The Anatomy of Financial Vulnerabilities and Banking Crises

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Seung Jung Lee[†]
Kelly E. Posenau[#]
Viktors Stebunovs[‡]

Abstract: We extend the framework of Aikman, Kiley, Lee, Palumbo, and Warusawitharana (2017) that maps vulnerabilities in the U.S. financial system to a broader set of financial vulnerabilities in 27 advanced and emerging economies. We capture a holistic view of the evolution of financial vulnerabilities before and after a banking crisis. We find that, before a banking crisis, pressures in asset valuations materialize first and then a build-up of imbalances in the external, financial, and nonfinancial sectors occurs. After a crisis, these vulnerabilities subside, but sovereign debt imbalances rise as governments try to mitigate the consequences of the crises. Our main index, which aggregates these vulnerabilities, predicts banking crises better than the Credit-to-GDP Gap (CGG) or sector-specific vulnerability indexes, especially at long horizons. Our main index also predicts the severity of banking crises and the duration of recessions that follow better than the other indicators, as it incorporates possible spillover and amplification channels of vulnerabilities from one sector to another. Therefore, our framework is useful for macroprudential policy making and crisis management.

Keywords: banking crises; financial vulnerabilities; early warning indicators, Credit-to-GDP Gap; macroprudential policy; crisis management.

JEL Classifications: C82, D14, G01, G12, G21, G23, G32, H63.

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[†] Board of Governors of the Federal Reserve System, corresponding author; seung.j.lee@frb.gov.
[#] The University of Chicago Booth School of Business; kposenau@chicagobooth.edu.
[‡] Board of Governors of the Federal Reserve System; viktors.stebunovs@frb.gov.

1 Introduction

In this paper, we examine how various financial vulnerabilities evolve in the lead-up to and in the aftermath of banking crises in various advanced and emerging economies. We develop a holistic framework to track financial imbalances that may render the financial system highly vulnerable to shocks to the economy.

Our paper belongs to the strand of the academic literature on financial imbalances, financial crises, and systemic risk that has been brought to the forefront by the Global Financial Crisis (GFC). The GFC, which began as banking crises in the United States and the United Kingdom in 2007, ended up quickly spreading to other financial systems around the world. This experience has profoundly changed the global financial regulatory landscape. Central banks and other official institutions, in turn, have established various tools and early warning indicators to monitor financial stability risks.[1] Our paper draws from these advancements to put together a comprehensive early warning indicator that covers multiple areas where vulnerabilities can build up, that captures potential spillover and amplification channels of vulnerabilities, and that predicts at long horizons the timing of banking crises and the severity and durations of recessions that follow.

We posit a view that the advent of a financial crisis can be decomposed into a financial vulnerability or imbalances component and a shock component (as in Gorton and Ordonez (2014)). Understanding how financial vulnerabilities and imbalances evolve in the run-up to a banking crisis provides a better framework to understand the role that the first component plays in the realization of banking crises. Building upon research on how different types of vulnerabilities in the financial system have set the stage for a dramatic unraveling of financial imbalances (Ferguson, Hartmann, Panetta, and Portes (2007), Reinhart and Rogoff (2009), and Aikman, Kiley, Lee, Palumbo, and Warusawitharana (2017)), our aim is to shed light on whether both the occurrence and severity of banking crises are correlated with the level of vulnerabilities present in the financial system prior to banking crises.

[1] For example, the Office of Financial Research and the International Monetary Fund publishes the Financial Stability Report and the Global Financial Stability Report, respectively, on a regular basis. In addition, the European Systemic Risk Board also maintains a "Risk Dashboard," which is a set of quantitative and qualitative indicators of systemic risk in the EU financial system.

We extend the framework of in Aikman, Kiley, Lee, Palumbo, and Warusawitharana (2017) that maps vulnerabilities in the U.S. financial system to a broader set of 27 advanced and emerging economies. The key contribution of Aikman, Kiley, Lee, Palumbo, and Warusawitharana (2017) was to develop an algorithmic approach which uses a large set of indicators to monitor vulnerabilities that can identify imbalances in the U.S. financial system. Because of banking crises in the United States have been infrequent, Aikman, Kiley, Lee, Palumbo, and Warusawitharana (2017) could not formally test the predictive power of their index with respect to banking crises. They provided only a narrative. In contrast, since we look at a broader set of vulnerabilities for a panel of nearly 30 countries, some of which have experienced multiple banking crises, we can determine the predictive power of our vulnerability index that is derived from a bottom-up, holistic framework. That is, we can establish the power of such an indicator to predict the timing of a banking crisis and the severity and duration of a recession that follows. In addition, we can compare our findings with the performance of the Credit-to-GDP Gap (CGG), which has been touted as the best predictor of banking crises at longer horizons and, hence, is argued to be the benchmark in setting counter-cyclical capital buffers (see Drehmann and Juselius (2014)).

We categorize different vulnerabilities that may contribute to the amplification of economic and financial shocks stemming from five sectors in a financial system. We start from the three main categorizations of vulnerabilities used in Aikman, Kiley, Lee, Palumbo, and Warusawitharana (2017): risk appetite and valuation pressures, financial sector vulnerabilities, and nonfinancial sector vulnerabilities. Due to data availability, we adjust the subcomponents of these vulnerabilities. For example, risk appetite has three main subcomponents; the equity market, the housing market, and the bond market, where excessive risk appetite can lead to a build-up of imbalances and a quick correction can lead to a destabilizing unraveling of other financial imbalances. Financial sector vulnerabilities has two main subcomponents; the banking sector and nonbank financial sector, as does the nonfinancial sector vulnerabilities; the household sector and the corporate sector. Excessive credit in all of these sectors have been associated with a variety of different banking crises. The banking sector is, in turn, composed of four additional subcomponents; leverage, maturity transformation, reliance on short-term wholesale funding, and cross-border interconnectedness, all of which make the financial system more susceptible to financial or economic shocks and appears to have played a role in the GFC and its contagion.

Next, we introduce two types of vulnerabilities that are absent in Aikman, Kiley, Lee, Palumbo, and Warusawitharana (2017): external sector vulnerabilities, as motivated by the sudden stops and the currency/banking twin crisis literature (Mendoza (2010), Frankel and Rose (1996), and Kaminsky and Reinhart (1999)), and sovereign sector vulnerabilities, as motivated by the recent European sovereign debt crisis and the emerging market debt crisis literature (Lane (2012) and Dawood, Horsewood, and Strobel (2017)). Excessive borrowing from abroad has sometimes been associated with debilitating consequences when confidence of foreign investors wane; whereas governments' strained budget and debt positions have, in many cases, been a consequence of banking crises (Reinhart and Rogoff (2011)). Tracking these types of vulnerabilities provides a more complete picture of how different vulnerabilities evolve around banking crises.

We find that vulnerabilities in risk appetite and the external sector are especially elevated two to three years prior to a banking crisis. As an earlier warning indicator, imbalances in asset valuations tend to peak a couple of years before banking crises and corrections to valuations are well under way even before the crises occur. External and financial sector vulnerabilities also become elevated well before and peak around the onset of financial crises. Nonfinancial sector vulnerabilities also become elevated nearing the onset of crises and remain elevated even afterwards. In our sample of 27 countries that have gone through a financial crisis in the past 30 years (1986-2015), sovereign vulnerabilities have played a minimal role prior to banking crises. In fact, sovereign vulnerabilities appear to be lagging indicators. The level of sovereign vulnerabilities usually becomes elevated as governments mitigate the consequences of a crisis through an increase in sovereign debt and as they experience declines in tax revenue.

We show that our bottom-up index—the Lee-Posenau-Stebunovs (LPS) Index—that aggregates vulnerabilities in multiple categories outperforms top-down aggregate measures, such as the CGG and the total debt service ratio, in addition to the myriad of sector-specific subindexes constructed through our framework. We show that at a horizon that is relevant for policy making—two to three years prior to banking crises—the LPS Index outperforms the CGG in predicting crises. While we examine the performance of the LPS Index's components, we show that the predictive power of the overall index is, in part, attributable to the External Sector Vulnerability Index. In addition, we show that the LPS Index predicts the severity of banking crises as the aggregation takes into account possible spillover and amplification channels of vulnerabilities across the sectors. We also show that it is the Nonfinancial Corporate Sector Vulnerability Index that drives the LPS Index's superior predictive performance for economic output losses after banking crises. This finding suggests that the balance sheets of corporations are a key in determining how severe banking crises will turn out to be (even though vulnerabilities in the nonfinancial sector are not good at predicting the onset of banking crises). We also show that the LPS + Sovereign Index, driven by its risk appetite component for housing, provides a good predictor for the duration of recessions that follow banking crises. Overall, the aggregate LPS Indexes appear to strike a good balance in terms of predicting both the onset and severity of banking crises.

The key contribution of this paper, therefore, is showing that a bottom-up, holistic approach to financial stability monitoring can produce indicators that can predict both the onset and severity of banking crises and that can outperform top-down and sector-specific early warning indicator metrics that are touted in the literature. This contribution, in turn, has important policy implications for both macroprudential and crisis management policy making.

The outline of the rest of the paper is as follows. In the next section, we provide a framework for understanding how banking crises arise and conclude. In Section 3, we describe the data used for our analysis and the aggregation method, drawing heavily from Aikman, Kiley, Lee, Palumbo, and Warusawitharana (2017). In Section 4, we examine the evolution of different vulnerabilities leading up to and after banking crises. In Section 5, we compare the aggregate LPS Indexes with the CGG measure in predicting both the occurrence and severity of banking crises, in addition to comparing how the subindexes fair relative to the CGG. In Section 6, we do the same for the onset, duration, and depth of recessions. In the last section, we conclude with a discussion of the implications of our findings, how our framework could be used for detecting other types of financial crises, and how measures of aggregated vulnerabilities, such as the aggregate LPS Indexes, can be used for policy purposes.

2 Vulnerabilities and Financial Shocks

In this section, we provide a framework to analyze banking crises. Danielsson, Valenzuela, and Zer (2016), Claessens and Kose (2014), Ferguson, Hartmann, Panetta, and Portes (2007), and Reinhart and Rogoff (2009) provide a more modern view of how financial crises come to fruition and develop by looking at conditions that are breeding grounds for the build-up of financial vulnerabilities. Classical references in the literature include Kindelberger (1978) and Eichengreen and Portes (1987). Eichengreen and Portes (1987), in particular, look closely at the full-fledged global crisis in the 1930s and point to linkages between debt defaults, exchange-market disturbances, and bank failures that are crucial in understanding the critical role played by institutional arrangements in that era.

The origins of banking crises can be very diverse, but, as seen in the literature, there are some common themes we exploit. We posit that financial crises fundamentally arise from shocks to the economy. An example from the recent financial crisis in the United States could be the sudden realization that subprime mortgage-backed securities were not as safe as their ratings would imply or realizing collateral value was not what it seemed in the repo market (see Gorton and Metrick (2012) and Gorton and Ordonez (2014)). From many of the peripheral European countries' perspective, contagion could presumably arise from financial shocks in the U.S., the U.K. and core European countries. However, not all shocks lead to financial or banking crises. Indeed, financial systems around the world, more often than not, are able to withstand shocks to the economy as vulnerabilities or imbalances in the financial system may be very subdued at the time of the financial or economic shock.

For illustrative purposes, Figure 1 allows us to visualize our basic framework for understanding banking crises. Point A, for example, represents an economy with relative subdued vulnerabilities or imbalances in its financial system. Even if this state of the world may be a drag on the real economy, given that a very large shock would be necessary to move the financial system to the "crisis" state, the likelihood of a financial crisis would be fairly low. At point B, however, when vulnerabilities are elevated, even a small shock can trigger a change into the crisis state. As the shock makes its way through the system, vulnerabilities and imbalances unwind or, in a sudden correction, unravel to less elevated levels to point C. The unwinding or unraveling of vulnerabilities leads to financial disintermediation. The point at which the shock materialized, therefore, may have implications for the severity of the crisis, if a crisis occurs. This decomposition between vulnerabilities (which one can more confidently define and measure) and shocks allows us to posit research questions in a tractable manner.

Moreover, our prior is that vulnerabilities in "aggregate," that take into account possible spillover and amplification channels of both excessive credit creation and financial stress from one sector to another in the economy, should be better at detecting both the build-up and explaining the onset/severity of banking crises rather than a simple top-down metric such as the CGG or vulnerabilities in a specific sector in the financial system, which may be good at predicting the onset, but not the severity, or *vice versa*.

In this context, we can set forth two hypotheses from our framework for understanding financial crises. First, using extensive data, we will see whether vulnerabilities or imbalances in the financial system as a whole can shed light on the likelihood of an onset of a banking crisis as argued in Ferguson, Hartmann, Panetta, and Portes (2007) and Reinhart and Rogoff (2009). If we find that it can, we can argue that not only shocks (which by definition can trigger crises), but the state of imbalances in the financial system provide fertile grounds for a banking crises.

For the second hypothesis, we focus on the aftermath of banking crises. We will see if t elevated vulnerabilities or imbalances in aggregate right before a crisis have any bearing on the severity of the crisis once it occurs. We look to see if there is a positive and significant relationship between aggregated vulnerability measures just prior to crises and output loss after the crises have occurred.

3 Data and Aggregation Methodology

3.1 Data for Financial Crises and Output Losses

Our primary data source for banking crisis episodes is from Laeven and Valencia (2013) during 1986-2012. Table 1 provides the years and quarters at which these banking crisis episodes began and the output loss associated with these episodes for 27 countries, eight of which can be considered developing or emerging market economies.[2] Although the majority of the episodes are those of advanced economies in the recent GFC, a dozen include the banking crises of Scandinavian countries in the early 1990s, the banking crises of East Asian countries in the late 1990s, and other episodes of crises in other emerging markets in the sample period. Banking crises are defined as having significant signs of financial distress in the banking system (bank runs, losses in the banking system, and bank liquidations) and significant banking policy intervention measures in response to significant losses in the banking system.

Output loss is also taken from Laeven and Valencia (2013) and is computed as the cumulative sum of the differences between actual and trend real GDP over four years, expressed as a percentage of trend real GDP starting from the year of the crisis. Trend real GDP is computed by applying an HP filter (with $\lambda = 100$) to the log of real GDP series over the previous 20 years (or shorter if data is not available with a minimum of four years).

In looking at determinants of output loss after banking crises, we contribute to the literature that associates different types of crises to output loss. For example, Blanchard, Cerutti, and Summers (2015) looks at the effects of recessions on output. Howard, Martin, and Wilson (2011) attempts to compare how recoveries are affected by different types of recessions—those that are related to banking crises and those that are not. Finally, Kroszner, Laeven, and Klingebiel (2007) looks at 38 developed and developing countries that experienced financial crises during the last quarter century, and find that those sectors that are highly dependent on external finance tend to experience a substantially greater contraction

[2] These emerging market economies are Brazil, China, Malaysia, Mexico, Russia, South Korea, Thailand, and Turkey.

of value added during a banking crisis in countries with deeper financial systems than in countries with shallower financial systems. Claessens, Kose, and Terrones (2012) and Taylor (2015) also examine the relationship between business cycles and financial disruptions.

Following the financial cycle literature, we restrict our sample of analysis to the past 30 years (1986-2015) to account for financial cycles that are longer than business cycles (see Borio (2014). In addition, the financial systems in these countries have likely experienced significant structural shifts since prior to 1986 and, therefore, data may be subject to structural breaks going further back in time.

3.2 Data for Vulnerabilities

As for our data related to vulnerabilities and imbalances in the financial system, we begin by starting with the three vulnerability categories emphasized in Adrian, Covitz, and Liang (2015) and Aikman, Kiley, Lee, Palumbo, and Warusawitharana (2017); risk appetite and valuation pressures, financial sector vulnerabilities, and nonfinancial vulnerabilities. We also consider two additional vulnerability categories: external sector vulnerabilities and sovereign vulnerabilities, which have been crucial in understanding banking crisis episodes in emerging markets and, more recently, in the European sovereign debt crisis.

Risk appetite We estimate valuation pressures using three components: housing market pressures, equity market pressures, and junk bond issuance, where excessive risk appetite could lead to a build-up of imbalances and a quick correction can lead to a destabilizing unraveling of other financial imbalances (Cecchetti (2008)). For housing market pressures, we use price-to-rent ratios for OECD countries, along with either nominal price to income or nominal price to GDP. We use nominal price to GDP for countries where personal disposable income is not readily available. Equity market pressures includes the weighted average price/earnings ratio, based on 12-month forward earnings and also dividend to yield ratios (with negative sign), which are backwards-looking but have a longer time series than our forward P/E ratios.[3] Finally, junk bond issuance is calculated as the 12-month moving sum

[3]for the United States, price/earnings ratios go back further in time and we do not use the dividend to yield ratio.

of high-yield nonfinancial issuances over the 12-month moving sum of total issuances.

Financial sector vulnerabilities Financial sector vulnerabilities are split into the banking vulnerabilities and nonbank financial sector vulnerabilities.

Under the banking sector, there are four components: leverage; maturity transformation; reliance on wholesale funding; and interconnectedness, all of which make the financial system more susceptible to financial or economic shocks and appears to have played a role in the GFC and its contagion (see Geanakoplos and Pedersen (2012), Brunnermeier, Gorton, and Krishnamurthy (2013), and Gertler and Kiyotaki (2015). Indicators used for each component may differ between countries and are also derived from studies such as Demirguc-Kunt and Dtragiache (1997) and Borio and Lowe (2002), which study factors that lead to banking crises. In order to maintain consistency, we use data on a residential basis for domestic banks and deposit-taking institutions (excluding central banks). In some cases, due to data availability, we may use data on a consolidated basis or incorporate other types of lenders, such as development banks. For leverage, in all countries, we use bank credit to the private nonfinancial sector to GDP (relative to a 10-year moving average) and either capital and reserves to total assets of the banking system or equity capital to total assets (with negative signs). Depending on country data availability, we also include regulatory leverage ratios, such as a simple leverage ratio and a regulatory capital to risk-weighted assets ratio (again with negative signs). Maturity transformation is measured across countries using a loans to deposits ratio, although the exact variables used to construct the numerator and denominator may differ between countries. In general, we measure nonfinancial loans to nonfinancial deposits in order to maintain consistency across country the best we can. Reliance on wholesale funding also varies across countries. In general, we proxy the reliance on short-term wholesale funding by monetary financial institutions (MFI) liabilities to total assets. When available, we also add other short-term liabilities to MFI liabilities. We incorporate other indicators into the wholesale funding component when data is available. These indicators may include a regulatory liquidity ratio, liquid assets to short-term liabilities (both with negative signs), and short-term liabilities to total assets. Finally, we consider interconnectedness to be foreign assets to total assets. For some countries, foreign assets is unavailable; for instance, euro-area countries foreign assets only includes exposures to other euro-area countries. Therefore, we supplement this indicator with cross-border claims from the Bank of International Settlements (BIS) locational banking statistics to total banking sector assets.

As for the nonbanking financial sector, we are motivated by Gennaioli, Shleifer, and Vishny (2013) and Neuhann (2017) and we proxy nonbank leverage across countries as nonbank-provided credit to the private nonfinancial sector to GDP (relative to a 10-year moving average). Nonbank-provided credit is approximated by subtracting the BIS measure of credit from the banking sector to the private nonfinancial sector from total credit to the private nonfinancial sector. Although this is an imperfect measure of nonbank leverage, it provides an aggregate view of how much credit is being provided by the nonbanking sector relative to its history. For the United States, we also add other measures of nonbank financial sector leverage as in Aikman, Kiley, Lee, Palumbo, and Warusawitharana (2017).

Nonfinancial sector vulnerabilities Nonfinancial sector vulnerabilities have two components: the corporate sector and the household sector. Excessive credit in any of these sectors have been associated with a variety of different banking crises. In particular, Mian and Sufi (2009) and Mian and Sufi (2014) show that household leverage lead to crises and has negative consequences for employment. Depending on data availability, we judge corporate sector vulnerabilities to include the following indicators: aggregated corporate debt to equity, the 90th percentile of corporate debt to equity ratios, the corporate interest coverage ratio, business debt to GDP (relative to a 10-year moving average), and the nonfinancial corporation debt service ratio. Some countries, such as the United Kingdom, have additional information on CRE loan-to-value ratios. Vulnerabilities in the household sector are measured using credit to households and NPISHs to GDP (relative to a 10-year moving average) and the household debt service ratio. Again, some countries have addition information, such as mean loan-to-value ratios on mortgages.

External sector vulnerabilities We introduce the external sector vulnerabilities into our framework, as motivated by the sudden stops and the currency & banking twin crisis literature (Mendoza (2010), Frankel and Rose (1996), and Kaminsky and Reinhart (1999)). Excessive borrowing from abroad have sometimes been associated with debilitating consequences when confidence of foreign investors wane. The external sector vulnerabilities index is created using the following three indicators: external debt to GDP (relative to a 10-year moving average), the current account deficit to GDP, and reserves to GDP (with a negative sign), following the currency crisis literature (Kaminsky, Lizondo, and Reinhart (1998)).

Sovereign vulnerabilities We also introduce sovereign vulnerabilities, as motivated by the recent European sovereign debt crisis and the emerging market debt crisis literature (Lane (2012) and Dawood, Horsewood, and Strobel (2017)). In particular, governments' strained budget and debt positions have, in many cases, been a consequence of banking crises Reinhart and Rogoff (2011). The sovereign vulnerabilities category is comprised of three indicators, differing from the previous two categories. We estimate sovereign vulnerabilities using the aggregation of government debt to GDP (relative to a 10-year moving average), the fiscal deficit to GDP, and government revenue to GDP (relative to a 10-year moving average, with a negative sign), which are some key factors in the sovereign debt crisis literature (Detragiache and Spilimbergo (2001), Manasse, Roubini, and Schimmelpfennig (2003), Lee (2009), and Manasse and Roubini (2009)).

Table 2 shows the number of variables used in each vulnerability category. As for details on each data series, see Appendixes in Lee, Posenau, and Stebunovs (2017) for data sources for non-U.S. countries and Aikman, Kiley, Lee, Palumbo, and Warusawitharana (2017) for data sources for the United States. The number of variables used for each country ranges from 17 to 30 depending on data availability. For the United States, we first stripped out vulnerability series that could not be categorized in the new categorization scheme in this paper and augmented with variables that were available for other countries, such as various breakdowns of credit to and from different sectors in the economy relative to GDP. On net, this decreased the number of data series from 46 to 30 indicators to be used in this paper.

3.3 Data Cleaning and Aggregation Methodology

The data cleaning and aggregation methodology closely follows Aikman, Kiley, Lee, Palumbo, and Warusawitharana (2017) and the steps are as follows.

1. After detrending some of the variables with generally obvious time trends by subtracting its recent 10-year moving average (as mentioned in the previous Section 3.2), we standardize each indicator time series, denoted by indicator l and time t, by subtracting the sample average values (at most 30 years worth) and then dividing by the sample standard deviations. Denote the vulnerability category or subcomponent as k. $X(l, k, t)$ is now the standardized indicator[4]

2. Each component or subcomponent index is the simple weighted average of the standardized indicators for that component or subcomponent as in Equation 1.[5] Importantly, an indicator time series may have different start dates. This enables us to incorporate additional indicators as more data become available, covering a wider range of vulnerabilities since the late 1990s and early 2000s. We require at least 10 years of data for the indicator to be included in our set-up.

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

3. We estimate the distribution of each component using a non-parametric kernel estimator.[6] The observation for each component is then transformed onto the (0, 1) interval based on its quantile in its historical distribution. The indicators we collect are at the monthly, quarterly, or annual frequency, and the indexes we construct are at the monthly frequency. Our analysis is based on the quarterly frequency of the monthly indexes created by our methodology.

[4] We also explore the implications of our analysis using a one-sided, pseudo real-time standardization in our analysis.

[5] The only exception on equal weighting is when we combine the banking sector and nonbank sector to formulate the financial sector vulnerabilities. Instead, we weight by credit outstanding at banks and the nonbanking sector, respectively.

[6] We use the default bandwidth in MATLAB, which is theoretically optimal for estimating densities for the normal distribution.

4. At each aggregation step, for example aggregating from the various banking sector components to the an aggregate banking sector vulnerability index, we follow the steps in 2 and 3. Therefore, each vulnerability index will range between 0 and 1.

5. Finally, we define the Lee-Posenau-Stebunovs (LPS) Index as the overall country-level vulnerability index composed of four of the five main vulnerability categories; risk appetite, financial sector, nonfinancial sector, and external sector vulnerabilities. We also construct another aggregate index that includes sovereign vulnerabilities (the LPS + Sovereign Index) for comparison.

Our aggregate and subcomponent vulnerability indexes for each country are indicative of how vulnerable each sector is (or how much imbalances each sector has) relative to their own history. There is no cross-country component to our indicators. The reason we do not pool the data and also compare across countries is because of severe accounting, reporting, or structural differences across countries in terms of financial sector development. In addition, data availability varies widely across countries.

Figure 2 illustrates how data is categorized into to relevant categories and subcategories of vulnerabilities. Each rectangle represents a vulnerability index that is created in our framework, but we focus on the five main vulnerability indexes; the Risk Appetite Index, the Financial Sector Index, the Nonfinancial Sector Index, the External Sector Index, and the Sovereign Index, in addition to the two aggregate indexes at the country level; the LPS Index and the LPS + Sovereign Index.

Extensive research has been done on how different detrending methods on a selected number of indicators and different weighting schemes affect aggregate vulnerability measures; for example, Aikman, Kiley, Lee, Palumbo, and Warusawitharana (2017) consider different detrending horizons and weighting schemes and find that as long as the underlying indicators are correlated to a certain extent, not much changes to the aggregate vulnerability index in the United States. More specifically, whether one detrends the data using 5 to 20 year moving averages do not change the results; while using arithmetic averages, geometric averages, root mean squares, or principal components, also lead to a similar aggregate index. Fisher and Rachel (2017), meanwhile, for a handful of countries, analyze how simple detrending methods such as subtracting moving averages compare with Hodrick-Prescott (HP) filter-based approaches and find that aggregate vulnerability measures are not materially affected on average, arguing that aggregation is fairly robust to different views of the underlying trend. Hamilton (2017) goes so far as to say that the HP filter should never be used due to its production of series with spurious dynamic relations that have no basis in the underlying data-generating process and other reasons. We stick with the same detrending method used in Aikman, Kiley, Lee, Palumbo, and Warusawitharana (2017), subtracting the 10-year moving average with generally obvious time trends for a handful of the 17 to 30 indicators per country, as it appears to strike a balance of having to need a long time series and providing a view of time trends with sufficient history.

What we have found that has a more of a material effect on aggregation methodology is different categorizations of the data. For comparison, Figure 3 compares the LPS Index for the United States, which strips out some more detailed aspects of certain vulnerabilities compared to the aggregate index used in Aikman, Kiley, Lee, Palumbo, and Warusawitharana (2017) (AKLPW Index), but also augments the AKLPW Index with some sector specific credit metrics and an external sector vulnerability measure. There are relatively large differences between the AKLPW Index and the LPS Index, which occur in the mid-1990s and since after the crisis, largely due to the consideration of the external sector vulnerabilities in the LPS Index and the additional risk appetite measures in the AKPLW Index that have been kept out of the LPS Index (such as forward-looking volatility measures are not available for other countries). Still, to the extent that the primary use of these measures is to detect the build-up of aggregate vulnerabilities in the financial system, the LPS Index and the AKPLW Index are qualitatively similar compared to the full-sample CGG; both the LPS Index and the AKLPW Index appear to lead the CGG and be better as early warning indicators of the build-up to vulnerabilities in the U.S. financial system prior to the GFC. The peak of vulnerabilities according to the AKPLW Index occurs in 2007:Q2; whereas, the peak of vulnerabilities according to the LPS Index is only a quarter later, in 2007:Q3. In contrast, the CGG peaks in 2008:Q4, well after the United States has entered its banking crisis in

2007:Q3. Most importantly, both the LPS Index and the AKLPW Index show vulnerabilities are elevated even starting in 2003, presaging the financial crisis many years prior to the GFC.

4 Vulnerabilities around Banking Crises

In this section, we show how our estimated component-based vulnerability measures evolved around banking crises. Figure 4 shows how the mean of the various indexes we construct (as in Figure 2) behave. As the indexes have a ceiling of one, the medians are higher than the means, but are more jagged due to the number of observations (at most 31). Therefore, we plot the smoother mean series to describe our results, which are qualitatively similar not only to looking at means, but other percentiles as well.[7]

The top left panel shows how the means of the various subindexes that compose risk appetite evolve around banking crises. In general, both equity prices (relative to earnings) and junk bond issuance (relative to total) peak one and a half to two years before the onset of a banking crisis and, in many countries, are notable even three years prior. House prices (relative to rent and/or income), though in certain countries like the United States rise and fall before crises, the mean across the countries in our sample stays notable for a sustained period of time around banking crises. In aggregate, the Risk Appetite Index, as shown in the solid line on the bottom left panel, appears to provide the breeding grounds to the build-up of vulnerabilities well in advance of a crisis.

The top right panel shows the behavior of various banking sector vulnerabilities around banking crises. Both bank leverage and maturity mismatch are notable well in advance of banking crises. Then both become more elevated along with reliance on wholesale funding and exposure to abroad a year prior to crises. All of the vulnerabilities subside by the time it is one year into a banking crisis.

The middle left panel shows the aggregate Bank Vulnerability Index that shows a similar hump-shaped pattern reminiscent of Figure 1, where a build-up of vulnerabilities are

[7]To get a complete picture of how the distribution of the various indexes behave around banking crises, see Lee, Posenau, and Stebunovs (2017).

followed by a shock, which pushes the financial system into a crisis state and financial disintermediation. In contrast, the Nonbank Financial Vulnerability Index rises quickly after a crisis from a moderate level of vulnerabilities, but continues to build up afterwards. Again, the cross-country experience is slightly different from the United States example, where nonbanks played a role in excessive credit creation (through leverage) prior to the GFC. First, in most countries, the nonbanking sector is far smaller than the banking sector in comparison to the United States, and the nonbanking sector generally appears to have substituted in providing credit that banks were reluctant to provide after a banking crisis occurred.[8] According to the Financial Sector Index, plotted in the bottom left panel, which aggregates the Bank Vulnerability Index and the Nonbank Financial Vulnerability Index, we can see the contours follow the Bank Vulnerability Index because we weight the two vulnerabilities by the amount of credit provided by each sector.

The middle right panel plots the two components that make up the Nonfinancial Sector Index. Indeed, a build-up of credit and debt servicing in the household sector appears to be a worst portent of things to come relative to the build-up of credit, debt servicing, and leverage in the corporate sector, which peaks a year after a banking crisis occurs. This is consistent with the view that more often than not, excessive credit to households have been the culprit behind banking crises. Although the majority of the banking crises in our sample is from the GFC, even if you look at the non-GFC episodes, the build-up of household leverage presages banking crises. Business and corporations appear to be negatively affected by banking crises, which brings down earnings, increases debt, and negatively impacts interest coverage ratios. This will have implications for how severe banking crises become in Section 5.

The bottom left panel describes the evolution of the four main vulnerability indexes; the Risk Appetite Index, the Financial Sector Index, the Nonfinancial Sector Index, and the External Sector Index. As mentioned earlier, definitive lead-lag relationships between these indexes exist. First, valuation pressures develop and then experiences a correction almost two years prior to banking crisis. External vulnerabilities remain elevated throughout the

[8] In addition, as with the credit data used for the CGG, to the extent that, for vulnerabilities in the nonbanking sector, we rely mostly on aggregate measures of credit provided by the nonbanking sector, it may be susceptible to the same flaws as the CGG in terms of being more of a lagging indicator.

three years prior to banking crises; whereas financial and nonfinancial sector vulnerabilities become more and more elevated during this period. After an economic or financial shock to the financial system, a banking crisis occurs and imbalances unwind or unravel. The exception is risk appetite, which grows back to levels prior to the crisis after two to three years after a banking crisis.

The bottom right panel shows the evolution of the aggregate LPS Index in the solid line, which is a summary statistics of the dynamics of different vulnerabilities described in the previous paragraph. The hump-shaped pattern is, again, reminiscent of Figure 1. When we look at the Sovereign Vulnerability Index, however, we see a very different pattern of behavior; indeed sovereign vulnerabilities in terms of government debt, fiscal deficit, and revenue are low and spikes up after a banking crisis. This is consistent with the findings in Reinhart and Rogoff (2011), where the governments' finances become strained due to automatic stabilizers and various actions to deal with the consequences of a banking crises. Although most of the countries in our sample are advanced economies, many emerging markets in the past have suffered a sovereign debt crisis at the same time as or right after banking crisis. Indeed, many European countries were at the brink of sovereign debt crises after the GFC; Greece can be considered an example where its banking crisis played a large part in its sovereign debt crisis.

5 Predicting the Onset and Severity of Crises

In this section, we analyze whether our measures of vulnerabilities has both significant power in predicting banking crises and the severity of such crises. We consider our four sector-specific indexes and the aggregate LPS Index and the LPS + Sovereign Index. Our benchmark is the CGG that has been touted as one of the more useful measures in predicting banking crises and has been set forth a main guide variable for determining countercyclical capital buffers by the Basel Committee on Banking Supervision in Basel III. Drehmann and Juselius (2014) show that, for a large cross section of countries and crisis episodes, the CGG is a robust single indicator for the build-up of financial vulnerabilities. They compare the six most popular early warning indicators– the CGG, debt service ratio, non-core liabilities, credit growth, property price growth GDP growth–and show that the CGG is statistically the best early warning indicator for forecast horizons between five and two years. The other indicators have an inferior predictive performance and often fail to satisfy the stability property in the sense that they reverse direction within the forecast horizon until the crisis. We also compare our aggregate LPS Index with the total debt service ratio as well, though total debt service only begins in 1999 for most of the countries in our sample.

We note that financial stress indexes (FSIs) are not appropriate benchmarks for comparison with our vulnerability measures. FSIs are coincident indexes rather than leading indexes, that is, they are designed to measure developments as they occur. Indeed, the results of Vermeulen, Hoeberichts, Vašíček, Žigraiová, Šmídková, and de Haan (2015) suggest only a very weak relationship between FSIs and the onset of a banking crisis. Therefore, they caution that policymakers should be aware of the limited usefulness of FSIs as an early warning indicator. For example, for the United States, as shown in Figure 5, the financial stress indexes that were put together by Federal Reserve Banks suggested below normal or normal stress levels five-to-two years ahead of the financial crisis.[9] That is, if supervisors of financial institutions were to rely on those, they would not have timely activated macroprudential tools. Furthermore, this argument applies to a larger set of indicators based on market prices, such as systemic risk measures such as CoVAR, Granger-Causality measures, and SRISK, which provide insight regarding the degree of financial shocks and contagion within the financial system, but does not regarding sustained gradual build-up of vulnerabilities.

Occurrence of Banking Crises We compare how our aggregate LPS Indexes and subindexes compare with the CGG when it comes to predicting banking crises for our sample period. However, the CGG is calculated based on credit to the private nonfinancial sector and GDP data from the BIS that go as far back in time as they can for each country for detrending purposes.[10] Indeed, such long time series is one advantage of the CGG as a metric to detect

[9]The figure shows the indexed that are used by the Cleveland, Kansas City, and St. Louis Federal Reserve Banks. These indexes are constructed using primarily using price metrics from a variety of financial markets.

[10]For the CGG, we use the same 2-sided Hodrick-Prescott (HP) Filter to calculate the credit-to-GDP gap using the 400,000 lambda smoothing parameter as in Drehmann and Juselius (2014).

a build-up of vulnerabilities.

Following the exercise used in Drehmann and Juselius (2014), we estimate the receiver operating characteristic (ROC) curve and calculate the area under the curve (AUC) as a summary measure to determine which variable provides predictive power for banking crises. Any predictor for a discrete outcome has a trade-off between true-positive rates and false-positive rates, or Type I and Type II errors in classical statistics, due to the inherent noise associated with any signal. The ROC curve is a mapping of all these tradeoffs; the larger the AUC is, the better the signaling quality the variable has, accounting for all true-positive and false-positive rate mappings (see Elliott and Lieli (2013).)

Five key differences differentiate our comparison to what Drehmann and Juselius (2014) do in their study relative to other measures of financial imbalances. First, we have a different sample of countries. Their 26 countries include countries such as the Czech Republic, New Zealand, and South Africa, which we do not have; whereas, we include countries such as Austria, Brazil, China, Luxembourg, Mexico, Russia, Singapore, and Turkey, which they don't have. In addition, since the LPS Index and other sector-specific indexes are solely based on a country's history, we do not include countries that have not experienced a banking crisis (during the time span we have data for) such as Australia, Canada, and Poland, as they might follow a different credit cycle.[11] Second, Drehmann and Juselius (2014) use varying time periods starting from 1980 or up to 2004 and ending all in 2012:Q2. We begin all our data from 1986 the earliest and continue our analysis to the last quarter of 2012. Third, though they also conduct their analysis based on their full-sample, their main analysis is in real time. We follow Aikman, Kiley, Lee, Palumbo, and Warusawitharana (2017) in conducting our main analysis based on the full sample of data due to data limitations, as real-time analysis requires sufficient data to begin any series. For example, our full sample analysis begins in 1986; whereas, our real-time analysis begins in 1996, which eliminates quite a few banking crises in our sample. Fourth, their main crises dates are for systemic

[11] The interpretation of the indexes would be counterintuitive because a country may be in a perpetual state of financial stability, but would always have a certain percentage of "elevated" vulnerabilities based on estimated historical distributions of the data. Adding these three countries to our analysis does not change our results, however.

banking crises, which occur one or two quarters after the initial banking crises occurs in most countries. In addition, Drehmann and Juselius (2014) also make some adjustments and do not consider data up to two years post crisis. We, in contrast, consider the initial date of the banking crisis and remove periods from the crisis date to three years after a crisis ends. Once in a crisis state, policy makers would presumably be focused more on crisis management rather than predicting the next crisis. Looking at the advent of even non-systemic banking crises provides more variation to exploit when we analyze severities of crises in the next subsection.

Our results for predicting the onset of banking crises are described in Table 3. As mentioned above, the higher the AUC, the more true positives and less false negatives there are from the model. The AUC can range from zero to one, with a value of one implying that the model provides perfect discriminatory power. An AUC below 0.5 would mean that the model does worse than a random draw in predicting the outcome. We use a normal probit function to estimate our results, but estimating nonparametrically does not change our results. We compare each vulnerability index to the CGG. As some indexes have more data underlying them, each comparison is based on a slightly different sample. The results, however, consistently show that sector-specific vulnerability indexes rarely outperforms the CGG, with the exception of the External Sector Vulnerability Index. Although sometimes the AUC based on the External Sector Vulnerability Index is higher than the one based on the LPS Index, it is still the LPS Index that shows the most consistency and stability across all the different horizons ranging from 12 to 1 quarter prior to a banking crisis when predicting a crisis. In particular, the LPS Index outperforms the CGG beginning 6 quarters prior to a crisis, and this outperformance is statistically significant. The LPS + Sovereign Vulnerability Index outperforms the CGG starting 9 quarters prior to a crisis.

In Table 3, we also conduct ROC analysis for just the eight emerging market economies in our sample. We find that the LPS Index is no longer statistically different from the CGG in its discriminatory power to predict banking crises. Indeed, compared to the full sample results with all the countries, the AUC is slightly lower for the LPS Index and slightly higher for the CGG, implying that the LPS Index does relatively better at predicting the onset of banking crises mainly in advanced economies; whereas the CGG has better predictive power for emerging markets. This may partly be due to the fact that in general there are longer time series available in advanced economies, so the length of the variables for advanced economies is less of a drawback when computing the LPS Index.

Finally, the aggregate LPS Index outperforms the total debt service ratio for all horizons in our sample with a more limited set of countries and primarily based on data since 1999. In other words, the banking crisis episodes are predominantly from the GFC in this comparison.

The fact that the aggregate LPS Index outperforms not only the CGG but also the total debt service ratio and other sector specific vulnerability indexes point to the fact that a bottom-up holistic approach to financial stability monitoring may have some value-added benefits. First, a holistic approach can provide more information across an array of different vulnerabilities such that pinpointing which vulnerability is elevated when can be done with ease. Second, in aggregation, the indexes appear to convey useful properties for predicting the onset of banking crises as they summarize the entire evolution of how vulnerabilities build up in a financial system.

Furthermore, in the context of financial stability monitoring, the aggregate LPS Index outperforms the CGG in a manner that may be consistent with the preferences of a financial-stability-related policy maker. Assuming that policy makers would have more tolerance for relatively more false positives than false-negatives, given a relatively higher false-positive rate, the indicator with the higher true-positive rate would be preferred. Indeed, this is precisely the part of the ROC curve that the LPS Index outperforms the CGG. Figure 6 shows the ROC curves for the LPS Index and CGG for four different horizons prior to banking crises. AUCs are higher when the estimated curve gets closer to the top left corner. Figure 6 shows that conditional on higher values of false-negative rates, the ROC value (or true-positive rate) is always higher for the LPS Index compared to the CGG. Confidence intervals (at the 90 percent level) are shown for false-positive rates equal to 0.5. At the two-year horizon, the confidence interval for true-positive rates do not even overlap between that of the LPS Index and that of the CGG. Even if the AUCs are very similar between the LPS Index and the CGG (as in the one-quarter horizon case), this characteristic of the curves would lead a policy maker to prefer the LPS Index even if the AUCs were similar if his or her loss function weights missing crises more severely in the policy maker's loss function.

When we conduct our AUC analysis in pseudo real-time, assuming data is available up to the point in which the various indexes and CGG are calculated, our index has severe limitations. First, unlike the total credit series used in the CGG, our more granular data is not that available going far back in time. Indeed this is one of the primary advantages of looking at the CGG; one can consider credit trends over a long period of time. In contrast, since we need a certain amount of data to begin calculating our indexes, we can only reasonably begin in 1996. Table 4 shows the ROC results for our analysis in real time. When we compare our aggregate indexes with the CGG in this manner, we find that the AUCs using our indexes are generally similar to those using the CGG close to banking crises, but are, again, far superior two to three years prior. Both the LPS Index and the LPS + Sovereign Index are superior to the CGG at far horizons. All indicators perform relatively poorly as you get nearer a banking crisis.

Besides its long history, some benefits of the CGG is that it is directly comparable across countries and theoretically should convey information about a country relative to others. The fact that the LPS Index is superior in many dimensions may, in contrast, highlight some less attractive features of the CGG measure. First, large drops in output (the denominator) may influence the measure (whereby an increase in the gap is caused primarily by a decrease in the GDP). Second, the CGG may also be biased as a measure of financial imbalances as sharp increases in credit (as seen in the recent financial crisis) may temporarily elevate the gap measure as well (but from precautionary motives). These first two considerations explain why the CGG tends to lag our vulnerability measures. Third, there is difficulty in estimating the trend that is taken away from the credit-to-GDP ratio in calculating the gap (though the HP-filter is widely used).[12] Fourth, as mentioned earlier, more recent literature has shown that vulnerabilities may not only come from credit booms per say, but may also arise from the different types of funding of such booms, so it is less surprising that a holistic approach

[12]Hamilton (2017) argues that the HP filter should never be used due to a variety of econometric reasons such as the HP filter producing spurious dynamic relations that have no basis in the underlying data-generating process.

leads to an earlier warning signal when it comes to crises. Finally, measuring vulnerabilities may need to be done on a country-by-country basis as each country may have very different levels of financial deepening that the trend CGG does not account for.[13]

Severity of Banking Crises Next, we look at how elevated vulnerability indexes are associated with loss in output from banking crises. The output loss is measured by the real GDP gap, which is the cumulative difference in trend GDP and the actual GDP as in Laeven and Valencia (2013). We take the measures of vulnerabilities one quarter immediately prior to the banking crises and scatter plot different measures of financial vulnerabilities with the output losses in Figure 7.

We notice the following observations. First, the vulnerability index or measure with the highest correlation with the output loss after a banking crisis is the Nonfinancial Sector Index and, in particular, the Corporate Index. This is interesting because it was one of the worst in predicting the onset of a crisis (compared to other measures). The business corporate sector's vulnerability level appears to play an important role in how severe a banking crisis is; stronger balance sheets at businesses may provide a cushion for adverse economic and financial shocks. Second, the aggregate LPS Index and the LPS + Sovereign Index also have significant positive relationships with output loss, implying that our measures are also useful in detecting possible amplification channels of crises to other parts of the financial system and real economy. In contrast, the External Sector Vulnerability Index appears not to be as correlated, showing that even if a vulnerability is one of the best at predicting the onset of a banking crisis, it may not be the best at predicting the severity. The Financial Sector Vulnerability Index (not shown) and the CGG both show very low correlation, possibly due to the fact that they convey less information about the amplification channels of banking crises.

Although we do not have that many observations, in order to show this relationship econometrically, we use the following regression model:

[13] See Edge and Meisenzahl (2012) for more details on the drawbacks of the credit-to-GDP measure as a guide variable for macroprudential policy.

$$Y(i,t) = \alpha_k + \beta_k V_{k,i,t-1} + \epsilon_{i,t}, \tag{2}$$

where $Y_{i,t}$ is the output loss associated with banking crisis that begins in time t for country i and $V_{k,i,t-1}$ is the vulnerability index or measure for vulnerability category k for country i one quarter before the onset of a banking crisis at time t. α_k is a constant for each vulnerability category k and ϵ is a simple Gaussian error term.

Table 5 shows a simple regression that describes our results. Consistent with the scatter plots in Figure 7, the Corporate Index in column (2) explains the most of the variation in output loss as does the Nonfinancial Sector Vulnerability Index in column (1). After that, the two aggregate indexes, the LPS + Sovereign Index and the LPS Index (columns (5) and (4), respectively) both explain about 17 to 18 percent of the variation. The coefficient on the External Sector Vulnerability Index is also significant, but the index explains only about 12 percent of the variation. For all the indicators, the estimated coefficients imply that if a country goes from a vulnerability level of somewhere in the vicinity of the 25th percentile of its historical distribution to the 75th percentile, the expected cumulative output loss were a banking crisis to occur would increase in the range of 40 to 60 percent, a nontrivial amount. Lastly, the CGG is not statistically significant, though it does have a positive coefficient.

When we omit three outlier countries in terms of output loss; Ireland, Mexico, and Thailand, and remove the first banking crisis episode in Brazil (which has data for LPS but not for CGG), we are left with 26 output loss observations. Here, the LPS + Sovereign Index far outperforms the CGG and the LPS Index, explaining about 36 percent of the variation (not shown). The CGG and the LPS Index explains 28 and 24 percent, respectively. Likewise, the output loss results are sensitive to outliers and the number of observations due to the small sample size.

In sum, the LPS Indexes, which by definition accounts for imbalances in multiple sectors in the financial system, is superior to the CGG, especially in predicting the occurrence at long horizons, and also at predicting the severity of banking crises (though the results are based on a small sample). In addition, the LPS Indexes outperform the External Sector Vulnerability Index when it comes to predicting the severity of banking crises, though the

External Sector Index does well in predicting the onset. These results are not surprising as our aggregation set-up, by definition, considers possible spill-over effects and amplification channels of financial stress to other sectors in the economy, and could motivate policy makers to consider such dynamic and holistic approach to financial stability monitoring.

6 The Duration and Severity of Recessions

In this section, we analyze whether our measures of vulnerabilities have both significant power in predicting the onset, duration, and severity of recessions. This allows us to expand our number of observations, but we lose China due to data availability. All told, over 90 recessions are in our sample for 26 countries from 1986 to 2015. We continue to compare against the CGG measure, but simply to see if aggregate build-up of credit is superior to predicting the onset, duration, and severity of recessions. The recessions data is from Howard, Martin, and Wilson (2011) and measures the length or duration of the recession as the quarters between the peak and trough of the relevant economic activity. The depth of the recession is simply how much economic activity fell between the peak and the trough.

First, none of the measures of financial vulnerabilities appear to be particularly useful in predicting recessions across the various horizons. The AUCs based on our vulnerability indexes and CGG top off with a range of 0.60 to 0.65 and never reaches anywhere close to the 0.80 sometimes estimated in the AUCs for determining banking crises. In general, our financial vulnerability measures and the CGG are poor indicators of predicting the onset of recessions.

Second, when it comes to the duration and severity of recessions, we now use the following regression:

$$Y(i,t) = \alpha_{k,i} + \beta_k V_{k,i,t-1} + \epsilon_{i,t}, \tag{3}$$

where $Y_{i,t}$ is now either the length or depth of a recession that begins in time t for country i and $V_{k,i,t-1}$ is, again, the vulnerability index or measure for vulnerability category k for country i one quarter before the onset of a recession at time t. Due to multiple recessions experienced in our sample period, we include country fixed effects, $\alpha_{k,i}$.

Table 6 shows our results. We find that the Risk Appetite Index is statistically significant in explaining the duration of regressions. Looking at the subcomponents, this is driven by pressures in housing prices. If a country goes from a risk appetite vulnerability level of somewhere in the vicinity of the 25th percentile of its historical distribution to the 75th percentile, the expected cumulative output loss were a recession to occur would increase in the length of a recession by one to two quarters, which is considerable considering that an average recession in our sample lasts four. Whereas the External Sector Vulnerability Index and the LPS Index have no power in predicting the length of recessions, the LPS + Sovereign Index is significant, as governments' balance sheet positions may be an important factor in dealing with recessions as well. This is consistent with our findings in Table 5.

Finally, to see if banking crisis episodes drive these results, we only look at the length of recessions if they are not associated with a banking crisis. As this shrinks the sample by a third, we drop country fixed effects. Table 7 shows the results for this smaller sample, which are consistent with our findings for the full sample of recessions. Mainly, the Risk Appetite and House Price Index appear to be highly predictive of the length of recessions; whereas the aggregate LPS + Sovereign Index remain significant as well. One difference from Table 6 is that now the LPS Index also show up as a significant contributor to explaining the duration of recessions.

These results do not convey to our regressions of the depths of recessions (not shown). None of the vulnerability indexes are particularly helpful in explaining the depths of the recessions as measured by the difference between the peak and trough. This could be due to measurement error.

7 Conclusions

We use a bottom-up approach in creating vulnerability measures within the financial system. This allows us to investigate how different broad categories of vulnerabilities and imbalances in financial systems evolve around banking crises. In particular, we showed how valuation pressures mount, then external, financial sector, and nonfinancial sector vulnerabilities become elevated prior to financial crises. An aggregate measure of our individual vulnerability indexes has some nice features — mainly, it appears to be helpful in predicting banking crises. In addition, aggregate measures of vulnerabilities in the financial system can even give an idea of how severe a crises may be after the crises has occurred as the aggregation considers the dynamics of overheating of the financial system and the subsequent unwinding or unraveling, affecting many sectors as a banking crisis runs its course. Although vulnerability measures appear to be less associated with the onset of recessions, aggregate measures of financial system vulnerabilities seem to explain some of the length of recessions once they do occur, as disruptions to economic activity can be spread through the financial system.

Our findings have potential to have important policy implications. Mainly, as a financial stability monitoring tool, our framework has not only the power to detect the build-up of vulnerabilities and imbalances in the financial system two to three years before the onset of financial crises, it would also presumably provide useful information regarding how forcefully a government may want to intervene when dealing with financial crises once they have occurred. Not only would measures such as the LPS or LPS + Sovereign Indexes be useful before financial crises for macroprudential policy (such as for calibrating triggers for setting counter-cyclical capital buffers), but potentially even afterwards in the context of crisis management policy as well. The results regarding the aggregate indexes to explain some of the length of recessions also has similar policy implications.

There are some other important caveats to our analysis. First, we base our analysis on crisis data largely from the 2007-2008 crises episodes. Still, the results in this paper are consistent with the literature on financial crises dating back to several decades ago. Second, which is related to the first caveat, is that our analysis is restricted to vulnerability categories for which data is readily available. The next financial crisis may arise from a sector that has yet to be developed or is difficult to obtain data for or even in a sector that was less relevant for the onset of the 2007-2008 global financial crisis, such as sovereign vulnerabilities. That is why it may still be important to keep track of sovereign vulnerabilities because there has been a history of sovereign debt crises that have accompanied full-blown financial crises for many countries in the past. Third, our methodology may have less meaning for countries that have never experienced financial crises. However, to the extent that we can learn from such countries' experiences, tracking vulnerabilities and imbalances in such countries in our framework may still provide useful insights regarding the prevention of financial crises and the alleviation of severe economic activity. Out holistic framework has the potential to help pick up build-ups of vulnerabilities and strains in the financial system even for those countries who have never experienced financial crises in the past.

References

ADRIAN, T., D. COVITZ, AND N. LIANG (2015): "Financial Stability Monitoring," *Annual Review of Financial Economics*, 7(1), 357–395.

AIKMAN, D., M. KILEY, S. J. LEE, M. G. PALUMBO, AND M. WARUSAWITHARANA (2017): "Mapping heat in the U.S. financial system," *Journal of Banking & Finance*, 81, 36 – 64.

BLANCHARD, O., E. CERUTTI, AND L. SUMMERS (2015): "Inflation and Activity – Two Explorations and Their Monetary Policy Implications," NBER Working Paper 21726, National Burearu of Economic Research.

BORIO, C. (2014): "The financial cycle and macroeconomics: What have we learnt?," *Journal of Banking & Finance*, 45, 182 – 198.

BORIO, C., AND P. LOWE (2002): "Assessing the Risk of Banking Crises," BIS Quarterly Review 157, BIS.

BRUNNERMEIER, M., G. GORTON, AND A. KRISHNAMURTHY (2013): *Liquidity Mismatch Measurement*pp. 99–112. University of Chicago Press.

CECCHETTI, S. (2008): "Measuring the Macroeconomic Risks Posed by Asset Price Booms," in *Asset Prices and Monetary Policy*, pp. 9–43. National Bureau of Economic Research, Inc.

CLAESSENS, S., AND M. A. KOSE (2014): "Financial Crises: Explanations, Types, and Implications," in *Financial Crises: Causes, Consequences, and Policy Responses*, ed. by S. Claessens, M. A. Kose, L. Laeven, and F. Valencia, pp. 3–59. International Monetary Fund.

CLAESSENS, S., M. A. KOSE, AND M. E. TERRONES (2012): "How do business and financial cycles interact?," *Journal of International Economics*, 87(1), 178 – 190, Symposium on the Global Dimensions of the Financial Crisis.

DANIELSSON, J., M. VALENZUELA, AND I. ZER (2016): "Learning from History: Volatility and Financial Crises," Finance and Economics Discussion Series 2016-093, Board of Governors of the Federal Reserve System.

DAWOOD, M., N. HORSEWOOD, AND F. STROBEL (2017): "Predicting sovereign debt crises: An Early Warning System approach," *Journal of Financial Stability*, 28, 16 – 28.

DEMIRGUC-KUNT, A., AND E. DTRAGIACHE (1997): "The Determinants of Banking Crises," Policy Research Working Paper 1828, World Bank.

DETRAGIACHE, E., AND A. SPILIMBERGO (2001): "Crises and Liquidity: Evidence and Interpretation," IMF Working Paper WP/01/2, International Monetary Fund.

DREHMANN, M., AND M. JUSELIUS (2014): "Evaluating early warning indicators of banking crises: Satisfying policy requirements," *International Journal of Forecasting*, 30(3), 759 – 780.

Edge, R. M., and R. R. Meisenzahl (2012): "the Unreliability of Credit-to-GDP Ratio Gaps in Real Time: Implications for Countercyclical Capital Buffers," *International Journal of Central Banking*, 7(4), 261–98.

Eichengreen, B., and R. Portes (1987): "Anatomy of Financial Crises," in *Threats to International Financial Stability*, ed. by R. Portes, and A. K. Swoboda, pp. 10–58. Cambridge University Press, New York.

Elliott, G., and R. P. Lieli (2013): "Predicting binary outcomes," *Journal of Econometrics*, 174(1), 15 – 26.

Ferguson, R. W., P. Hartmann, F. Panetta, and R. Portes (2007): *International Financial Stability*, Geneva Report on the World Economy. Center for Economic Policy Research.

Fisher, J., and L. Rachel (2017): "Assessing vulnerabilities to financial shocks in some key global economies," *Journal of Risk Management in Financial Institutions*, 10(1).

Frankel, J. A., and A. K. Rose (1996): "Currency crashes in emerging markets: An empirical treatment," *Journal of International Economics*, 41(3), 351 – 366, Symposium on Mexico.

Geanakoplos, J., and L. H. Pedersen (2012): *Monitoring Leverage*pp. 113–127. University of Chicago Press.

Gennaioli, N., A. Shleifer, and R. W. Vishny (2013): "A Model of Shadow Banking," *The Journal of Finance*, 68(4), 1331–1363.

Gertler, M., and N. Kiyotaki (2015): "Banking, Liquidity, and Bank Runs in an Infinite Horizon Economy," *American Economic Review*, 105(7), 2011–43.

Gorton, G., and A. Metrick (2012): "Securitized banking and the run on repo," *Journal of Financial Economics*, 104(3), 425 – 451.

Gorton, G., and G. Ordonez (2014): "Collateral Crises," *American Economic Review*, 104(2), 343–78.

Hamilton, J. D. (2017): "Why You Should Never Use the Hodrick-Prescott Filter," Working Paper 23429, National Bureau of Economic Research.

Howard, G., R. Martin, and B. Wilson (2011): "Are Recoveries from Banking and Financial Crises Really So Different?," International Finance Discussion Papers 1037, Board of Governors of the Federal Reserve System.

Kaminsky, G., S. Lizondo, and C. Reinhart (1998): "Leading Indicators of Currency Crises," IMF Staff Papers 1, International Monetary Fund.

Kaminsky, G. L., and C. M. Reinhart (1999): "The Twin Crises: The Causes of Banking and Balance-Of-Payments Problems," *The American Economic Review*, 89(3), 473–500.

Kindelberger, C. P. (1978): *Manias, Panics, and Crashes: A History of Financial Crises*. Wiley Investment Classics.

Kroszner, R. S., L. Laeven, and D. Klingebiel (2007): "Banking crises, financial dependence, and growth," *Journal of Financial Economics*, 84(1), 187 – 228.

Laeven, L., and F. Valencia (2013): "Systemic Banking Crises Database," *IMF Economic Review*, 61, 225–270.

Lane, P. R. (2012): "The European Sovereign Debt Crisis," *Journal of Economic Perspectives*, 26(3), 49–68.

Lee, S. (2009): "How Information Quality of Macro Aggregates Affects Sovereign Risk: An Empirical Investigation," *Review of International Economics*, 17(3), 510–532.

Lee, S., K. E. Posenau, and V. Stebunovs (2017): "The Anatomy of Financial Vulnerabilities and Crises," International Finance Discussion Papers 1191, Board of Governors of the Federal Reserve System.

Manasse, P., and N. Roubini (2009): "Rules of thumb for sovereign debt crises," *Journal of International Economics*, 78(2), 192 – 205.

Manasse, P., N. Roubini, and A. Schimmelpfennig (2003): "Predicting Sovereign Debt Crises," IMF Working Paper WP/03/221, International Monetary Fund.

Mendoza, E. G. (2010): "Sudden Stops, Financial Crises, and Leverage," *American Economic Review*, 100(5), 1941–66.

Mian, A., and A. Sufi (2009): "The Consequences of Mortgage Credit Expansion: Evidence from the U.S. Mortgage Default Crisis*," *The Quarterly Journal of Economics*, 124(4), 1449.

——— (2014): "What Explains the 20072009 Drop in Employment?," *Econometrica*, 82(6), 2197–2223.

Neuhann, D. (2017): "Macroeconomics Effects of Secondary Market Trading," Working Paper Seriesr 2039, European Central Bank.

Reinhart, C. M., and K. S. Rogoff (2009): *This Time Is Different: Eight Centuries of Financial Folly*. Princeton University Press, Princeton, New Jersey.

——— (2011): "From Financial Crash to Debt Crisis," *American Economic Review*, 101(5), 1676–1706.

Taylor, A. M. (2015): "Credit, Financial Stability, and the Macroeconomy," *Annual Review of Economics*, 7(1), 309–339.

Vermeulen, R., M. Hoeberichts, B. Vašíček, D. Žigraiová, K. Šmídková, and J. de Haan (2015): "Financial Stress Indices and Financial Crises," *Open Economies Review*, 26(3), 383–406.

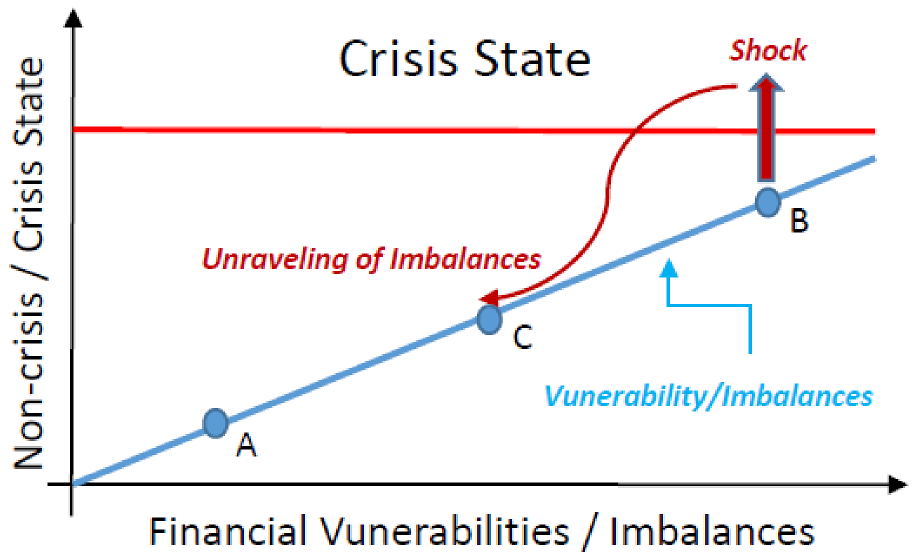

Figure 1: **Understanding Financial Crises**

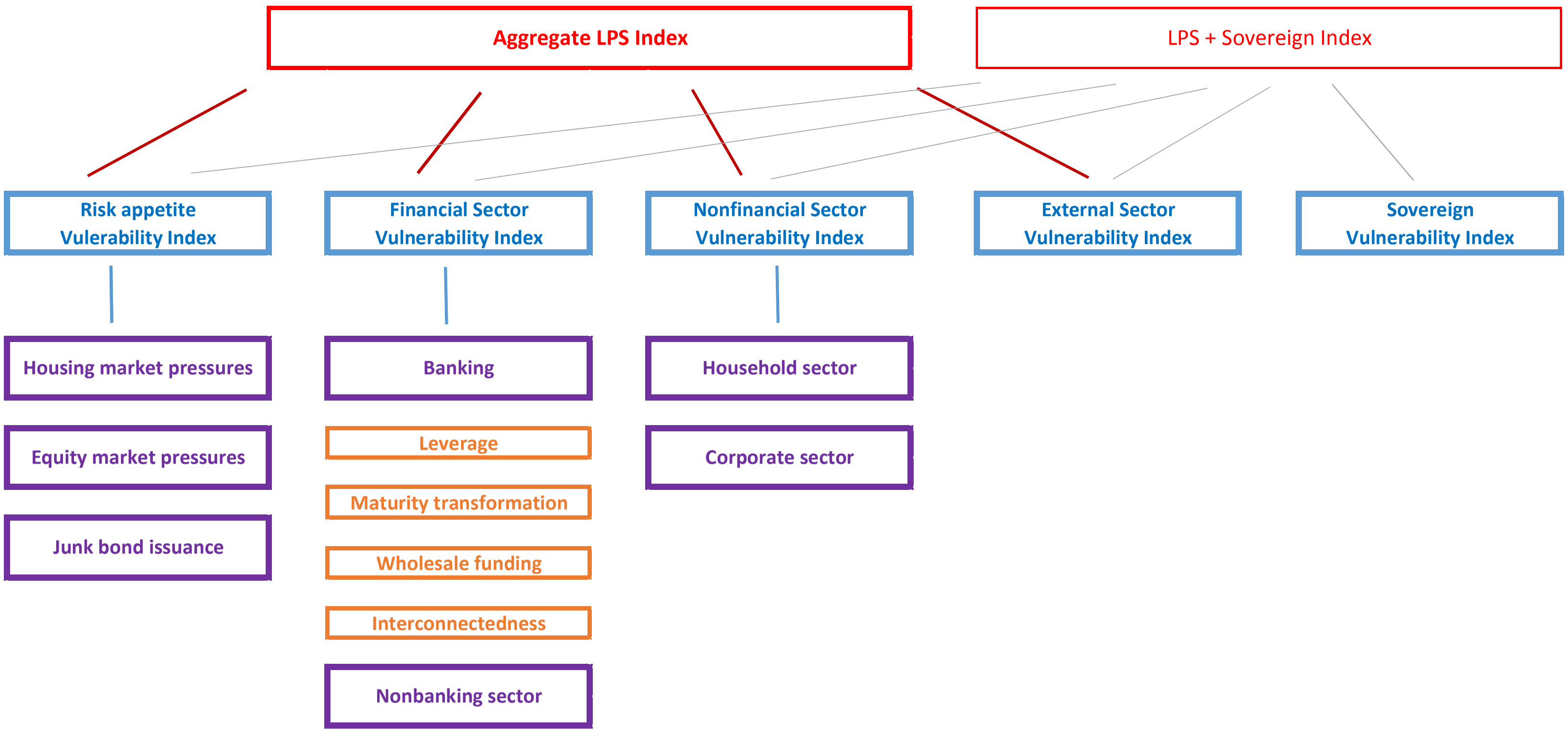

Figure 2: **Categorization of Vulnerabilities Schematic**

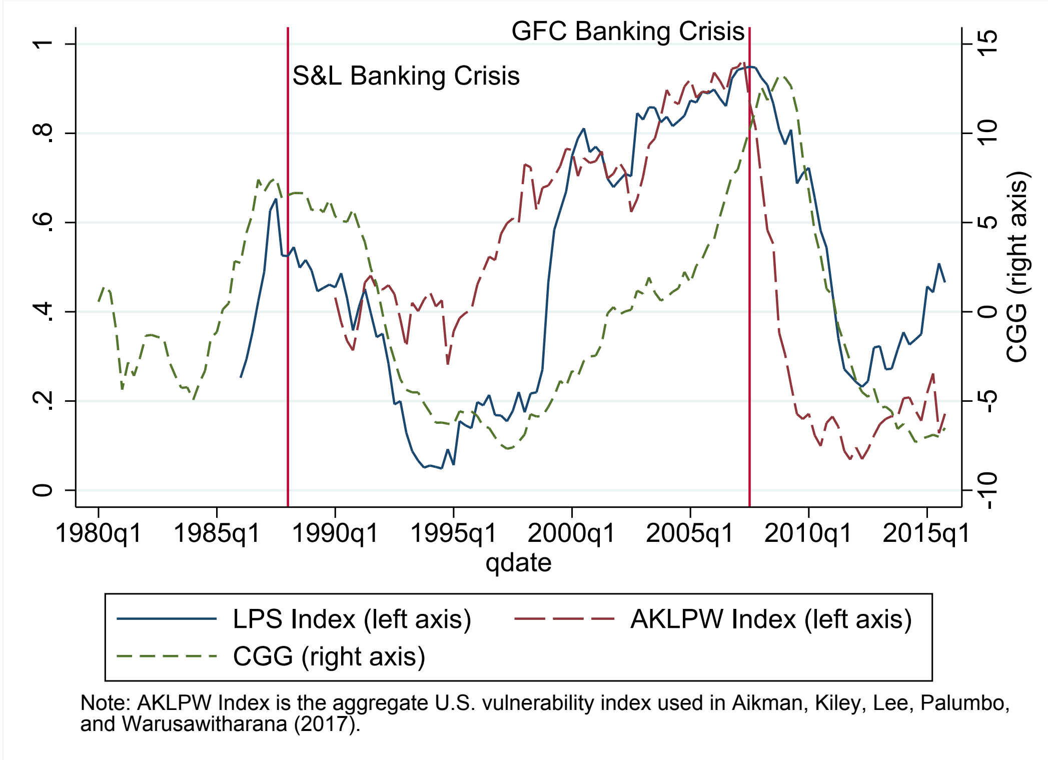

Figure 3: **Comparison of Vulnerability Measures for the United States**

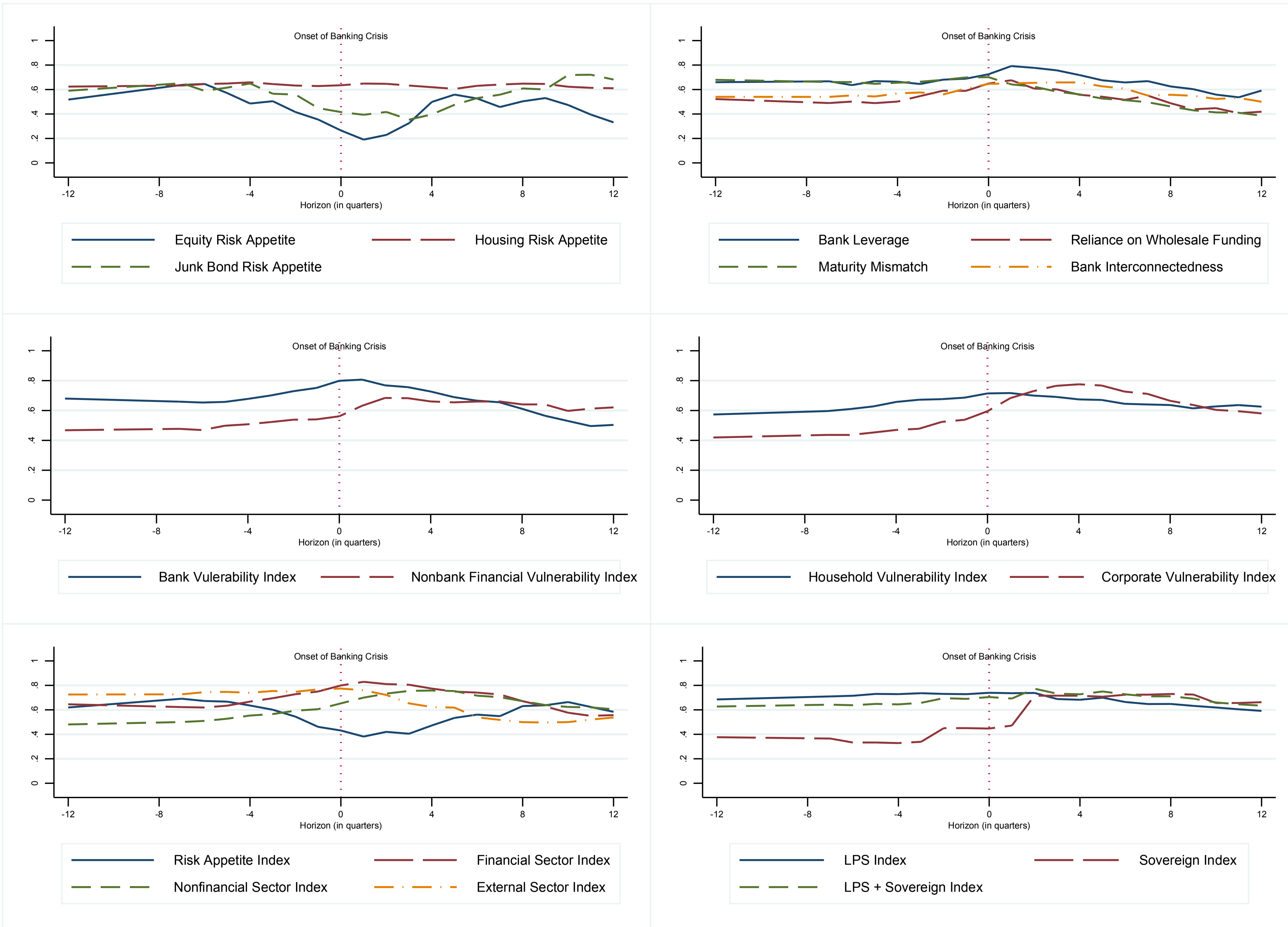

Figure 4: **Various Vulnerability Indexes around Banking Crises**

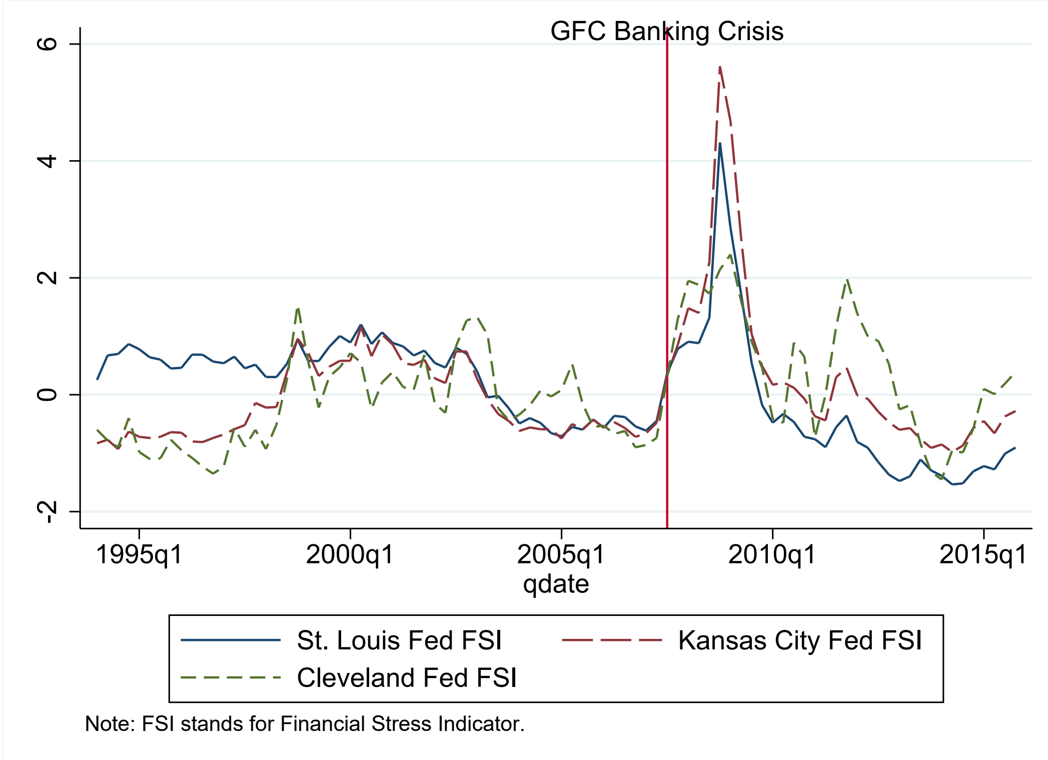

Figure 5: **Financial Stress Indicators for the United States**

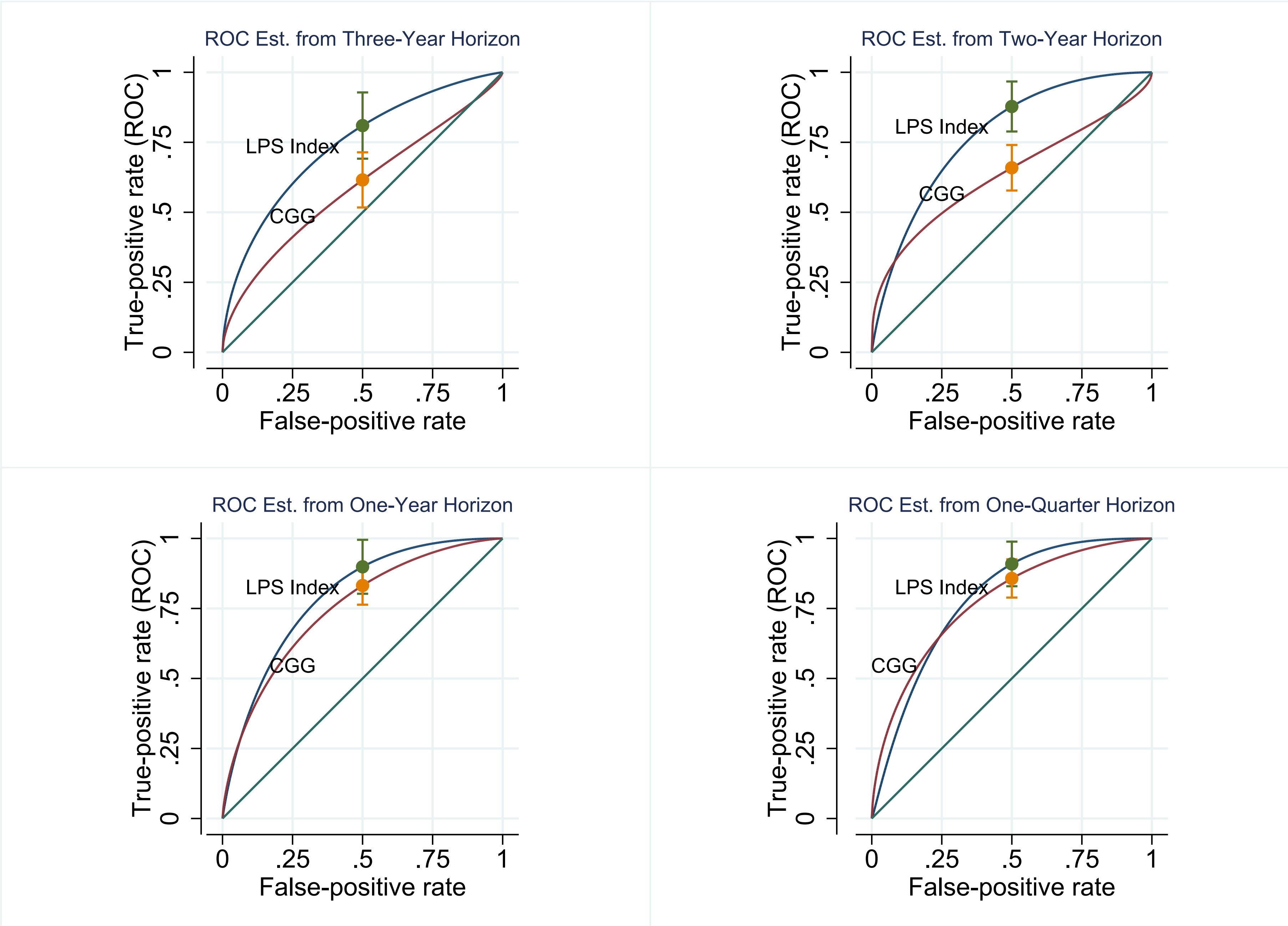

Figure 6: **Estimated ROC Curves and True-Positive Rate Confidence Intervals (given False-Positive Rate = 0.5)**

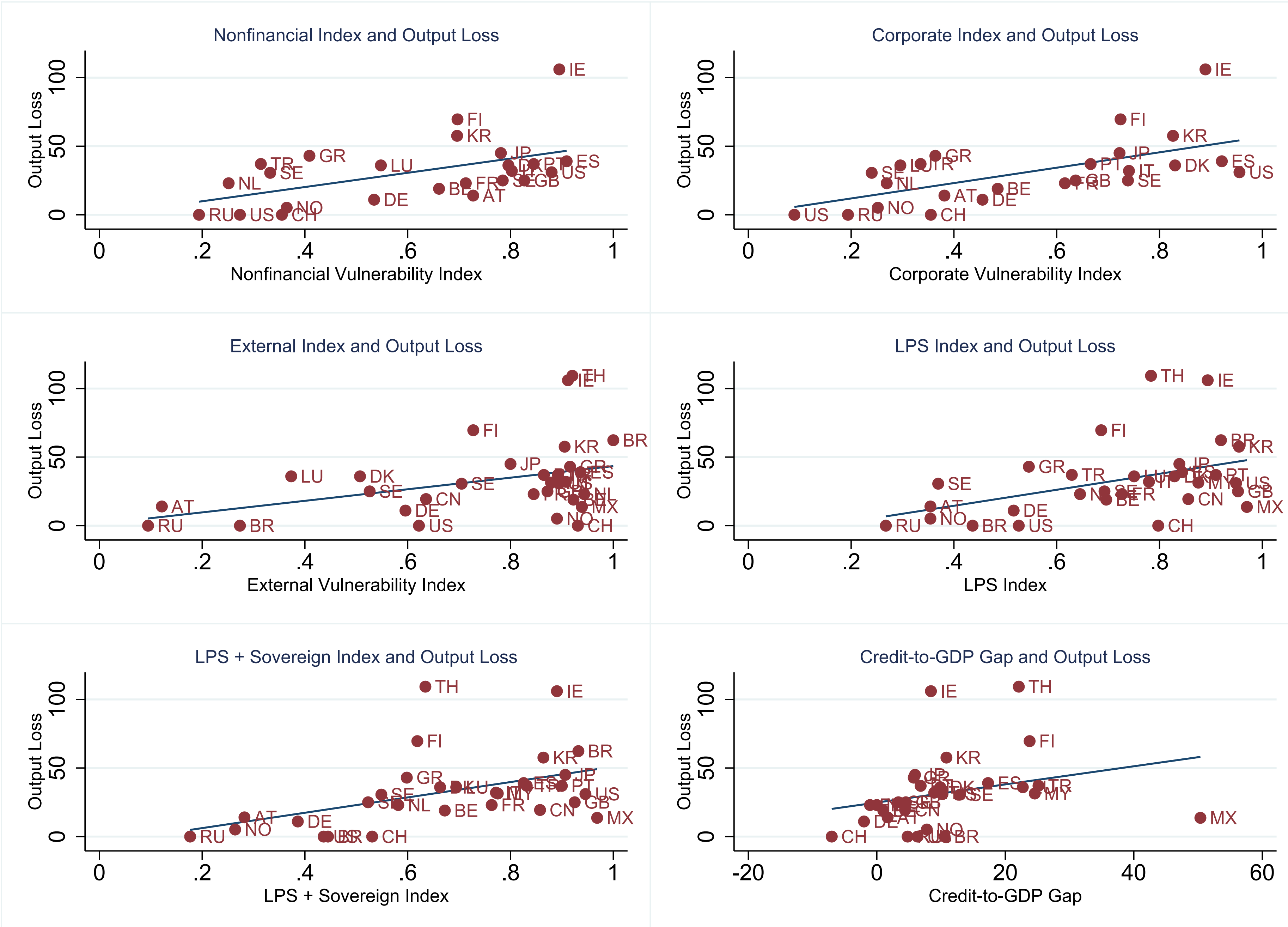

Figure 7: **Measures of Vulnerabilities and Output Loss**

Table 1: Banking Crises and Output Losses from Laeven and Valencia (2013)

Country	Banking Crisis	Output Loss (pct.)	GFC
Austria	2008:Q3	14.0	✓
Belgium	2008:Q3	19.0	✓
Brazil	1990:Q1	62.3	
	1994:Q4	0.0	
China	1998:Q3	19.4	
Denmark	2008:Q3	36.0	✓
Finland	1991:Q3	69.6	
France	2008:Q3	23.0	✓
Germany	2008:Q3	11.0	✓
Greece	2008:Q3	43.0	✓
Ireland	2008:Q3	106.0	✓
Italy	2008:Q3	32.0	✓
Japan	1997:Q4	45.0	
Luxembourg	2008:Q3	36.0	✓
Malaysia	1997:Q3	32.4	
Mexico	1994:Q4	13.7	
Netherlands	2008:Q3	23.0	✓
Norway	1991:Q4	5.2	
Portugal	2008:Q3	37.0	✓
Russia	1998:Q3	N/A	
	2008:Q3	0.0	✓
South Korea	1997:Q3	57.6	
Spain	2008:Q3	39.0	✓
Sweden	1991:Q3	30.6	✓
	2008:Q3	25.0	✓
Switzerland	2008:Q3	0.0	✓
Thailand	1997:Q3	109.3	
Turkey	2000:Q4	37.0	
United Kingdom	2007:Q3	25.0	✓
United States	1988:Q1	0.0	
	2007:Q3	31.0	✓

Note. Banking crisis beginning period and output loss from Laeven and Valencia (2013). Output loss is computed as the cumulative sum of the differences between actual and trend real GDP over four years, expressed as a percentage of trend real GDP starting from the year of the crisis.

Table 2: Data Series Count by Vulnerability Category

Country	Risk Appetite	Financial	Nonfinancial	External	Sovereign	Total
Austria	2	7	7	2	4	22
Belgium	4	7	7	2	4	24
Brazil	4	10	3	4	3	24
China	5	6	3	3	4	21
Denmark	4	5	7	2	4	22
Finland	5	7	7	3	4	26
France	5	7	7	2	4	25
Germany	5	7	7	3	4	26
Greece	4	7	7	2	4	25
Ireland	4	7	5	2	3	21
Italy	4	7	7	2	4	24
Japan	5	6	7	2	4	24
Luxembourg	2	5	4	2	4	17
Malaysia	4	6	3	2	4	19
Mexico	5	6	5	3	4	23
Netherlands	5	7	7	2	4	25
Norway	4	6	7	2	4	23
Portugal	4	7	7	3	4	25
Russia	5	6	3	4	3	21
South Korea	5	6	7	4	4	26
Spain	5	7	7	2	4	25
Sweden	5	7	7	2	4	25
Switzerland	5	6	5	2	4	22
Thailand	6	6	5	3	4	24
Turkey	5	6	5	3	3	22
United Kingdom	5	7	10	3	4	29
United States	5	12	7	2	4	30

Note. Data is from a variety of sources. See Appendixes in Lee, Posenau, and Stebunovs (2017) for data sources for non-U.S. countries and Aikman, Kiley, Lee, Palumbo, and Warusawitharana (2017) for data sources for the United States.

Table 3: Area Under the ROC Curve (AUC) prior to Banking Crises across Different Horizons

	-12	-11	-10	-9	-8	-7	-6	-5	-4	-3	-2	-1
Risk App. Index	0.67	0.66	0.74**	0.66	0.63	0.71	0.69	0.70	0.66	0.62	0.56	0.48
CGG	0.55	0.56	0.55	0.58	0.64	0.66	0.69	0.74	0.78*	0.78**	0.79***	0.80***
Fin. Index	0.72	0.74	0.73*	0.75	0.75	0.72	0.71	0.73	0.75	0.78	0.82	0.84
CGG	0.60	0.62	0.61	0.63	0.65	0.67	0.69	0.73	0.76	0.76	0.78	0.78
Nonfin. Index	0.58	0.61	0.62	0.62	0.62	0.64	0.65	0.66	0.68	0.69	0.71	0.72
CGG	0.60	0.62	0.61	0.62	0.63	0.64	0.66	0.71	0.76	0.76	0.77	0.79
External Index	0.79***	0.80***	0.79***	0.81***	0.79***	0.77**	0.78	0.78	0.77	0.77	0.75	0.77
CGG	0.59	0.62	0.61	0.62	0.64	0.65	0.67	0.72	0.75	0.75	0.77	0.78
LPS Index	0.74**	0.76**	0.80***	0.79**	0.78**	0.78**	0.79**	0.80	0.79	0.79	0.79	0.79
CGG	0.59	0.62	0.61	0.63	0.64	0.65	0.67	0.72	0.75	0.75	0.77	0.78
LPS + Sovereign	0.71*	0.74*	0.74**	0.74*	0.72	0.73	0.72	0.73	0.72	0.73	0.77	0.76
CGG	0.59	0.62	0.61	0.63	0.64	0.65	0.67	0.72	0.75	0.75	0.77	0.78
LPS Index (EMEs only)	0.73	0.76	0.77	0.80	0.74	0.74	0.75	0.79	0.76	0.76	0.79	0.82
CGG (EMEs only)	0.67	0.73	0.72	0.75	0.73	0.76	0.78	0.82	0.84	0.84	0.86	0.85
LPS Index	0.68*	0.66	0.77***	0.72**	0.72*	0.79***	0.76**	0.80***	0.80***	0.82***	0.79**	0.78**
Debt Service Ratio	0.51	0.52	0.52	0.53	0.55	0.56	0.57	0.58	0.60	0.61	0.62	0.63

Note. Each column signifies the horizon in which banking crises are predicted, which ranges from 12 quarters ahead to 1 quarter before the onset of banking crises. Each set of two columns looks out how the AUCs compare between two different indicators. Differences between an index and the CGG or the total debt service ratio are significant according to the following criterion– * $p < .1$, ** $p < .05$, *** $p < .01$.

Table 4: Area Under the ROC Curve (AUC) prior to Banking Crises across Different Horizons - Real Time Analysis

	-12	-11	-10	-9	-8	-7	-6	-5	-4	-3	-2	-1
LPS Index	0.73**	0.71*	0.72**	0.74**	0.69*	0.68	0.64	0.69	0.67	0.62	0.64	0.63
CGG	0.60	0.59	0.57	0.58	0.59	0.58	0.58	0.62	0.63	0.62	0.63	0.63
LPS + Sovereign	0.73*	0.71*	0.70*	0.71*	0.66	0.66	0.61	0.66	0.62	0.58	0.64	0.63
CGG	0.60	0.59	0.57	0.58	0.59	0.58	0.58	0.62	0.63	0.62	0.63	0.63

Note. Each column signifies the horizon in which banking crises are predicted, which ranges from 12 quarters ahead to 1 quarter before the onset of banking crises. Each set of two columns looks out how the AUCs compare between two different indicators. Differences between an index and the CGG are significant according to the following criterion–* $p < .1$, ** $p < .05$, *** $p < .01$.

Table 5: Output Loss and Financial Vulnerability Measures

	(1)	(2)	(3)	(4)	(5)	(6)
Nonfinancial Index	51.9***					
	(2.82)					
Corporate Index		56.1***				
		(3.66)				
External Index			42.2**			
			(2.25)			
LPS Index				58.3**		
				(2.61)		
LPS + Sov. Index					55.9**	
					(2.72)	
CGG						0.66
						(1.51)
Constant	−0.51	0.71	1.28	−8.79	−4.98	24.8***
	(−0.04)	(0.08)	(0.09)	(−0.53)	(−0.34)	(3.72)
Obs.	24	24	30	30	30	29
R-sq. adj.	0.23	0.35	0.12	0.17	0.18	0.04

Note. The explained variable: cumulative output loss until four years after a banking crisis. The explanatory variables: The Nonfinancial Index is the aggregated nonfinancial sector vulnerability index of the household and corporate sectors; the Corporate Index is the Corporate Vulnerability Index; the External Index is the External Sector Vulnerability Index; the LPS Index, which is an aggregate index of risk appetite, the financial sector, the nonfinancial sector, and the external sector vulnerabilities; the LPS + Sov. Index is an aggregate index of risk appetite, financial sector, nonfinancial sector, external sector, and sovereign vulnerabilities; the CGG is the Credit-to-GDP gap. t statistics in parentheses. * $p < .1$, ** $p < .05$, *** $p < .01$

Table 6: Length of Recession and Financial Vulnerability Measures

	(1)	(2)	(3)	(4)	(5)	(6)
Risk Appetite Index	4.38***					
	(3.20)					
House Price Index		3.77***				
		(2.90)				
External Index			1.86			
			(1.38)			
LPS Index				1.71		
				(1.28)		
LPS + Sov. Index					2.19*	
					(1.87)	
CGG						−0.00
						(−0.01)
Fixed effects	✓	✓	✓	✓	✓	✓
Obs.	82	72	87	91	93	95
R-sq. adj.	0.25	0.56	0.16	0.25	0.20	0.22

Note. The explained variable: length of recession is number of quarters a recession lasts. The explanatory variables: The Risk Appetite Index is the aggregated risk appetite vulnerability index of equity, housing, and junk bond market; the House Price Index measures the vulnerabilities coming from house price pressures; the External Index is the External Sector Vulnerability Index; the LPS Index, which is an aggregate index of risk appetite, the financial sector, the nonfinancial sector, and the external sector vulnerabilities; the LPS + Sov. Index is an aggregate index of risk appetite, financial sector, nonfinancial sector, external sector, and sovereign vulnerabilities; the CGG is the Credit-to-GDP gap. Fixed effects are country fixed effects. t statistics in parentheses. * $p < .1$, ** $p < .05$, *** $p < .01$

Table 7: Length of Recessions (not associated with banking crises)

	(1)	(2)	(3)	(4)	(5)	(6)
Risk Appetite Index	3.38***					
	(3.66)					
House Price Index		3.85***				
		(3.58)				
External Index			0.02			
			(0.03)			
LPS Index				2.03**		
				(2.15)		
LPS + Sov. Index					1.55*	
					(1.84)	
CGG						−0.00
						(−0.01)
Constant	2.11***	1.85***	3.88***	2.83***	3.04***	3.72***
	(4.00)	(2.99)	(6.68)	(5.33)	(6.29)	(14.32)
Obs.	55	50	57	61	63	64
R-sq. adj.	0.19	0.19	−0.01	0.06	0.04	−0.02

Note. The explained variable: length of recession is number of quarters a recession lasts for recessions not associated with banking crises. The explanatory variables: The Risk Appetite Index is the aggregated risk appetite vulnerability index of equity, housing, and junk bond market; the House Price Index measures the vulnerabilities coming from house price pressures; the External Index is the External Sector Vulnerability Index; the LPS Index, which is an aggregate index of risk appetite, the financial sector, the nonfinancial sector, and the external sector vulnerabilities; the LPS + Sov. Index is an aggregate index of risk appetite, financial sector, nonfinancial sector, external sector, and sovereign vulnerabilities; the CGG is the Credit-to-GDP gap. Regression sample is composed on nonbanking crisis-related recessions only. t statistics in parentheses. * $p < .1$, ** $p < .05$, *** $p < .01$