycle significantly, suggesting the potential for our approach to provide the timely information needed to guide macroprudential policy actions such as those pertaining to the countercyclical capital buffer.

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**Figure 1: Schematic of our overall vulnerability index and its components**

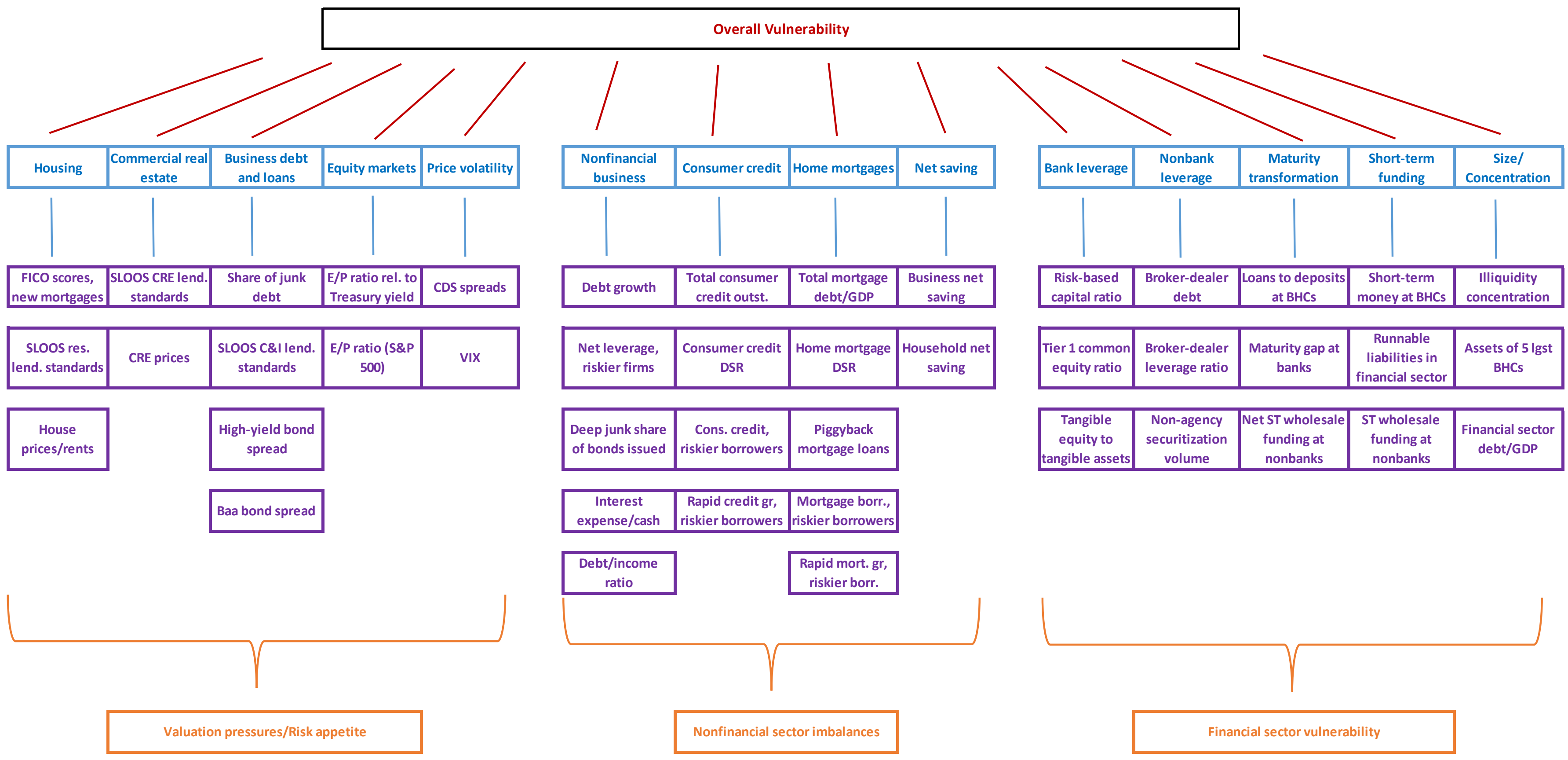
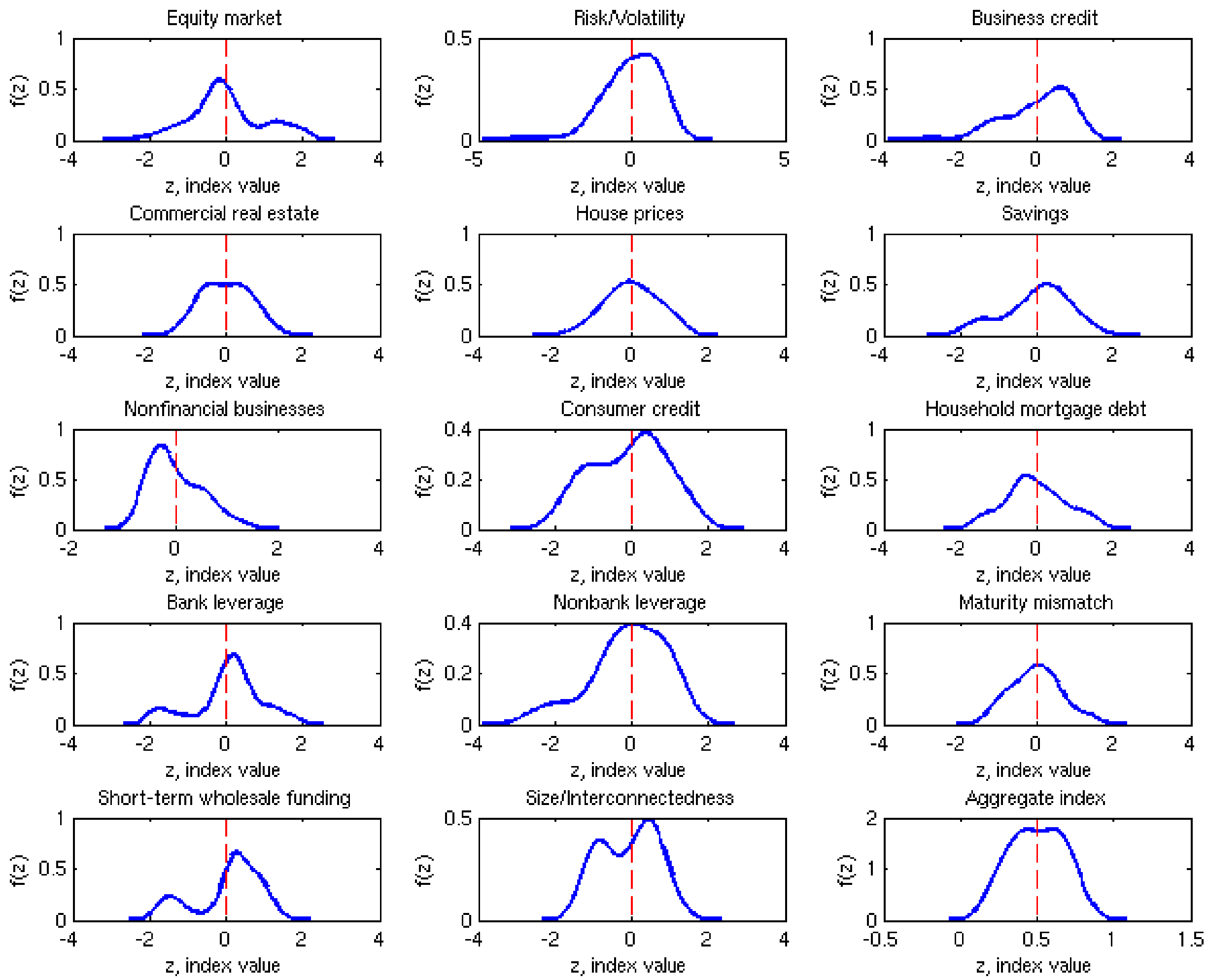
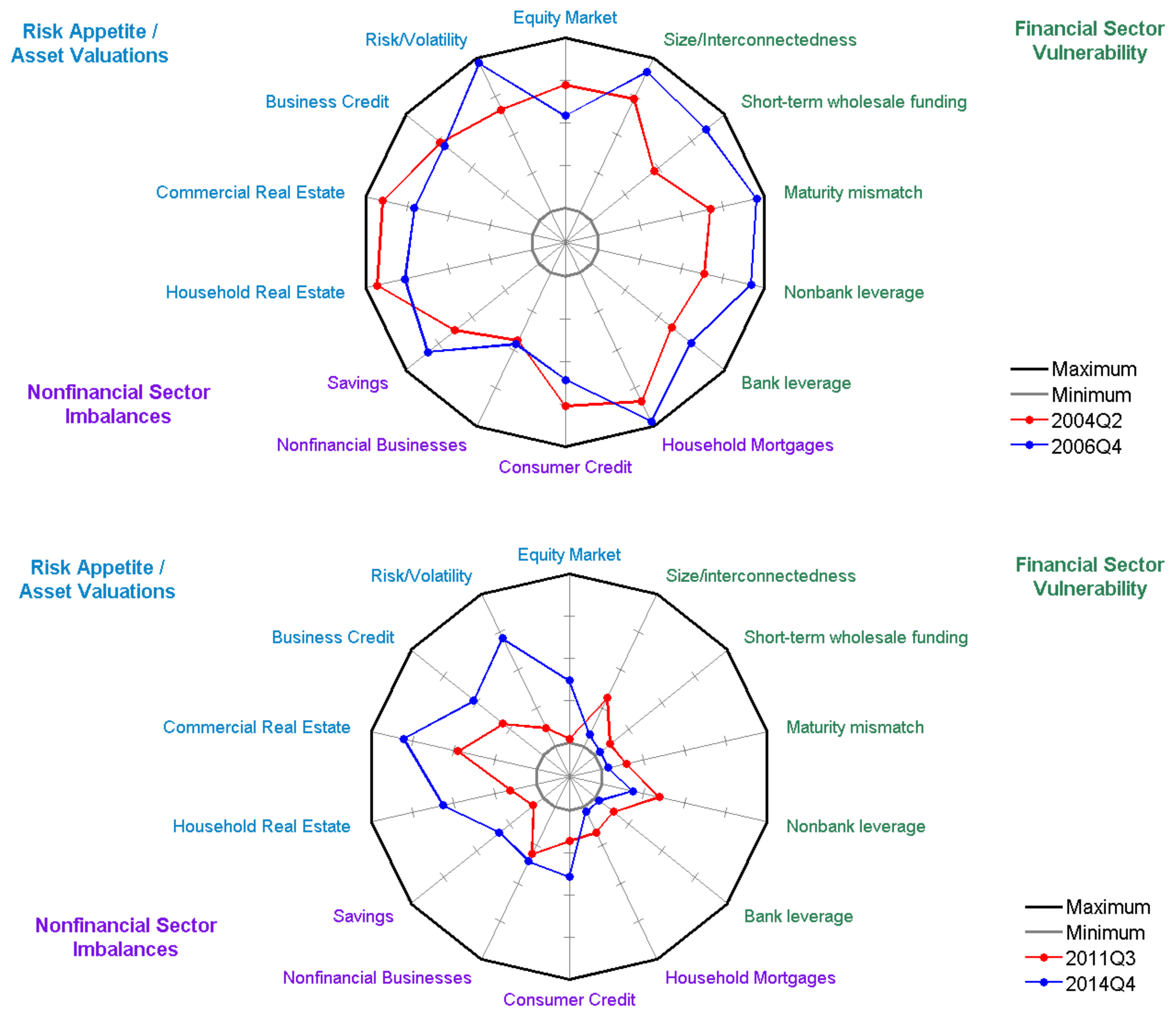


**Figure 2: Estimated probability density functions for component and aggregate indexes**



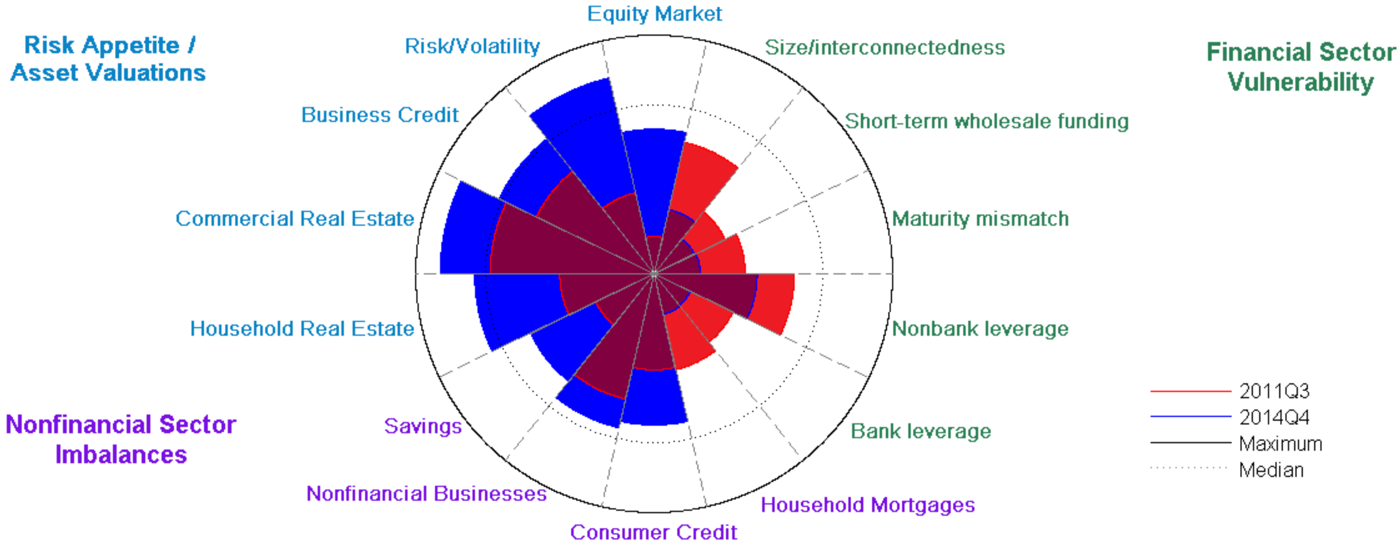

Note: The figure presents kernel estimates of the probability density functions of each of our fourteen component indexes and the aggregate index, derived as the average of the component indices.

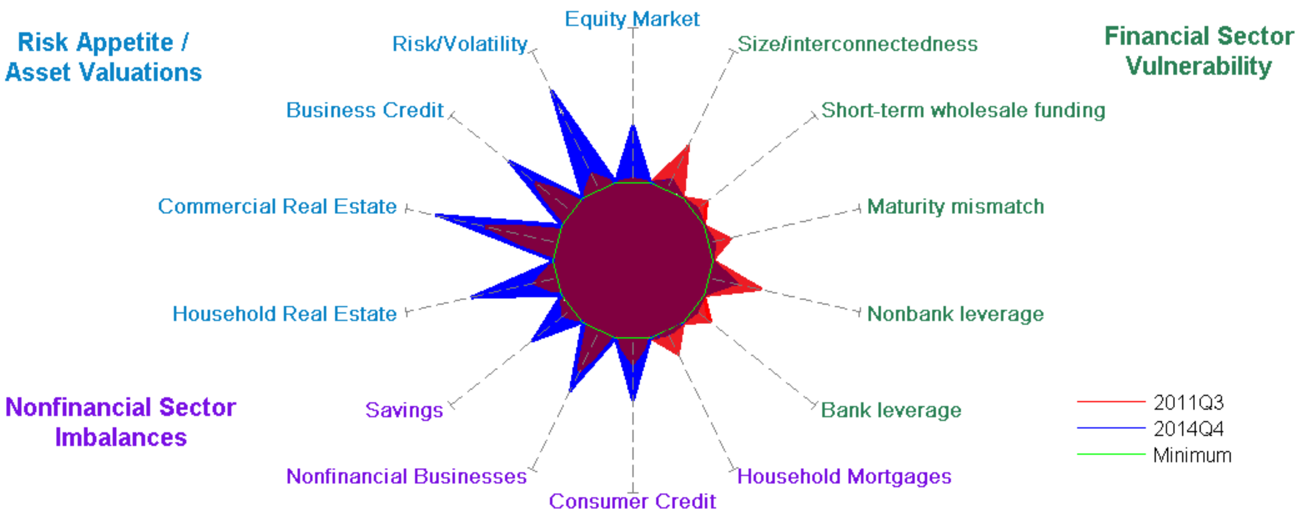
**Figure 3: Radar plot comparison of vulnerabilities across time**




Note: The figure presents radar charts of the fourteen components (within the three color-coded categories) underlying our aggregate index. Each data point is the estimated cumulative distribution function at the corresponding component value (i.e. the probability of observing a component value less than or equal to its reading on the date specified). The outer (black) and inner (grey) polygons corresponds to one and zero, respectively, and the tick marks correspond to the 25$^{th}$, 50$^{th}$ and 75$^{th}$ percentiles. The red and blue polygons in the upper panel present conditions as of 2004Q2 and 2006Q4, respectively; the red and blue polygons in the lower panel present conditions as of 2011Q3 and 2014Q4, respectively.

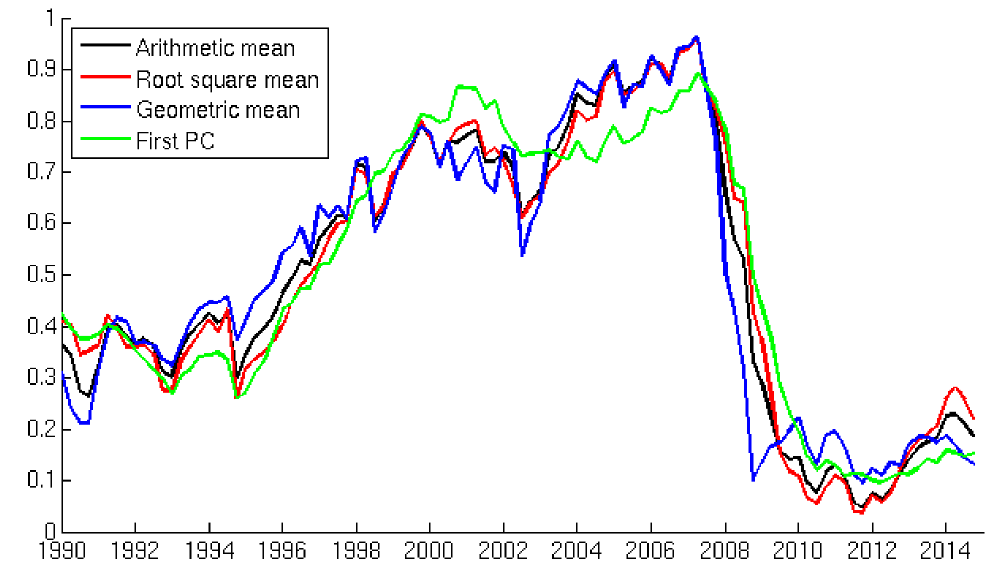
**Figure 4: Coxcomb and sun-burst plots**

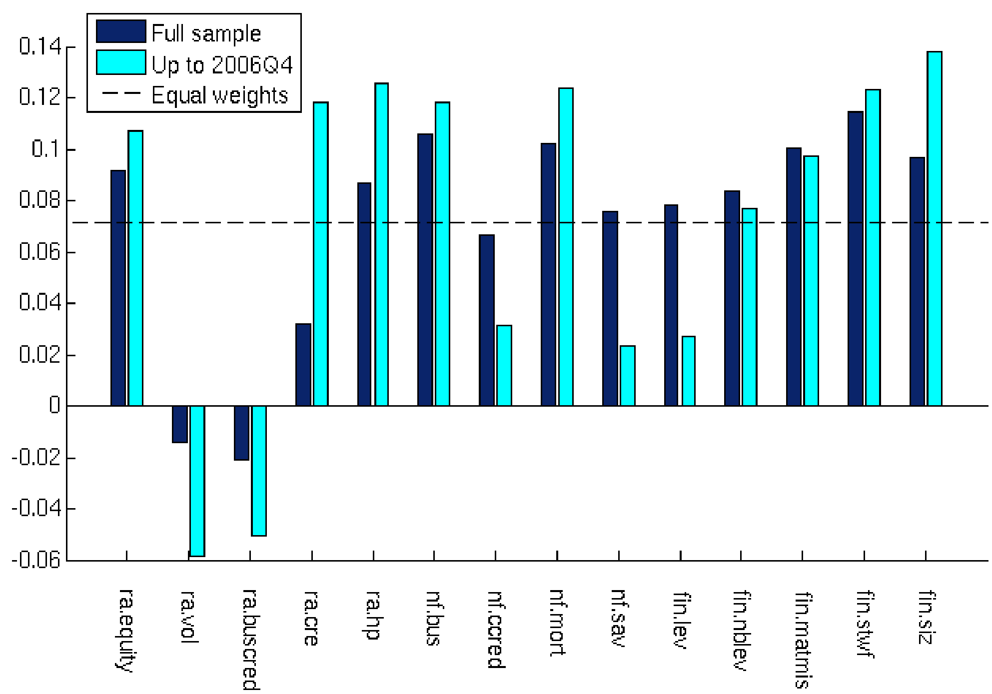



Note: The upper panel of this figure presents a coxcomb (polar area) chart of the fourteen components underlying our aggregate index. The lower panel presents a "sun-burst" chart of the fourteen components. The inner polygon (green) represents the minimum value of each component and the outer tick-marks (grey) represent the maximum. In both charts, the area of each slice corresponds to the components' values. The purple shaded areas reflect equivalent levels of vulnerabilities across the two periods; the red area represents the difference between the components when the 2011Q3 component values are higher; the blue area represents the difference between the components when the 2014Q4 values are higher.

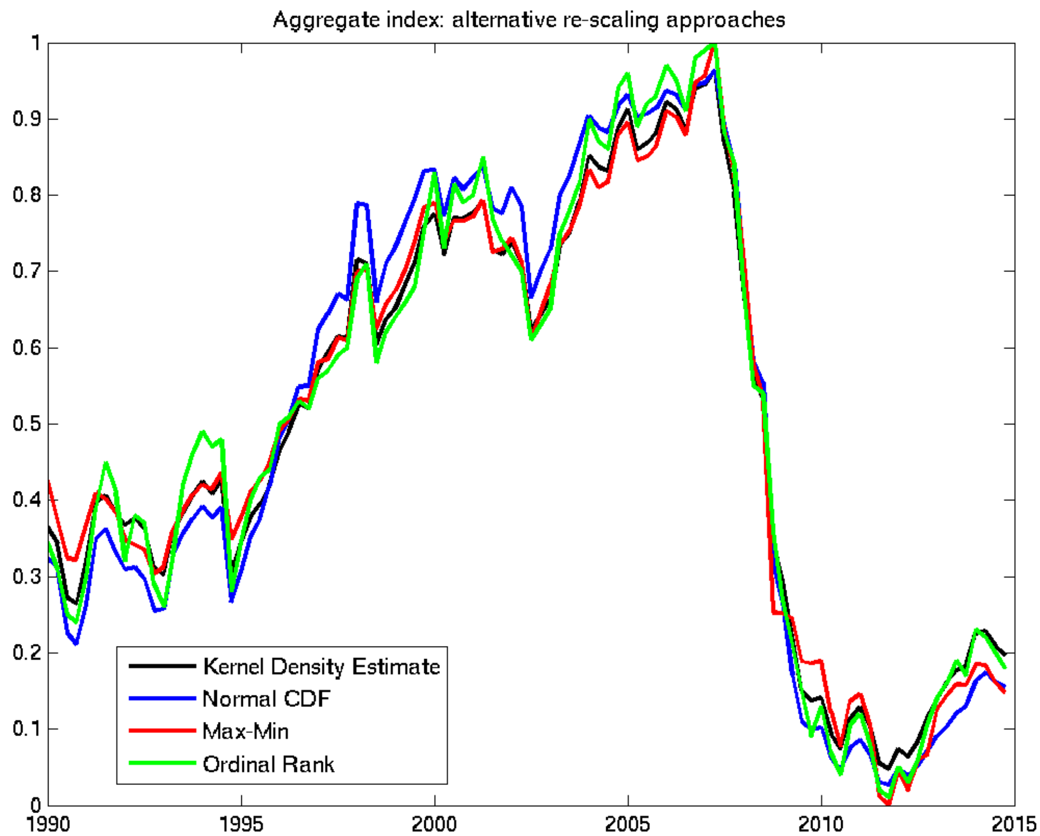
**Figure 5: Alternative approaches for generating an aggregate index**



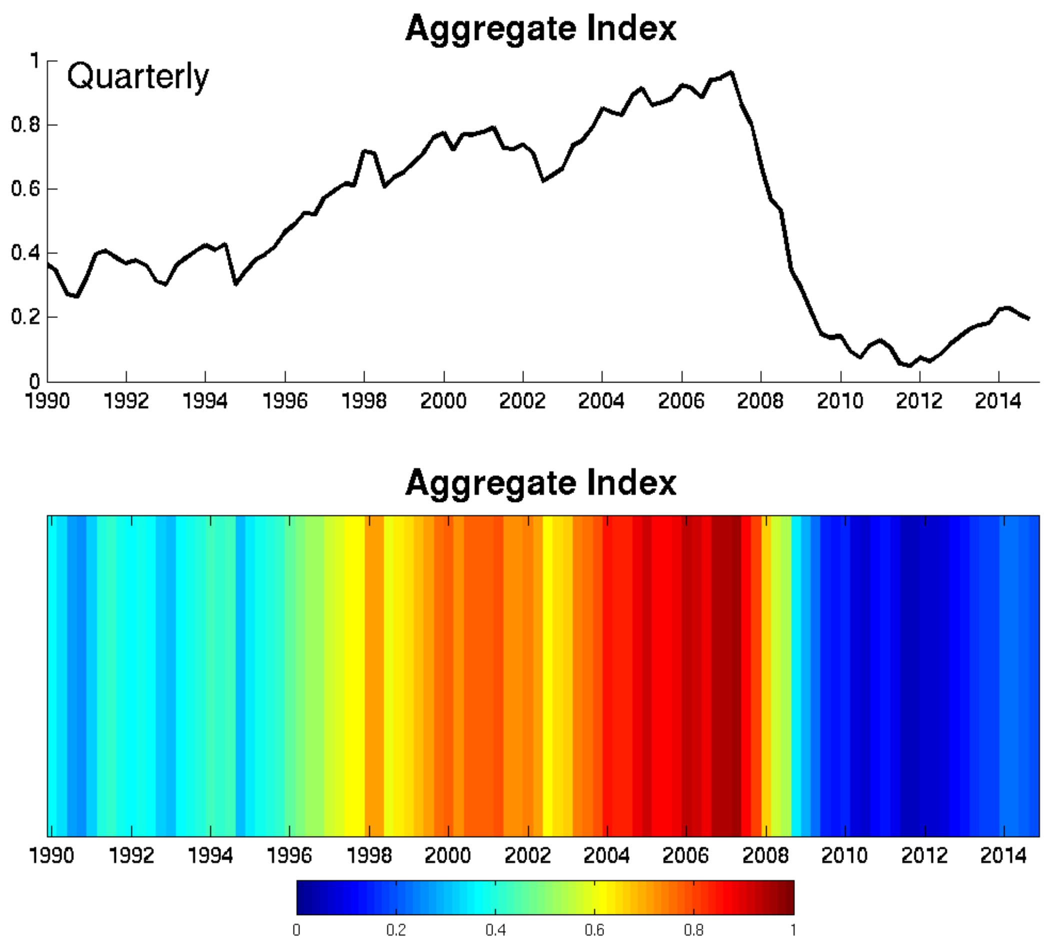

Note: The upper panel presents four alternative approaches for generating an overall vulnerability index. In each case, we rescale the implied aggregate index into probabilistic terms by using the kernel density estimate of its cumulative distribution function. The lower panel presents principal component weights for each of our fourteen component series, both for the full sample (deep blue bars) and for the sub-sample up to 2006Q4 (cyan). The dashed line corresponds to equal weights for all fourteen component series.

**Figure 6: Impact of alternative normalization approaches**



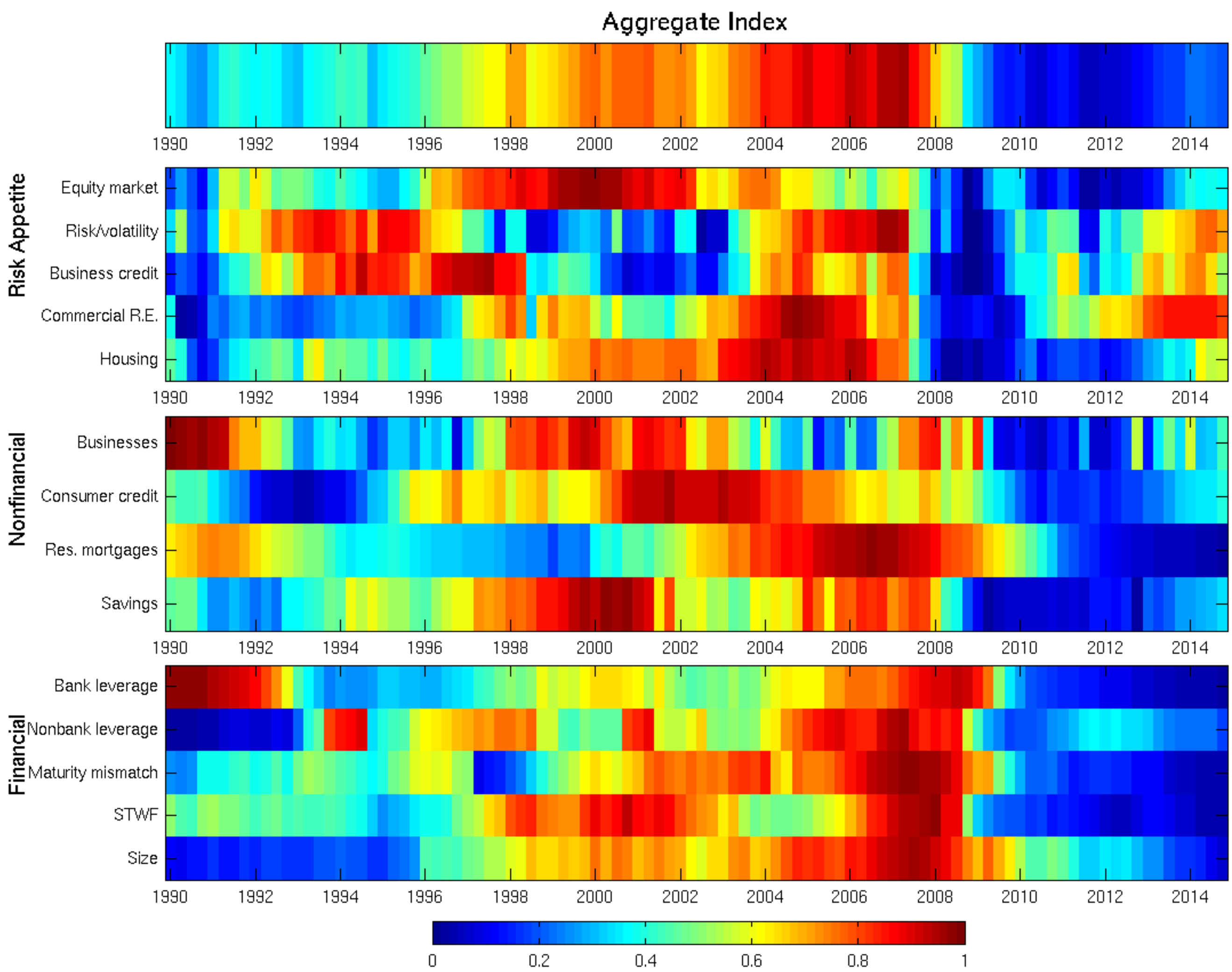

Note: The chart presents time series of our aggregate vulnerability index under various alternative normalization schemes. The black line is computed using a (nonparametric) kernel density estimate of the cumulative distribution function of our component and aggregate indices; the blue line applies a Normal cumulative distribution function to z-scores of our component and aggregate indices; the red line presents a linear rescaling relative to the maximum and minimum of these series; and the green line applies a rescaling based on ordinal ranks.

**Figure 7: Aggregate index of vulnerabilities in the U.S. financial system**



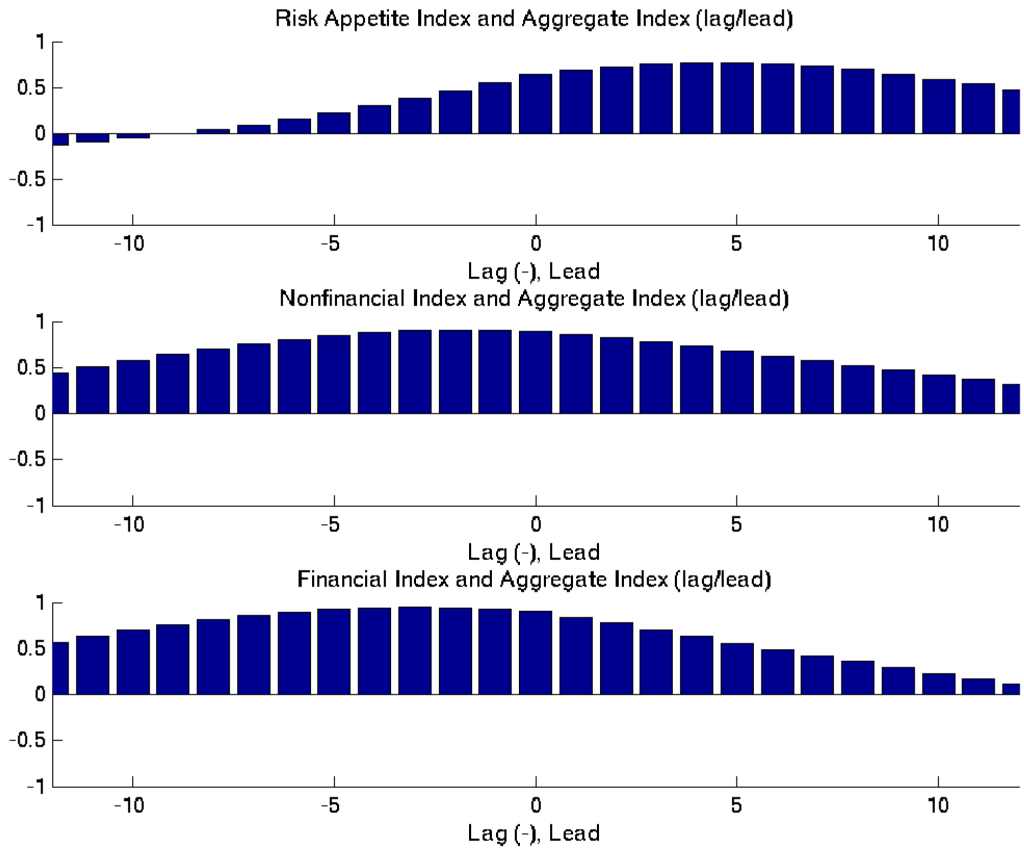

Note: The upper panel presents our aggregate vulnerability index, derived as the average of the fourteen component indices and rescaled into probabilistic terms by using the kernel density estimate of its cumulative distribution function. The second panel presents a heat map of the index. The color-bar at the bottom of the figure depicts the colors associated with percentiles of its distribution.

**Figure 8: Ribbon heat map of vulnerabilities in the U.S. financial system**



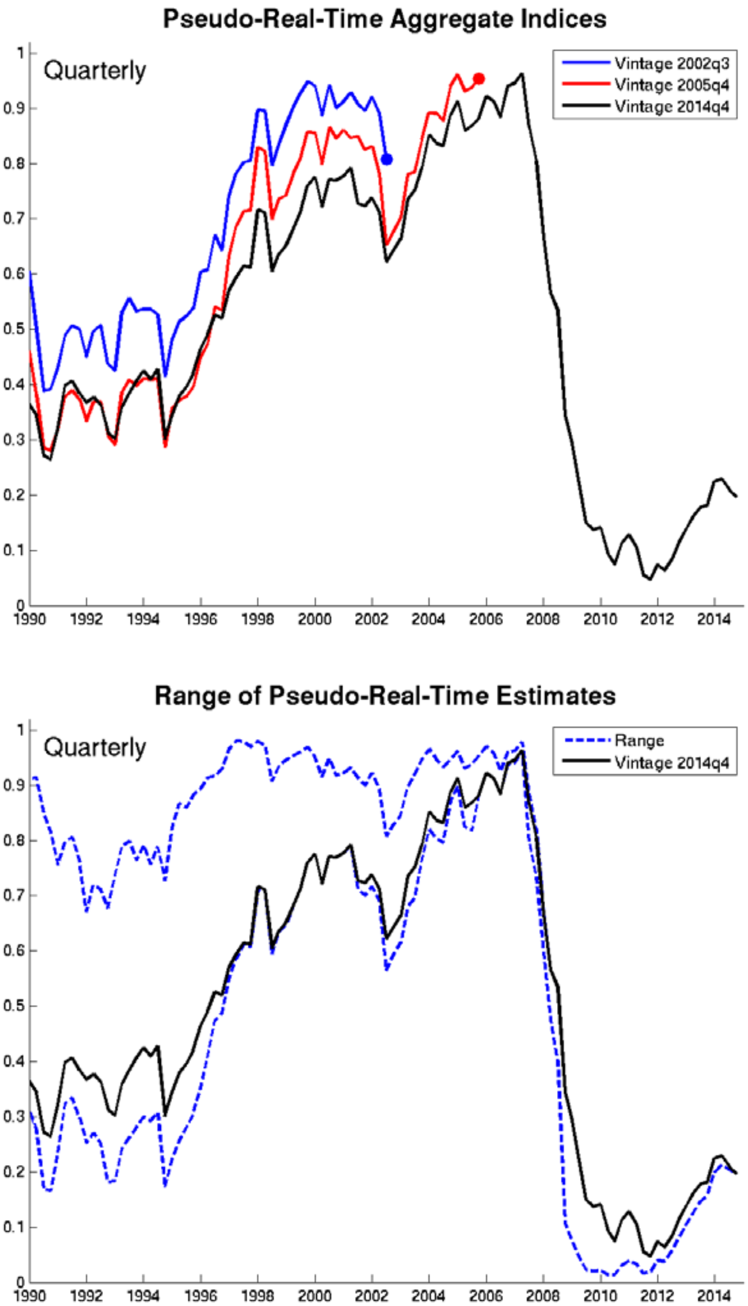

Note: The figure presents a heat map of the fourteen components that underlie our aggregate index; the aggregate index is shown in the top panel. Each index has been rescaled into probability-space by using the kernel density estimate of its cumulative distribution function. The color-bar at the bottom of the figure depicts the colors associated with percentiles of each distribution.

**Figure 9: Lead-lag relationship between vulnerability categories and overall index**



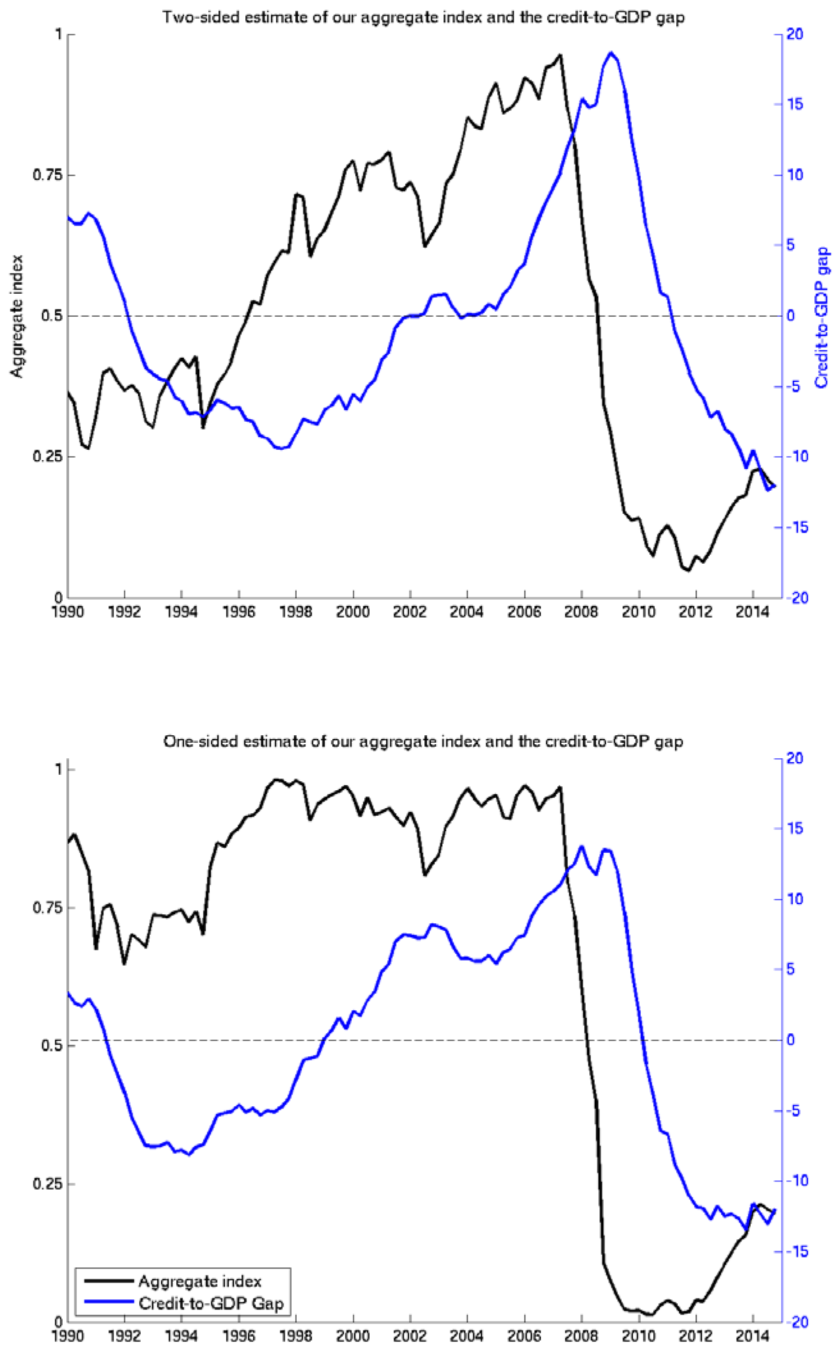

Note: The figure presents cross-correlations of our three category indices with leads and lags of the aggregate vulnerability index.

**Figure 10: Pseudo-real-time view of vulnerabilities**



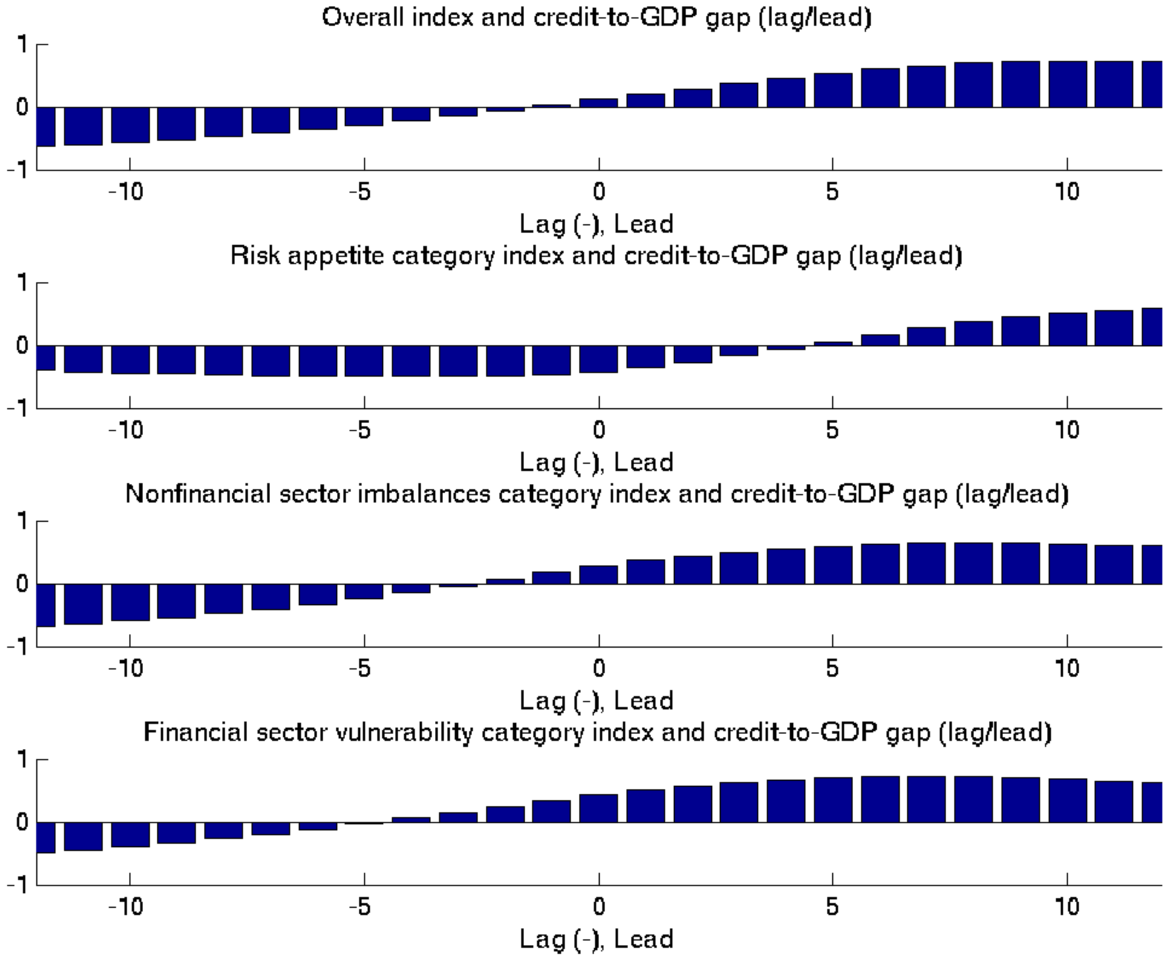

Note: The figure presents a real-time counterpart of our vulnerability indices, where in period *t* each indicator is standardized using the mean and standard deviation of data available up to that period, and component and aggregate indices are re-scaled using their estimated distribution functions up to that period. The upper panel presents vintages of our aggregate index from the perspectives of 2002Q3, 2005Q4 and 2014Q4, using a rolling 25-year window to construct each vintage. The lower panel shows minimum and maximum values for each period across these vintages (blue-dashed lines).

**Figure 11: The aggregate vulnerability index and the credit-to-GDP gap**



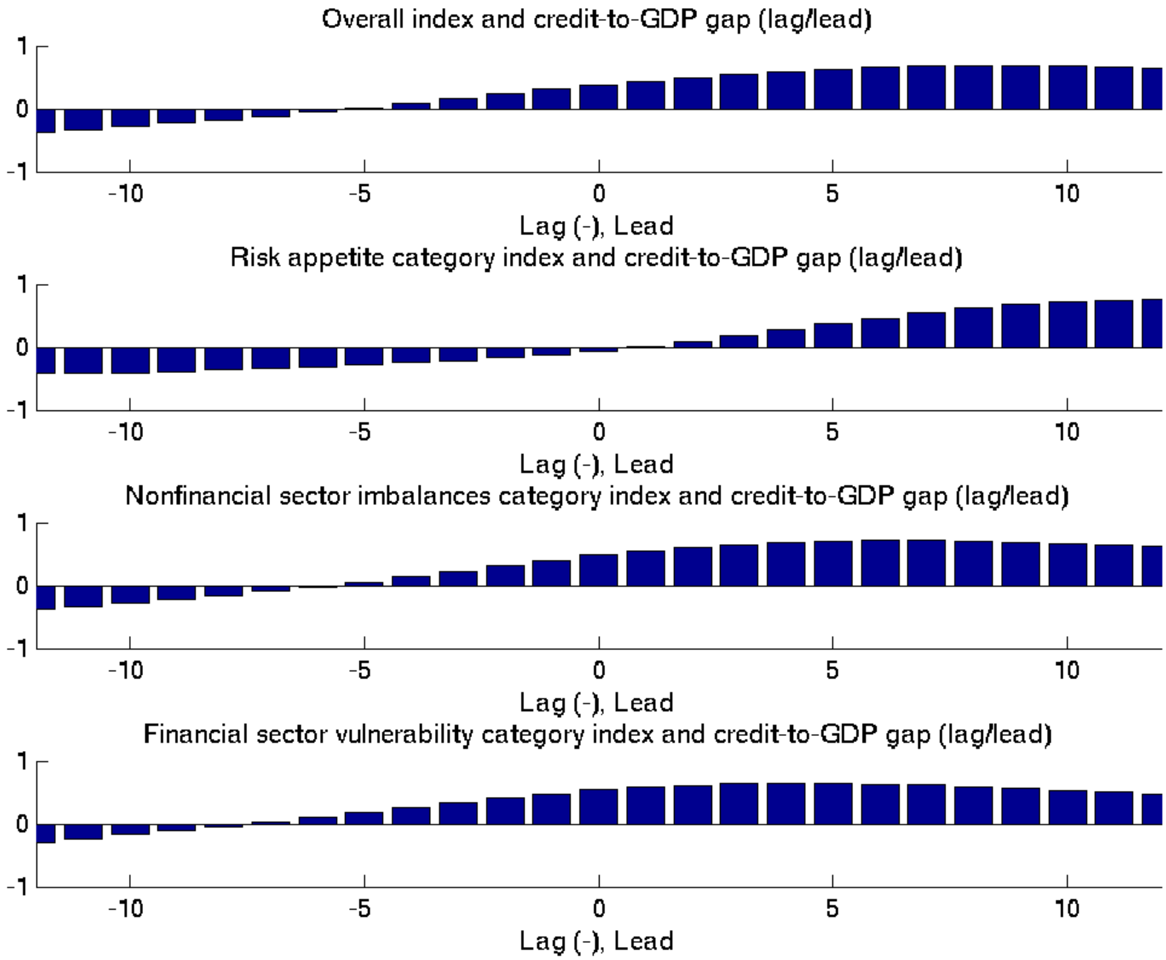

Note: The panels presents time series of our aggregate vulnerability index and the credit-to-GDP gap, where the trend is measured using a Hodrick-Prescott filter with a smoothing parameter of 400,000. The upper panel presents full-sample, "two-sided" estimates of these series; the lower panel shows pseudo-real time, "one-sided" estimates.

**Figure 12: Lead-lag relationship with credit-to-GDP gap, full sample**




Note: The panels present cross-correlations between our indices and leads and lags of the credit-to-GDP gap. All series represent full-sample estimates.

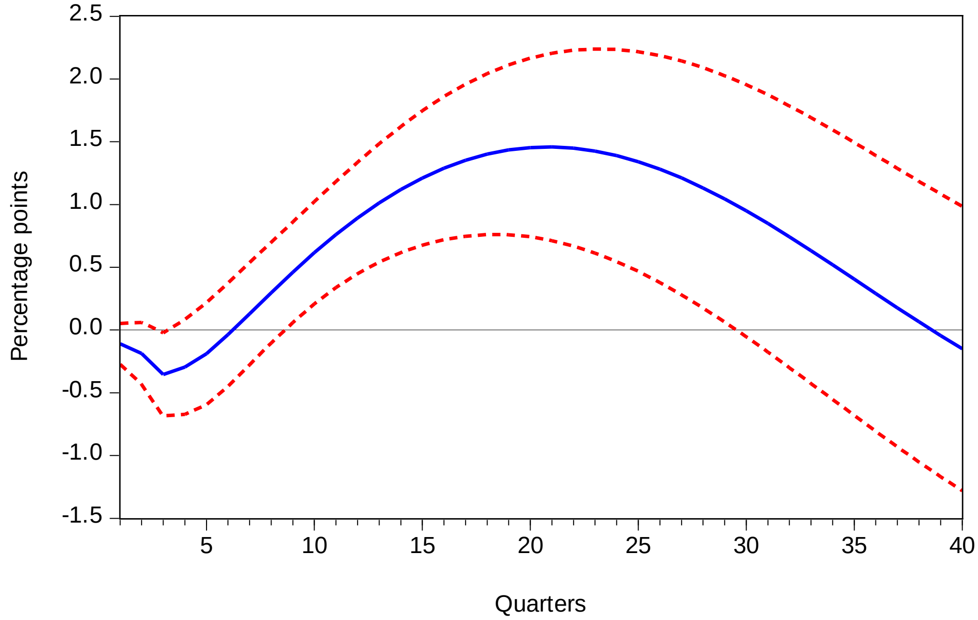
**Figure 13: Lead-lag relationship with credit-to-GDP gap, pseudo real time**



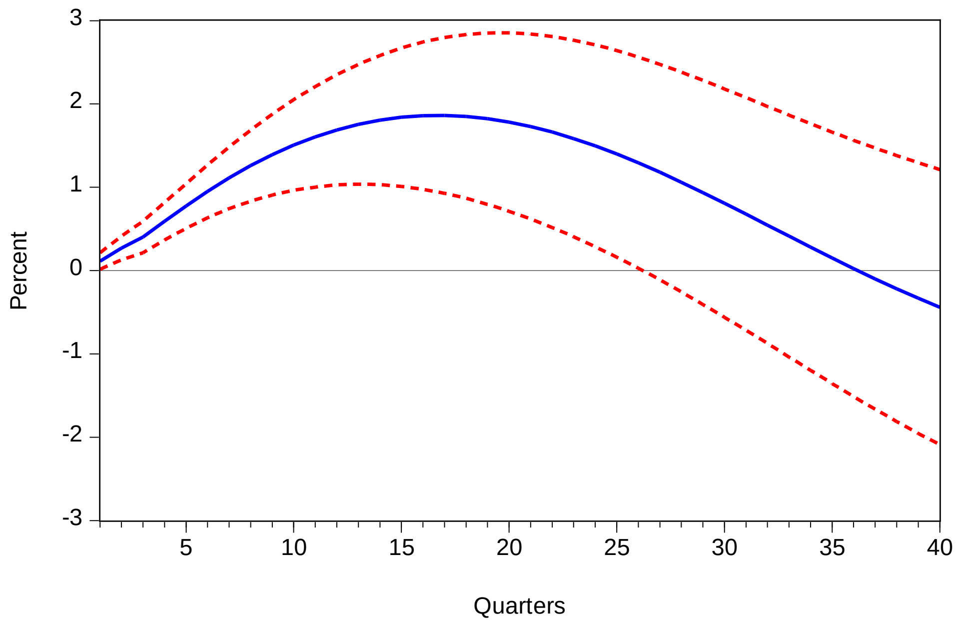

Note: The panels present cross-correlations between our indices and leads and lags of the credit-to-GDP gap. All series represent pseudo-real-time estimates.

**Figure 14: Impulse responses, full sample**

**(a) Response of credit-to-GDP gap to a one standard deviation shock to aggregate index**



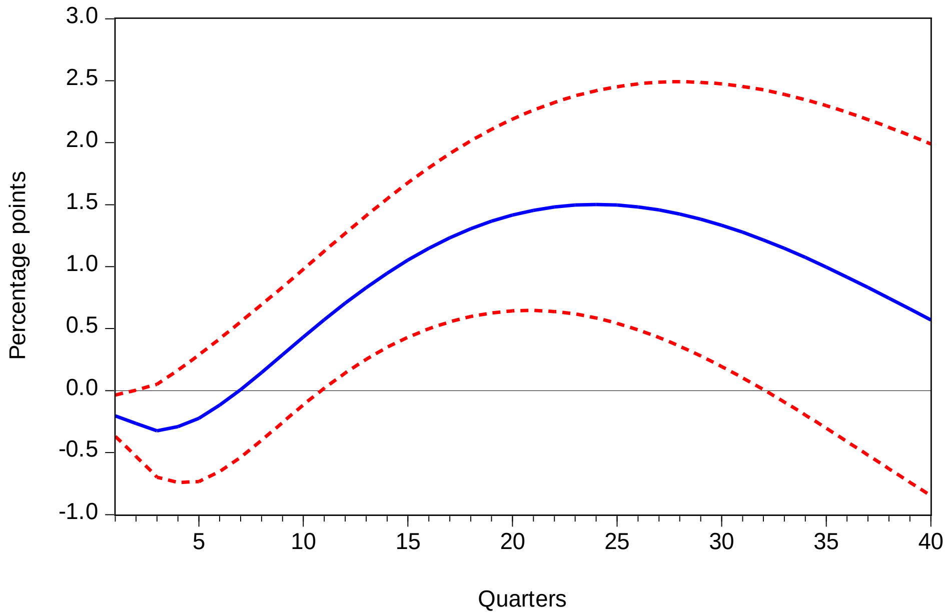

**(b) Response of credit level to a one standard deviation shock to aggregate index**



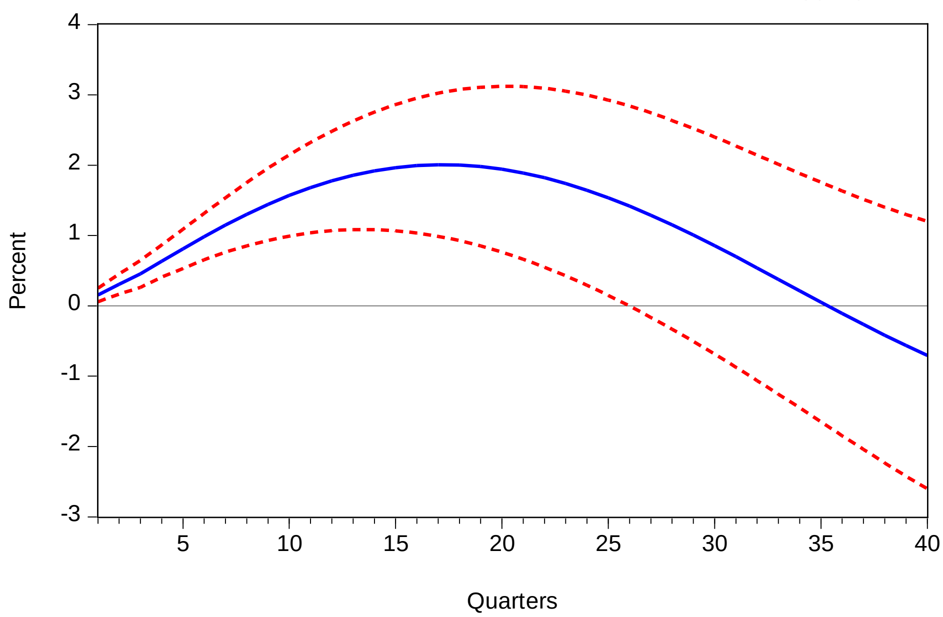

Note: Panel (a) presents the generalized impulse response of the credit-to-GDP gap to a one standard deviation shock to the aggregate index from a bivariate VAR containing these variables. Panel (b) presents the generalized impulse response of the level of credit to a one standard deviation shock to the aggregate index from a VAR containing these variables and a time trend. All variables are full sample estimates. Dashed lines show the associated 95 percent confidence interval. The VARs include three lags and are estimated over the sample 1990Q1-2014Q4.

**Figure 15: Impulse responses, pseudo real time**

**(a) Response of credit-to-GDP gap to a one standard deviation shock to aggregate index**

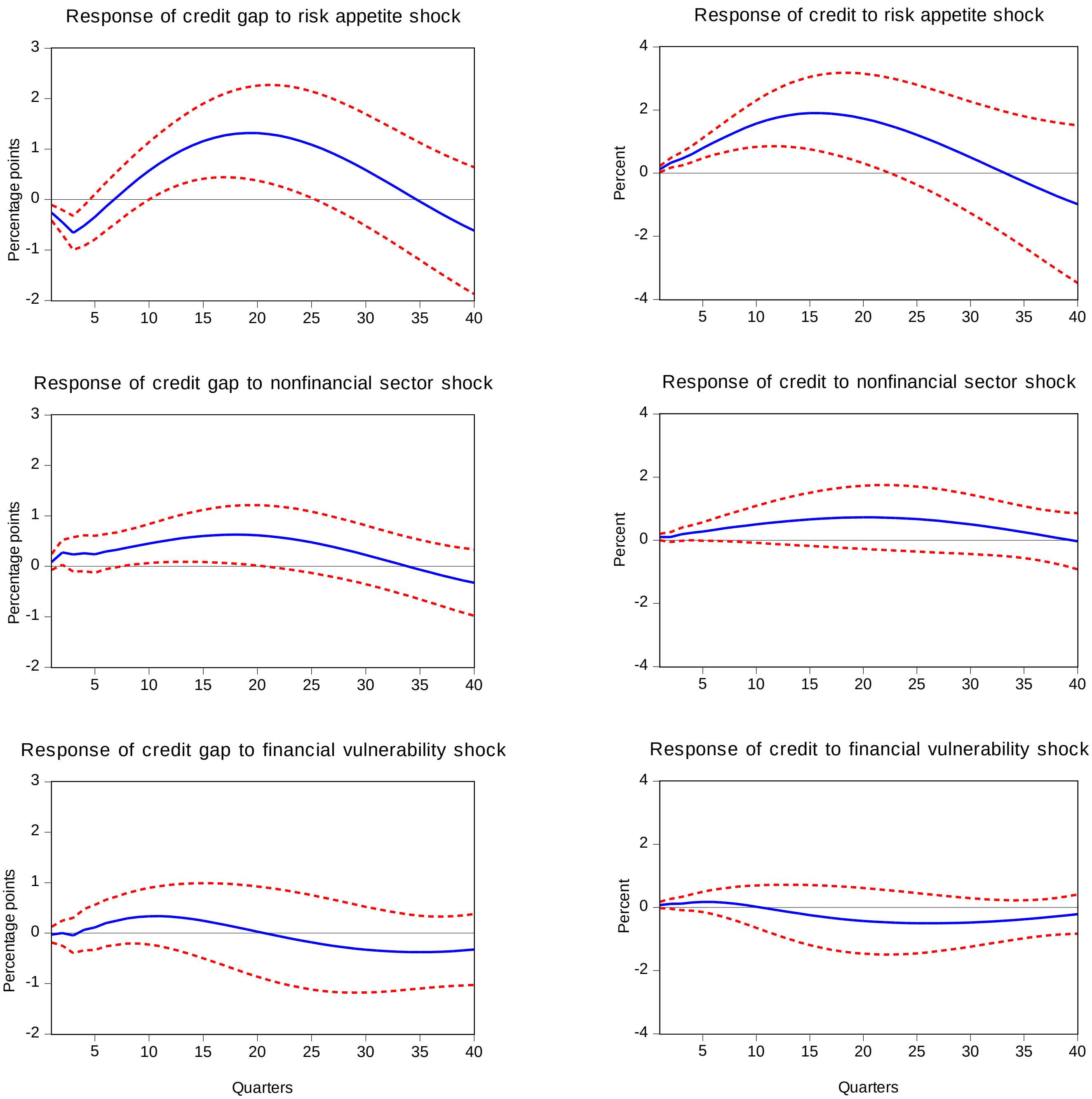



**(b) Response of credit level to a one standard deviation shock to aggregate index**



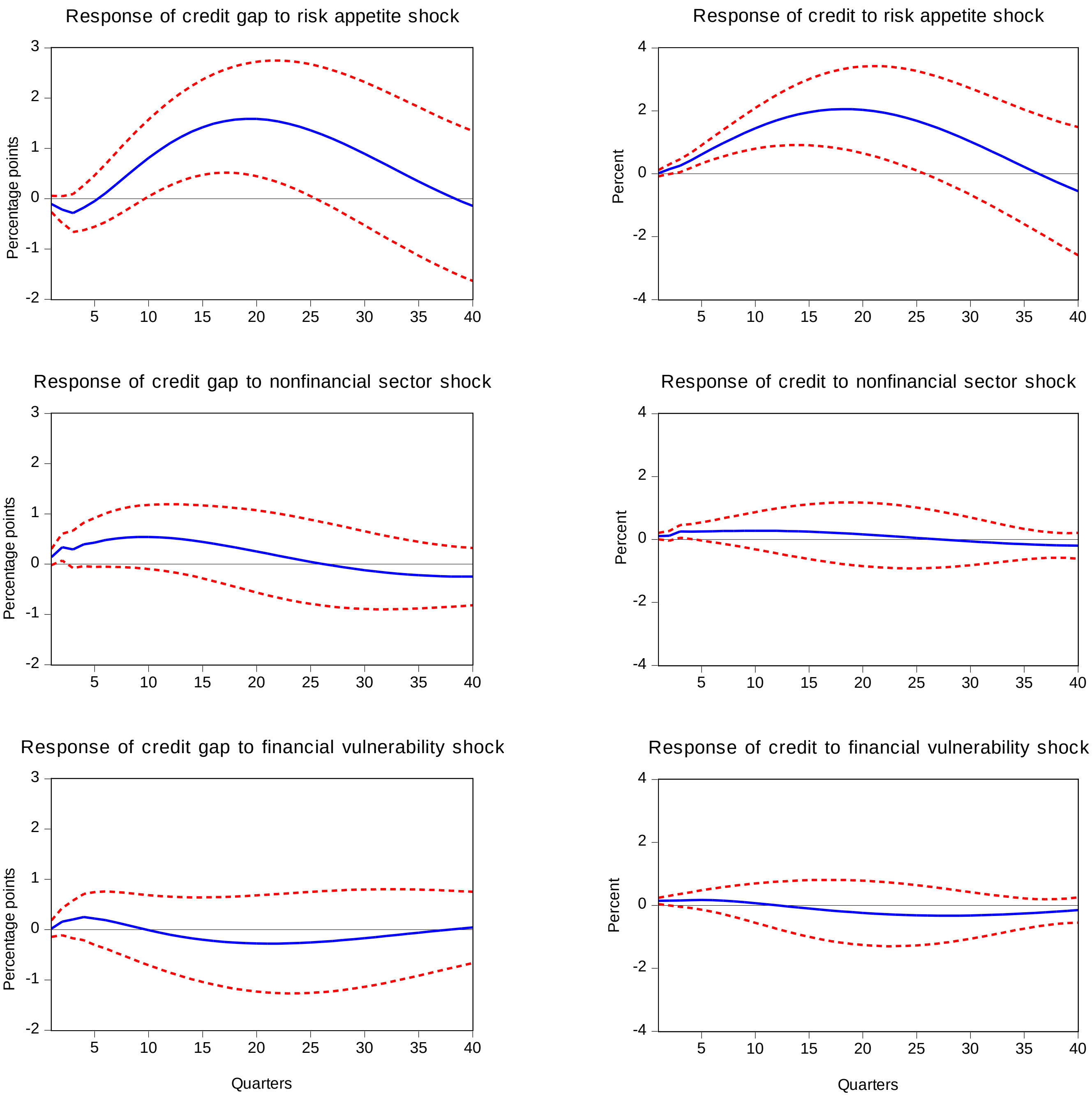

Note: Panel (a) presents the generalized impulse response of the credit-to-GDP gap to a one standard deviation shock to the aggregate index from a bivariate VAR containing these variables. Panel (b) presents the generalized impulse response of the level of credit to a one standard deviation shock to the aggregate index from a VAR containing these variables and a time trend. All variables are pseudo-real-time estimates. Dashed lines show the associated 95 percent confidence interval. The VARs include three lags and are estimated over the sample 1990Q1-2014Q4.

**Figure 16: Impulse responses, full sample**



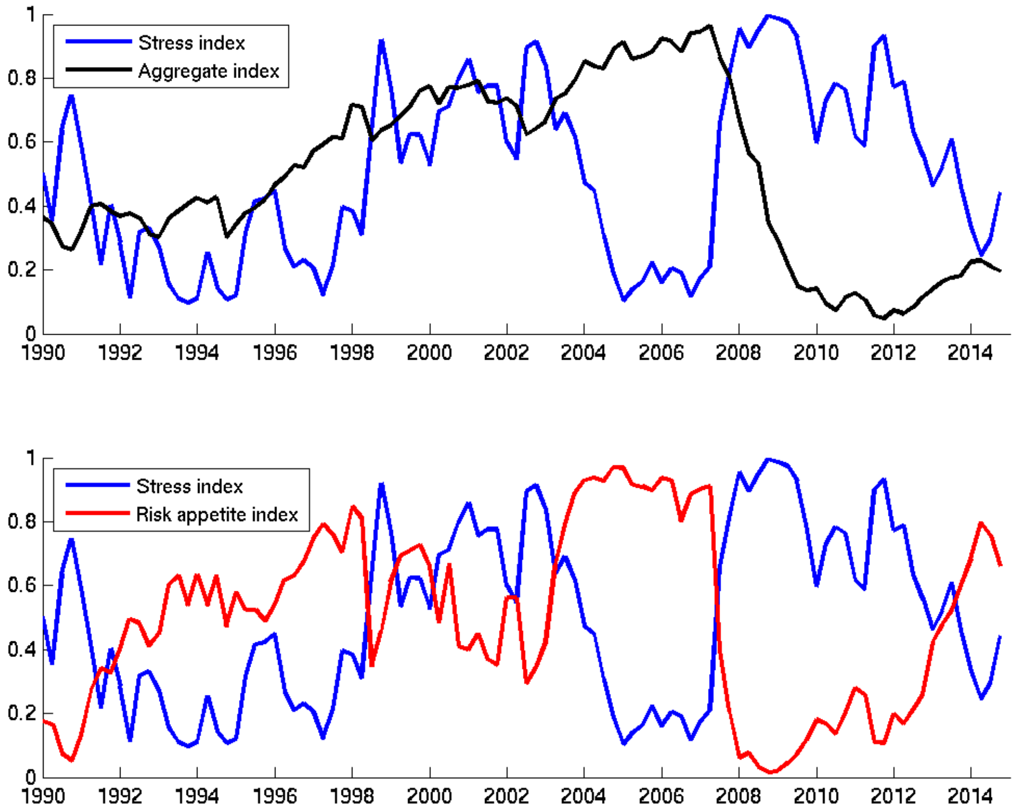

Notes: The left-hand panel presents generalized impulse responses of the credit-to-GDP gap to one standard deviation shocks to the risk appetite, nonfinancial sector imbalances and financial sector vulnerability category indices from a VAR containing these variables. All variables are full sample estimates. The right-hand side presents generalized impulse responses of the level of credit to these category index shocks from a VAR that contains these four variables and a time trend. Dashed lines show associated 95 percent confidence intervals. Both VARs include three lags and are estimated over the sample 1990Q1-2014Q4.

**Figure 17: Impulse responses, pseudo real time**



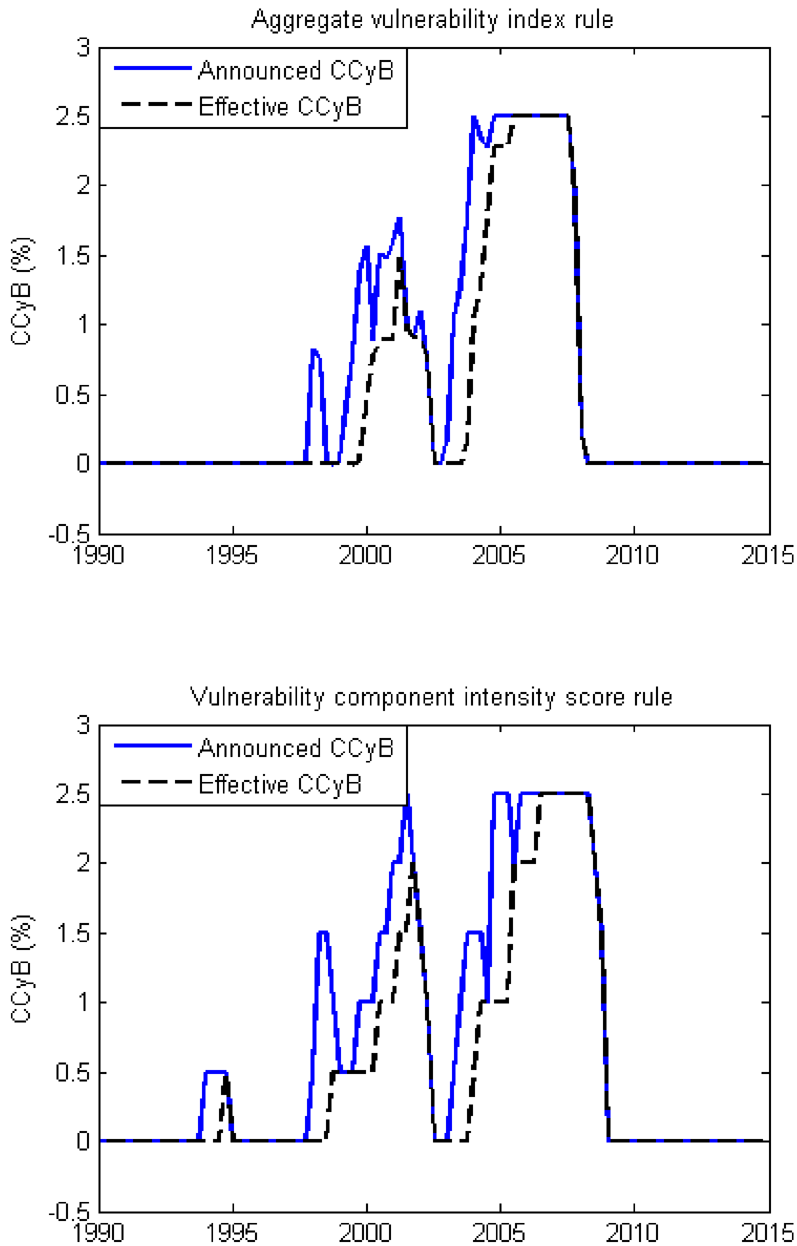

Notes: The left-hand panel presents generalized impulse responses of the credit-to-GDP gap to one standard deviation shocks to the risk appetite, nonfinancial sector imbalances and financial sector vulnerability category indices from a VAR containing these variables. All variables are pseudo-real-time estimates. The right-hand side presents generalized impulse responses of the level of credit to these category index shocks from a VAR that contains these four variables and a time trend. Dashed lines show associated 95 percent confidence intervals. Both VARs include three lags and are estimated over the sample 1990Q1-2014Q4.

**Figure 18: Comparison with the Nelson-Perli financial stress index**




Note: The upper and lower panels present time series comparisons of the Nelson-Perli financial stress index with our aggregate and risk appetite indices, respectively. All indices have been transformed into probabilistic terms using kernel density estimates of their cumulative distribution functions.

**Figure 19: Illustrative policy rules for the countercyclical capital buffer (CCyB)**




Note: The figure presents time series plots of two illustrative countercyclical capital buffer (CCyB) policy rules derived from the indices. The rule in the upper panel is a function of the aggregate vulnerability index: it switches on at the 65th percentile of this index and reaches the 2.5 percent maximum at the 85th percentile. The rule in the lower panel is a function of the component indices: it switches on when 3 components (of 14) cross their 80th percentile (either this quarter or last) – the "red zone" in Figure 8; and it reaches the 2.5 percent maximum when 7 or more components cross this threshold. The blue solid lines plot the outputs of these rules; the black dashed lines plot the implied "effective" CCyB, which takes into account that banks have one year to adjust to buffer increases but that decreases apply immediately.

**Table A1: Indicators for Risk Appetite/Asset Valuations**

| Category/Indicator | Data Availability | Motivation | Academic Studies | Direction of Increased Vulnerability | Detrending Method |
|---|---|---|---|---|---|
| **Housing** | | | | | |
| Price-to-rent ratio (national averages) | Mid-1970s to present | Excess valuations may pose risks to lenders and the broader system | Cecchetti (2008), Rogoff and Reinhart (2010) | + | Subtract 10-year moving average |
| Net fraction of banks reporting having tightened standards for home-purchase mortgages | 1990 to present | Lax standards pose risks to lenders and the broader system | | - | None |
| Median credit score of residential mortgages sold to GSEs | 2003 to present | Lax standards pose risks to lenders and the broader system | | - | None |
| **Commercial Real Estate** | | | | | |
| Commercial Real Estate Prices | 1950s-present | Excess valuations may pose risks to lenders and the broader system. | Cecchetti (2008) | + | Subtract 10-year moving average |
| Net fraction of banks reporting having tightened standards for CRE lending | 1990-present | Lax standards pose risks to lenders and the broader system | | - | None |
| **Business credit** | | | | | |
| Bond spreads (Baa and high yield) | 1980s-present or longer | Low spreads suggest strong risk appetite | | - | Use the log |
| Net fraction of banks reporting having tightened standards for C&I lending | 1990-present | Lax standards pose risks to lenders and the broader system | | - | None |
| Issuance of riskier corporate credit (high-yield bonds and leveraged loans) | 1997-present | Indicates strong risk appetite | | + | Use the log |
| **Equity Market** | | | | | |
| P/E ratio (adjusted for Treasury yields)` | Preferred measure, mid-1980s present | Indicator of risk appetite | | + | None |
| P/E ratio | | | Campbell and Shiller (1998) | + | None |
| **Volatility** | | | | | |
| VIX | 1990-present | Indicator of risk appetite | Brunnermeier-Sannikov (2014) | - | Use the log |
| CDS spreads | | | | - | Use the log |

## Table A2: Indicators for Nonfinancial Imbalances

| Category/Indicator | Data Availability | Motivation | Academic Studies | Direction of Increased Vulnerability | Detrending Method |
|---|---|---|---|---|---|
| **Home Mortgages** | | | | | |
| Total home mortgage debt owed by riskier borrowers (ratio to aggregate DPI) | 1999-present | Leverage among riskier borrowers signals financial fragility | Mian and Sufi (2009) | + | None |
| Incidence of very rapid mortgage borrowing by riskier borrowers (pct) | 2000-present | Riskier borrowers increasing their leverage signals lax underwriting | Mian and Sufi (2009) | + | None |
| Incidence of piggy-back mortgages with newly originated loans to riskier borrowers (pct) | 1999-2013 | Piggyback mortgages allow borrowers to take out high-LTV loans | Mayer, Pence, and Sherlund (2009) | + | None |
| Home mortgage debt ratio to GDP | 1952-2013 | Broad measure of homeowner leverage with a long historical record | | + | Subtract 10-year moving average |
| Mortgage debt service | 1980-2013 | Measure of mortgage affordability | | + | None |
| **Consumer Credit** | | | | | |
| Consumer credit ratio to GDP | 1952-2013 | Broad measure of consumer leverage with a long historical record | | + | Subtract 10-year moving average |
| Consumer credit debt service ratio to DPI | 1980-2013 | Measure of aggregate leverage that factors in interest rates | | + | None |
| Consumer credit owed by riskier borrowers (ratio to aggregate DPI) | 1999-present | Leverage among riskier borrowers signals widespread financial fragility | Mian and Sufi (2009) | + | None |
| Incidence of very rapid borrowing by riskier borrowers | 2000-present | Riskier borrowers increasing their leverage signals lax underwriting | Mian and Sufi (2009) | + | None |
| **Nonfinancial Business** | | | | | |
| Real debt growth | 1959-present | A rise in leverage portends increased risk | Schularick and Taylor (2012) | + | None |
| Net leverage of risky firms | 1982-present | Measures conditions of risky firms | | + | None |
| Deep junk issuance share | 1993-present | Captures availability of debt for riskiest firms. | Greenwood and Hansen (2013) | + | None |
| Interest expenses | 1982-present | Increased interest expenses strain firms | | + | None |
| Debt-to-income ratio | 1985-present | Ability to financing debt using cash flow | | + | Subtract 10-year moving average |
| **Savings** | | | | | None |
| Business saving | 1952-present | Low savings increase vulnerability of households to a shock. | | - | None |
| Personal saving | 1952-present | Low savings increase vulnerability of businesses to a shock. | | - | None |

## Table A3: Indicators for Financial Vulnerabilities

| Category/Indicator | Data Availability | Motivation | Academic Studies | Direction of Increased Vulnerability | Detrending Method |
|---|---|---|---|---|---|
| **Bank Leverage** | | | | | |
| Tangible equity to tangible assets ratio | 1986 - present | Micro and macroprudential motivation | Diamond and Rajan (2001), Berger and Bouwman (2013) | - | None |
| Tier 1 common ratio at all BHCs | 2001 - present | Used in SCAP and CCAR | | - | None |
| Total risk-based bank capital ratio | 1990 - present | Leverage at the commercial bank level | | - | None |
| **Non-bank Leverage** | | | | | |
| Broker-dealer leverage | 1951 - present | | Adrian and Shin (2010) | + | None |
| Broker-dealer financing | 2001 - present | Indicator of leverage at hedge funds | | + | None |
| Non-agency securitization issuance | 2002 - present | Credit transformation | Adrian, Covitz and Liang (2013) | + | None |
| **Maturity Mismatch** | | | | | |
| Loan-to-deposit ratio at BHCs | 1996 - present | Maturity transformation | | + | None |
| Maturity gap at commercial banks | 1997 - present | | Brunnermeier and Oehmke (2013) | + | None |
| Net short-term wholesale funding at nonbanks | 1956 - present | | Brunnermeier, Gorton and Krishnamurthy (2013) | + | Subtract 10-year moving average |
| **Short-term Wholesale Funding** | | | | | |
| Gross short-term wholesale funding at nonbanks | 1956 - present | Short-term liabilities subject to runs | Hahm et al (2013) | + | Subtract 10-year moving average |
| Short-term money at BHCs | 2001 - present | Funding risk | Krishnamurthy and Vissing-Jorgensen (2013) | + | None |
| Runnable liabilities in the financial sector | 1985 - present | Unstable funding | | + | Subtract 10-year moving average |
| **Size/ Interconnectedness** | | | | | |
| Ratio of financial sector liabilities to GDP | 1951 – present | Size of financial system | Greenwood and Scharfstein (2010); | + | Subtract 10-year moving average |
| Total assets of top 5 BHCs relative to total | 1987 - present | Concentration risk; Network fragility | Gai, Haldane, Kapadia (2012) | + | None |
| Illiquidity concentration | 2002 - present | Fire-sale externalities | Duarte and Eisenbach (2013) | + | None |

## Table A4: Use of Macroprudential Indicators by Official Sector Institutions

| Institution | Purpose | Organizing structure | Number of indicators | Visualization devices |
|---|---|---|---|---|
| International Monetary Fund[1] | • The "Global Financial Stability Map" is used for monitoring financial stability risks<br>• The aim is to combine economic and financial metrics with judgment based on market intelligence and staff assessment | • Indicators categorized into four 'risks' and two underlying 'conditions'<br>• Risks include macroeconomic, emerging market, credit, and market and liquidity<br>• Conditions include monetary and financial, and risk appetite | • 33 indicators, reflecting a balance of economic, market-based, and survey-based information | • The six composite indicators of risks and conditions are shown in a spider chart in each GFSR<br>• A more granular assessment of how specific indicators have changed since previous GFSR is also provided |
| Office of Financial Research[2] | • The "Financial Stability Monitor" is used to analyze threats to financial stability | • Indicators categorized into five risk groups: macroeconomic; market; credit; funding and liquidity; and contagion | • Multiple indicators – specific indicators not provided | • Heat map table presented in the annual report |
| European Systemic Risk Board (ESRB)[3] | • Risk dashboard used to monitor vulnerabilities | • Indicators grouped into six risk categories: interlinkages; macro; credit; funding and liquidity; market; profitability / solvency | • 41 distinct indicators | • Charts of each indicator published each quarter |
| Bank of England[4] | • Used to inform decisions on sectoral capital requirements and countercyclical capital buffer<br>• Decisions made by discretion | • Indicators divided into three categories: bank balance sheet stretch; non-bank balance sheet stretch; and conditions and terms in markets. | • 25 distinct indicators for countercyclical capital buffer; 22 indicators for sectoral capital requirements | • Indicators routinely published in simple table alongside historical average values, 2006 values, and min-max range |
| Norges Bank[5] | • Core indicators used to guide the Bank's advice to Ministry of Finance on the countercyclical capital buffer<br>• Policy advice made by discretion | • Indicators of imbalances in nonfinancial sector, property prices and financial institutions' funding | • 4 indicators: (a) the ratio of total credit to GDP; (b) the ratio of house prices to income; (c) commercial property prices; and (d) banks' wholesale funding ratio | • Charts of each indicator published alongside trends and average values |
| Reserve Bank of New Zealand (RBNZ)[6] | • Core indicators used to guide policy decisions on core funding ratio, countercyclical capital buffers, sectoral capital requirements and LTV restrictions<br>• Policy advice made by discretion | • Indicators divided into three categories: (a) the build-up of risk; (b) the materialization of stress; and (c) the banking system's capacity to absorb those risks. | • 34 distinct indicators | • Charts routinely published of each indicator |
| Swiss National Bank[7] | • Used to guide advice on countercyclical capital buffer | • Indicators divided into mortgage credit and real estate prices | • Specific indicators not published | • NA |

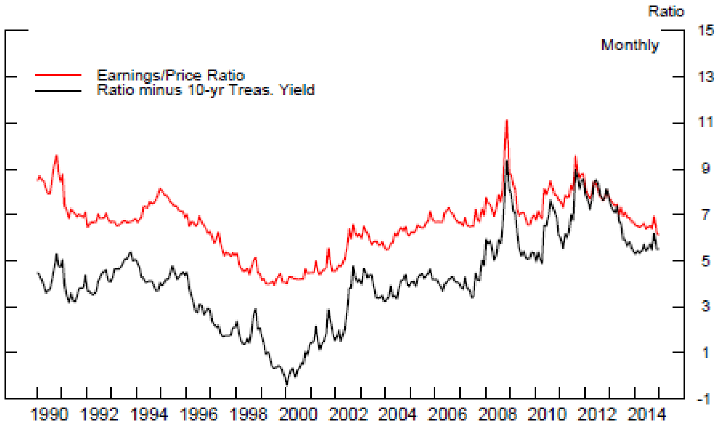
Notes: (1) See Annex 1.1 of the April 2010 Global Financial Stability Report and Dattels et al (2010) for a description of the methodology underlying the Global Financial Stability Map; (2) see Office of Financial Research (2013), page 11; (3) the ESRB's risk dashboard is available online at https://www.esrb.europa.eu/pub/rd/html/index.en.html; (4) see Bank of England (2014), tables C and D on pp40-43; (5) see Norges Bank (2013); (6) on the indicators used by the RBNZ, see Wolken (2013); on the macroprudential regime in New Zealand, see RBNZ (2013); (7) see Swiss National Bank (2014).

## Data appendix

Exhibit 1

### Indicators of Valuation Pressures and Risk Appetite I

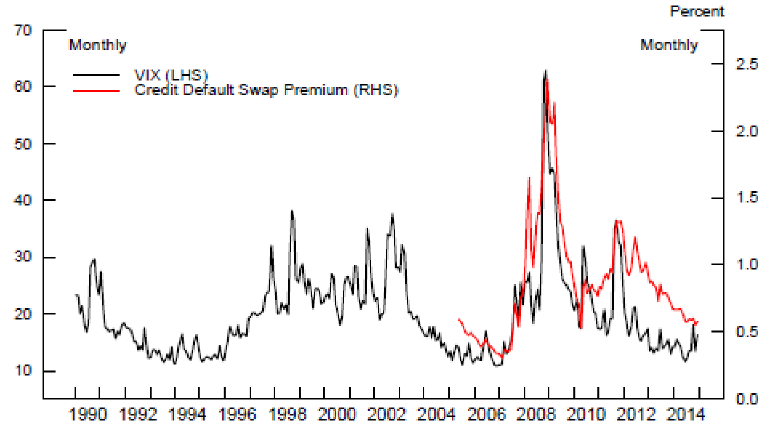
Equity Valuations




Note: Earnings/Price ratio is the ratio of expected earnings over the next 12 months divided by the value of the S&P 500.

Source: Bloomberg Finance LP; Thomson Reuters, IBES North American Summary & Detail Estimates.

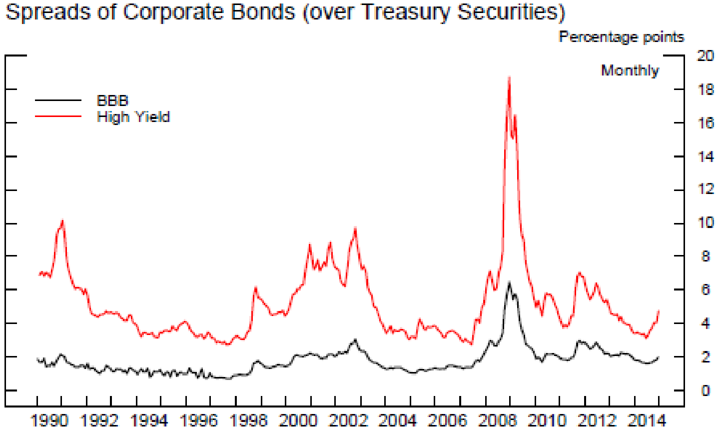
Indicators of Volatility




Note: VIX is the implied volatility on the S&P 500. Credit default swap premium is the spread of a composite of CDS on investment-grade corporations.

Source: Market Data Express, CBOE VIX Optsum and Open-Close End of Day Summary Data files; Markit Group Limited.

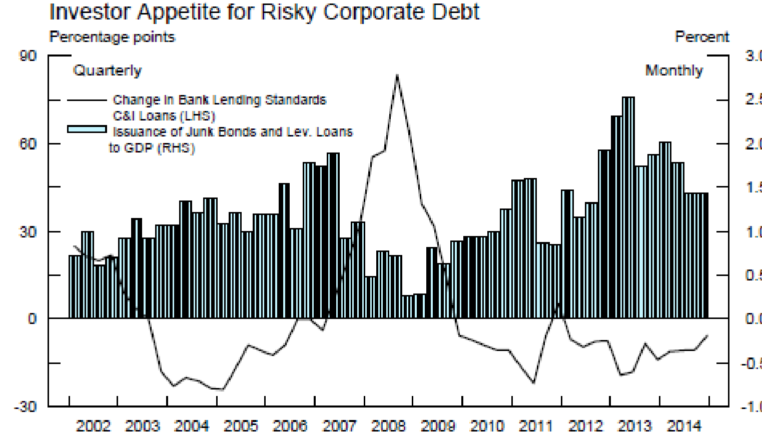
Spreads of Corporate Bonds (over Treasury Securities)




Note: BBB yield is computed from Merrill Lynch's corporate bond database using the Nelson Siegel yield curve model. High-yield is the Merrill Lynch High Yield Master II yield. Spread is the difference between these yields and the yield on a 10-year (zero-coupon) Treasury security as estimated from a smoothed yield curve. Corrections to match duration more closely have not been attempted.

Source: BofA Merrill Lynch, Bond Indices Data.

Investor Appetite for Risky Corporate Debt

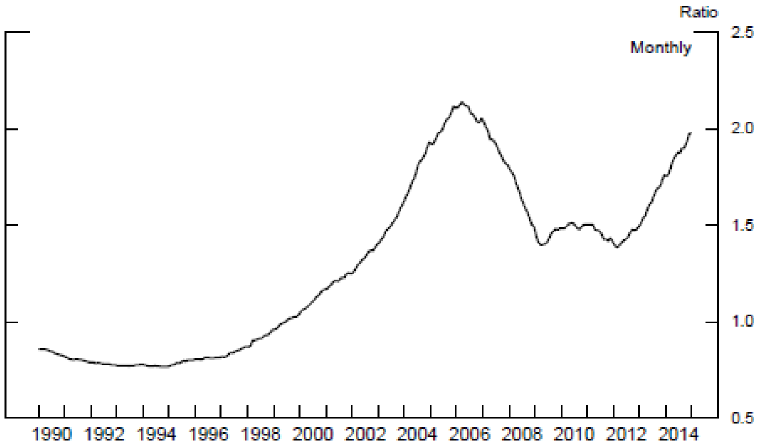



Source: Federal Reserve Board, Senior Loan Officer Opinion Survey on Lending Practices (FRB SLOOS), www.federalreserve.gov/boarddocs/SnLoansurvey/; Thomson Reuters, SDC Platinum.

Exhibit 2

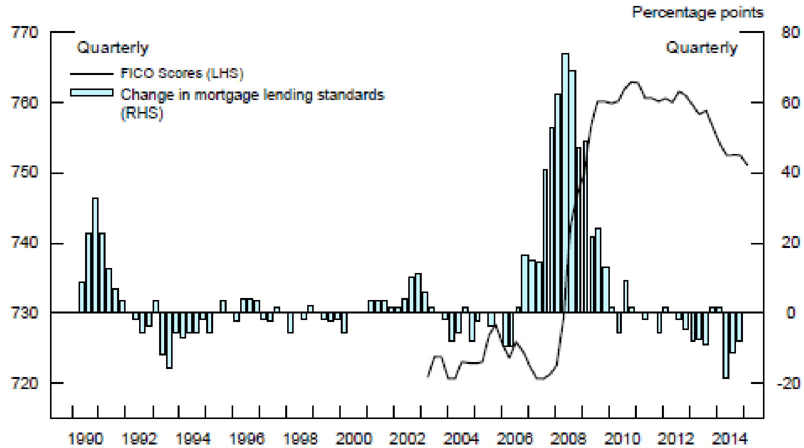
# Indicators of Valuation Pressures and Risk Appetite II

## National House Prices Relative to Rents



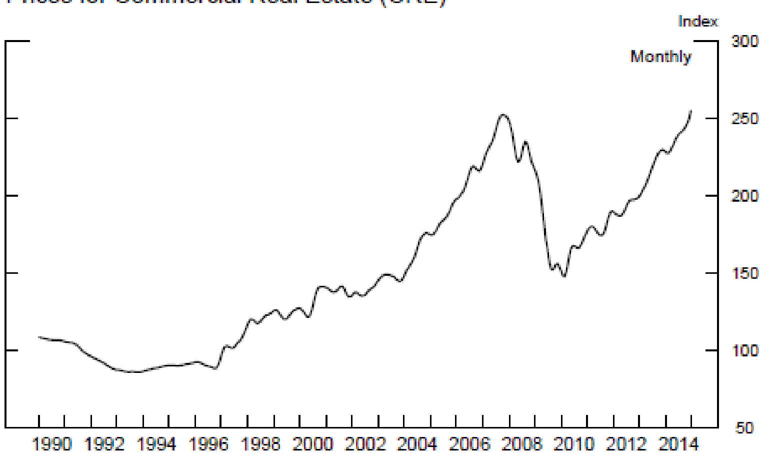

Source: CoreLogic Information Systems, Market Trends; U.S. Bureau of Economic Analysis, National Income and Product Accounts (BEA NIPA), www.bea.gov/national/.

## Mortgage Lending and FICO Scores



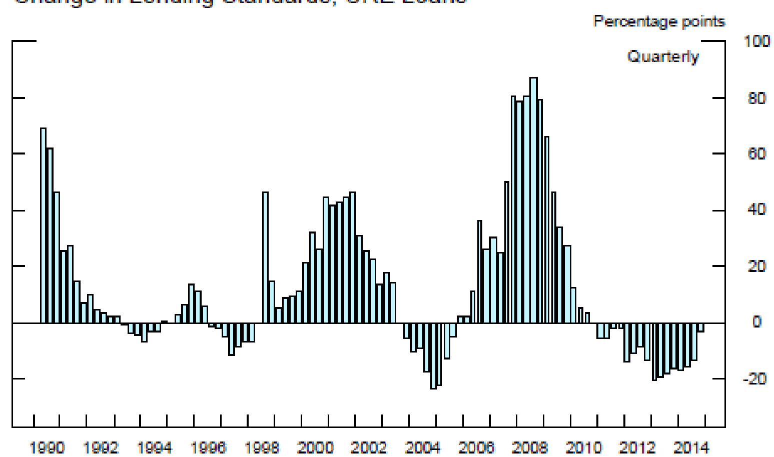

Source: Black Knight, LPS Applied Analytics Residencial Mortage Servicing Database; FRB SLOOS.

## Prices for Commercial Real Estate (CRE)




Source: Federal Reserve Board, Financial Accounts of the United States, www.federalreserve.gov/releases/z1/.

## Change in Lending Standards, CRE Loans

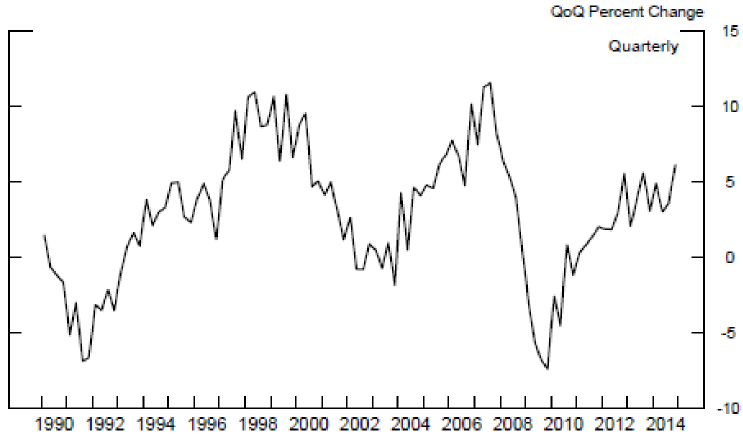



Source: FRB SLOOS.

Exhibit 3

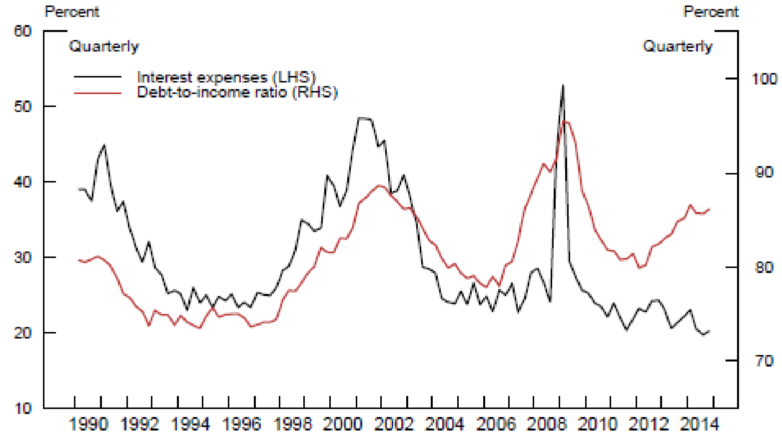
## Indicators of Nonfinancial Business Imbalances

### Real Debt Growth of Nonfinancial Businesses



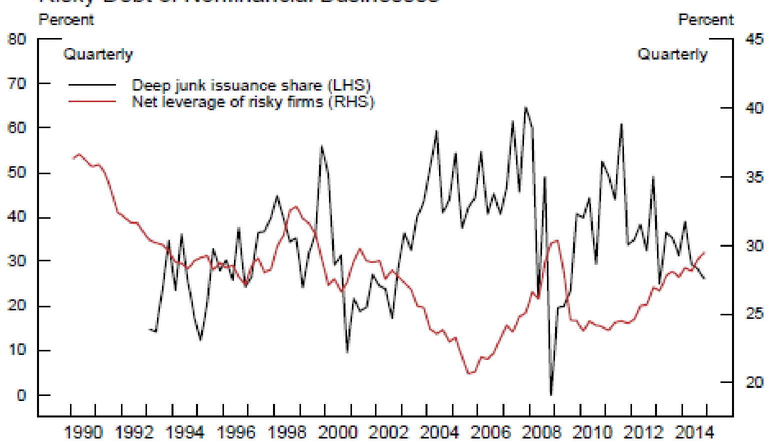

Note: The figure reports the quarter-on-quarter growth rate of aggregate debt of U.S. nonfinancial corporate businesses adjusted for inflation. Values are annualized by multiplying by four.
Source: Financial Accounts of the U.S.

### Debt Burden of Nonfinancial Businesses




Note: The figure reports the earnings-weighted average of interest expenses to earnings and the ratio of aggregate debt to income for U.S. nonfinancial corporate businesses.
Source: Financial Accounts of the U.S.; S&P, Capital IQ Compustat North America (Compustat).

### Risky Debt of Nonfinancial Businesses



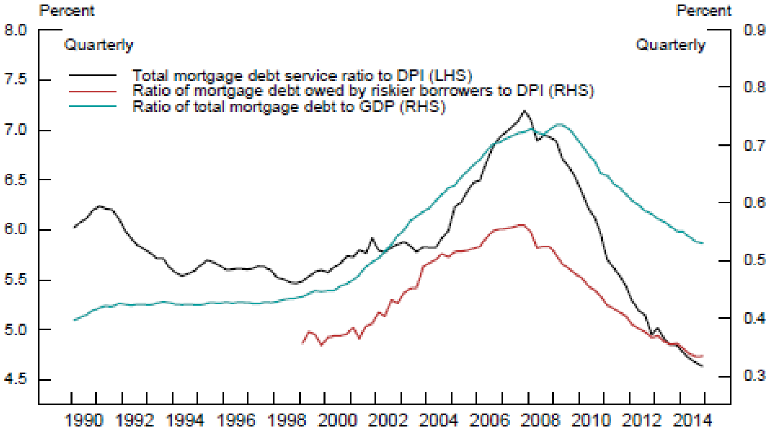

Note: The figure reports the share of high-yield debt issuance that is rated C or below and the asset-weighted average of debt to total assets of speculative grade firms and of unrated firms with debt.
Source: Compustat; Thomson Reuters, SDC Platinum.

### Ratio of Nonfinancial Business Savings to GDP


Note: The figure reports net saving less capital transfers minus net capital formation of the U.S. corporate business sector.
Source: Financial Accounts of the U.S.; BEA NIPA.

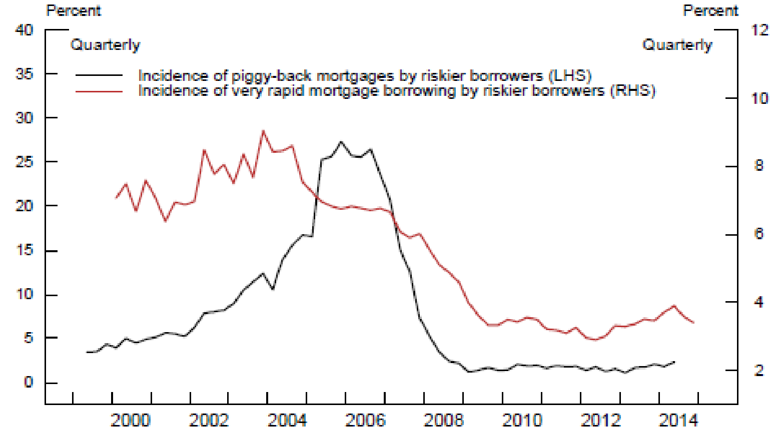
Exhibit 4
## Indicators of Household Mortgage and Consumer Credit Imbalances

### Home Mortgage Debt




Note: Riskier borrowers are those whith credit scores below 780.
Source: Federal Reserve Board, Household Debt Service and Financial Obligations Ratios (FRB DSR), http://www.federalreserve.gov/releases/housedebt/default.htm; FRBNY Consumer Credit Panel/Equifax Data; Financial Accounts of the U.S.; BEA NIPA.

### Mortgage Borrowing by Riskier Borrowers

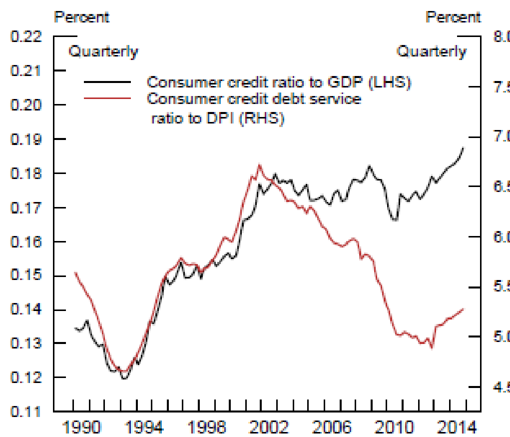



Note: Riskier borrowers are those whith credit scores below 780.
Source: FRBNY Consumer Credit Panel/Equifax Data.

### Ratio of Household Savings to GDP

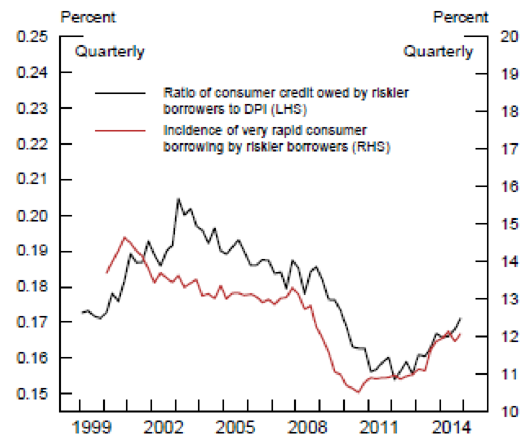

Note: The figure reports net saving less capital transfers minus net capital formation of the U.S. household sector.
Source: Financial Accounts of the U.S.; BEA NIPA.

### Consumer Credit




Source: FRB DSR; Financial Accounts of the U.S.; BEA NIPA.

### Consumer Credit of Riskier Borrowers

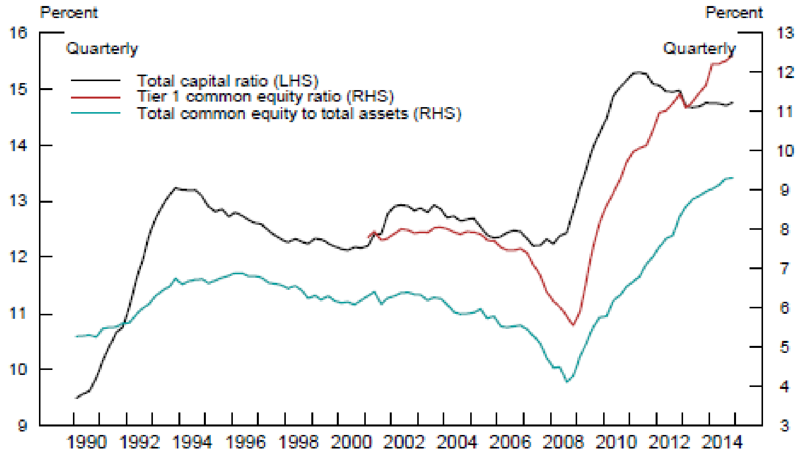



Note: Riskier borrowers are those with credit scores below 780.
Source: FRBNY Consumer Credit Panel/Equifax Data; BEA NIPA.

Exhibit 5

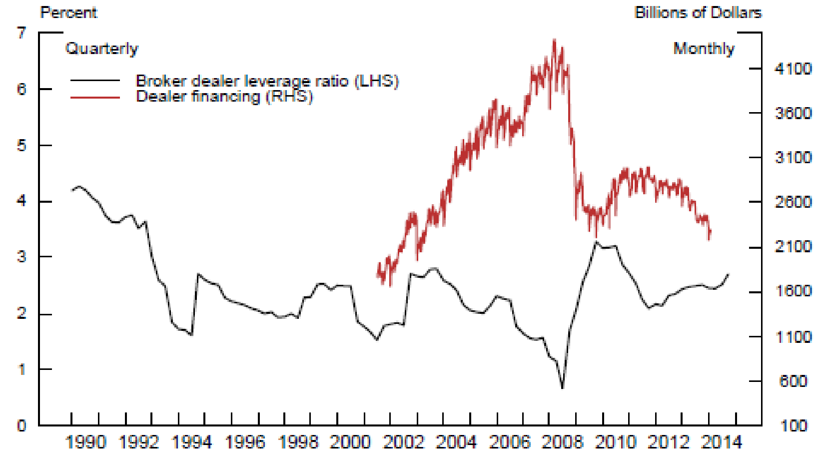
# Indicators of Financial Business Imbalances I

## Bank Leverage



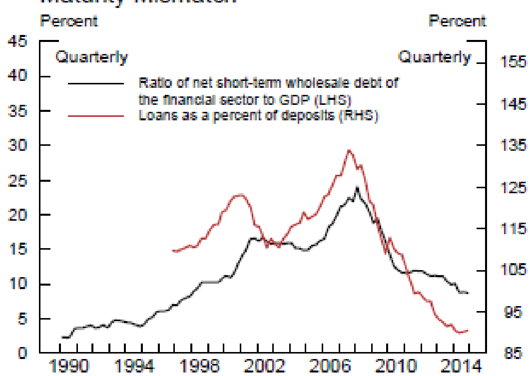

Source: Federal Reserve (FR) Y-9C (Consolidated Financial Statements for Holding Companies), http://www.federalreserve.gov/apps/reportforms/default.aspx ; FFIEC Consolidated Reports on Condition and Income (Call Report), www.ffiec.gov/forms031.htm.

## Broker Dealer Leverage




Source: Financial Accounts of the U.S.; FR 2004C, http://www.federalreserve.gov/apps/reportforms/default.aspx.

## Maturity Mismatch



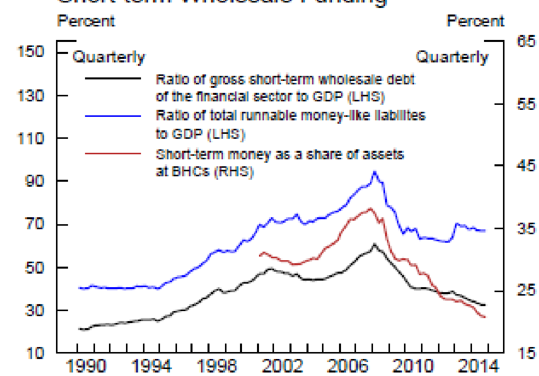

Source: FRB FAUS; FR Y-9C.

## Weighted Average Maturity Gap at Commercial Banks


Note: Maturity gap is the approximate weighted-average time to maturity or next repricing date of interest-bearing assets less the approximate weighted-average time to maturity or next repricing date of liabilities. The maturity approximations are based on the midpoint of the ranges in the Call Report. Liquid deposits are assumed to have a maturity of 1 year.

Source: Call Report.

## Short-term Wholesale Funding



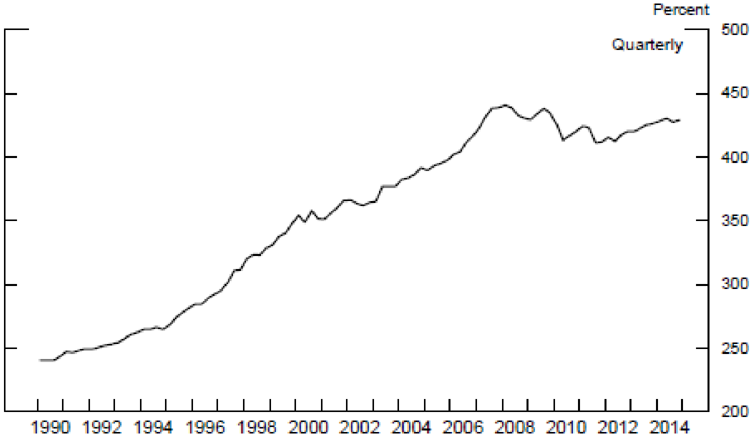

Note: Runnable money-like liabilities are defaultable, "pay-on-demand" liabilities (with explicit insurance) either with a short maturity or with the claimholder having a contractual put option that can be exercised on a short notice.

Source: Multiple sources; detail provided upon request.

Exhibit 6

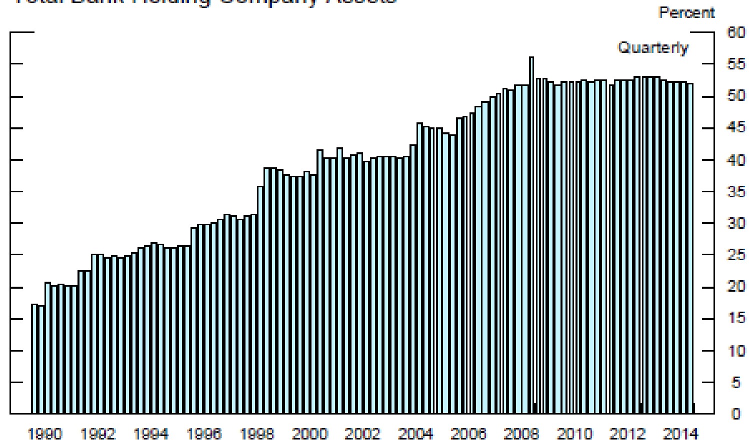
**Indicators of Financial Business Imbalances II**

Ratio of Total Financial Sector Liabilities to GDP



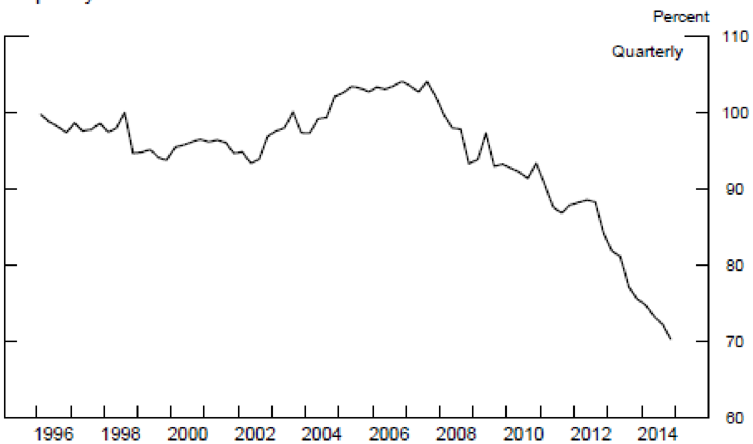

Source: Financial Accounts of the U.S.

Ratio of Total Assets Held by Top 5 Bank Holding Companies to Total Bank Holding Company Assets



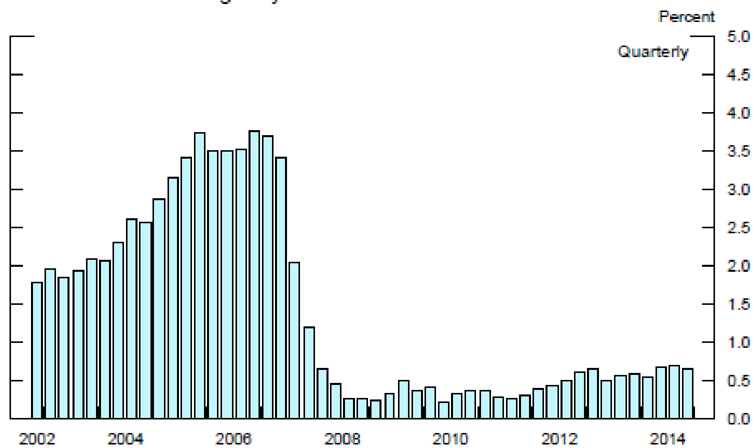

Source: FR Y-9C.

Illiquidity Concentration Indicator




Note: Illiquidity concentration is a measure of how clustered illiquid assets are in large and levered institutions.
Source: Duarte and Eisenbach (2013).

Ratio of U.S. Non-Agency Securitization Issuance to GDP




Source: Harrison Scott Publications, Asset-Backed Alert and Commercial Mortgage Alert.