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The Anatomy of Financial Vulnerabilities and Banking Crises

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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 indexes, which aggregate these vulnerabilities, predicts banking crises better than the credit-to-GDP gap (CGG) or sector-specific vulnerability indexes, especially at long horizons. Our aggregate indexes also explain the variation in the severity of banking crises and the duration of recessions relatively well, as it incorporates possible spillover and amplification channels of financial 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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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 the onset and severity of banking crises.

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 set the stage for an unwinding or 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.

We extend the framework of in Aikman, Kiley, Lee, Palumbo, and Warusawitharana

[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.

(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 one of the best predictors of systemic 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 look at how the different vulnerability measures compare when predicting banking crises as defined in Laeven and Valencia (2013), in addition to systemic crises as defined in 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 debt accumulation 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 appear 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 before the crises occur. External and financial sector vulnerabilities also become elevated and peak around the onset of banking 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. Rather, the level of sovereign vulnerabilities usually becomes elevated as governments mitigate the consequences of a crisis through an increase in sovereign debt due to declines in tax revenue and through automatic stabilizers, in addition to direct government intervention.

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 longer horizon predictive power of the overall index is, in large part, attributable to the Risk Appetite Index and 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 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 conceptual 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 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 are more likely to arise from shocks to highly vulnerable financial systems. 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 in an environment when households and large financial institutions were both highly leveraged and the financial sector relied heavily on wholesale short-term funding (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 can lead 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.

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. Any of these other metrics 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 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 systemic banking crises and banking crisis episodes is from Drehmann and Juselius (2014) and Laeven and Valencia (2013), respectively, during 1986-2012. In the second column of Table 1, we first consider systemic banking crises to benchmark our results to Drehmann and Juselius (2014) as a reference point to our empirical analysis. Drehmann and Juselius (2014) use systemic banking crises from Laeven and Valencia (2013), but omit crises driven primarily by cross-border exposures (as their primary credit-to-GDP gap measures domestic vulnerabilities only), and augment the data after private discussions with central banks. The second column in Table 1 provides the years and quarters in which systemic crisis episodes began for the 20 countries that overlap between our analysis and Drehmann and Juselius (2014). For a larger set of 27 countries for which various macro-financial data are readily available, the third column in Table 1 provides the years and quarters at which banking crisis episodes began. Eight of the 27 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 others 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

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

intervention measures in response to significant losses in the banking system. According to Drehmann and Juselius (2014), some banking crisis episodes were not associated with a systemic crisis caused by domestic financial vulnerabilities, such as in Germany, Sweden, and Switzerland in the GFC. In many cases, Drehmann and Juselius (2014) also mark the date of the onset of systemic crises one or a few quarters after the onset of a relevant banking crises. There are also some banking crises not associated with systemic crisis, for example, in the early 1990s in Italy, Switzerland, and in the United Kingdom.

The fourth column in Table 1 provides the output loss associated with banking crisis episodes. Output loss is 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 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.

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. We restrict our sample of analysis to the past 30 years (1986-2015) due to data availability. However, following the financial cycle literature, we believe that this is sufficient 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.

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 ratio for OECD countries, along with either the nominal price to income or the nominal price to GDP ratios. We use the nominal price to GDP ratio 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 the dividend to yield ratio (with a negative sign). The dividend to yield ratios are backwards-looking, but have a longer time series than our forward P/E ratios.[3] Finally, the junk bond issuance ratio is calculated as the 12-month moving sum of high-yield nonfinancial bond issuance over the 12-month moving sum of total bond issuance.

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

The banking sector vulnerabilities have 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

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

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, we use bank credit to the private nonfinancial sector to GDP ratio (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 sufficient 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 proxied by the 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. We also 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 proxied by 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.[4]

As for the nonbank financial sector, we are motivated by Gennaioli, Shleifer, and Vishny

[4]Interconnectedness on the liabilities side of banks' balance sheets are a subset of external debt, which is considered in the external sector vulnerabilities.

(2013) and Neuhann (2017) and we proxy nonbank leverage across countries as the nonbank-provided credit to the private nonfinancial sector to GDP ratio (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 nonbank sector relative to its history and trend. 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. Vulnerabilities in the household sector are measured using the credit provided to households (including to non-profit institutions serving households) to GDP ratio (relative to a 10-year moving average) and the household debt service ratio. Some countries have addition information, such as mean loan-to-value ratios on mortgages. Depending on data availability, we judge corporate sector vulnerabilities to include the following indicators: the aggregate corporate debt to equity ratio, the 90th percentile of the corporate debt to equity ratios, the corporate interest coverage ratio, the credit provided to businesses to GDP ratio (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.

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: the external debt to GDP ratio (relative to a 10-year moving average), the current account deficit to GDP ratio, and the reserves to GDP ratio (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. We estimate sovereign vulnerabilities using the aggregate government debt to GDP ratio (relative to a 10-year moving average), the fiscal deficit to GDP ratio, and the government revenue to GDP ratio (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 used for the United States 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.[5]

2. Each component or subcomponent index is the simple average of the standardized indicators for that component or subcomponent as in Equation 1.[6] 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.[7] 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.

[5]We also explore the implications of our analysis using a one-sided, pseudo real-time standardization in our analysis, which also estimates the distribution of each component using only data up to a given point in time.

[6]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.

[7]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 aggregate Bank 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, properties related to the timing of crises do not change whether one detrends the data using 5 to 20 year moving averages. In addition, using different aggregation methods such as arithmetic averages, geometric averages, root mean squares, or principal components, also leads 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.[8] 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 subsector specific vulnerability measures and an external sector vulnerability measure. There are some 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 that are not available for most 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 are better as early warning indicators for 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 began experiencing its

[8]That said, Hamilton (2017) points out 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.

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. The LPS Index depicts a sharper increase in vulnerabilities than the AKLPW Index in the macroeconomic overheating period in the late 1990s during the period of low unemployment and high output gaps. This overheating period ended with the Dot-com crash and subsequent recession. As for the vulnerability readings surrounding the S&L banking crisis in 1988, the LPS Index was also elevated and fell dramatically with the 1987 stock market crash, just prior to the onset of the S&L crisis.

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 median values of the various indexes we construct (as in Figure 2) behave. As the indexes have a ceiling of one, the medians are slightly higher than the means.[9]

The top left panel shows how the medians 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 at notable to elevated levels even 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) stay notable for a sustained period of time before 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 banking 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 prior to banking crises. All of the vulnerabilities subside by the time it is three years after a banking crisis.

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

The middle left panel shows the median aggregate Bank Vulnerability Index that shows a similar hump-shaped pattern reminiscent of Figure 1, where a build-up of vulnerabilities are followed by a banking crisis, followed by 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. The cross-country experience is slightly different from the United States example, where nonbanks played an important role in the large amount of credit provision prior to the GFC. First, in most countries, the nonbank financial sector is far smaller than the banking sector in comparison to the United States, and the nonbank financial sector generally appears to have substituted in providing credit that banks were reluctant to provide after a banking crisis.[10] According to the median 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 and the banking sector is usually larger than the nonbank financial 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 explaining variation in the severity of banking crises in Section 5.

The bottom left panel describes the evolution of the four main vulnerability indexes; the

[10]In addition, as with the credit data used for the CGG, because we rely on aggregate measures of credit provided by the nonbank financial sector, it may be susceptible to the same flaws as the CGG in terms of being more of a lagging indicator.

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 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 have significant power in predicting systemic crises, banking crises, and the severity of banking 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 systemic 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 publicly available total debt service data 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.[11] 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 do so for detecting sustained gradual build-up of vulnerabilities.

[11] 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 price metrics from a variety of financial markets.

Onset of Banking Crises We compare how our aggregate LPS Indexes and subindexes compare with the CGG when it comes to predicting systemic crises and 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.[12] Indeed, such long time series is one advantage of the CGG as a metric to detect 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).)

Four key differences differentiate our comparison to what Drehmann and Juselius (2014) do in their study. First, their main crises dates are for systemic banking crises stemming from domestic financial vulnerabilities, which usually occur one to a few quarters after the initial banking crises occur in most countries as shown in Table 1. In addition, Drehmann and Juselius (2014) also make some adjustments after discussions with central banks and do not consider data up to two years post crisis.[13] Although we first show results with an overlapping sample used in Drehmann and Juselius (2014) and for predicting systemic crisis according to Drehmann and Juselius (2014), our main analysis considers the initial date of the banking crisis according to Laeven and Valencia (2013). Because one of our subindexes is related to external vulnerabilities, we include crises stemming from abroad. Looking at the advent of even non-systemic banking crises also provides more variation to exploit when we analyze severities of banking crises in the next subsection. Second, we have

[12]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).

[13]We also remove data up to two years post crisis. Our results are robust to removing data up to three years post crisis.

a different sample of countries in our main analysis. 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.[14] Third, 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. Fourth, though Drehmann and Juselius (2014) do show their analysis based on the full-sample of data, their main analysis is in real time (given data available up to a given point in 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 interpreting any data 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 and data in our sample. However, the merit of the full-time analysis is that we account for a fuller set of information when conducting our analysis rather than relying on information available at a given point in time. Although real-time analysis may be more useful in thinking about policy responses, this may also result in more biased estimates of the true distribution of various vulnerability measures due to the reliance on more partial data.

Our first set of results for predicting the onset of systemic crises according to Drehmann and Juselius (2014) are described in Table 3 for an overlapping subsample of 20 countries that are in both Drehmann and Juselius (2014) and for which the LPS Index is available. As mentioned earlier, the higher the AUC, the higher the tendency in which the model produces more true positives and less false negatives with regards to predicting crises. The

[14]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.

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 as in Drehmann and Juselius (2014) does not change our results. We compare crisis-predicting performance of each vulnerability index to that of the CGG. As some indexes have more data underlying them, each comparison is based on a slightly different sample. First, we are able to replicate the AUCs for the CGG as in Drehmann and Juselius (2014) which peaks at around 0.90 at a one-quarter horizon. The results also consistently show that sector-specific vulnerability indexes rarely outperforms the CGG in predicting systemic crises, with the exception of the Risk Appetite Vulnerability Index and External Sector Vulnerability Index, especially at longer horizons. The aggregate LPS Index, however, shows the most consistency and stability across all the different horizons ranging from 12 to 1 quarter prior to a systemic crisis when predicting a systemic crisis. In particular, the LPS Index outperforms the CGG beginning 5 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 systemic crisis. The AUC from using the LPS Indexes peaks at a horizon of one quarter. At this horizon, the AUC is slightly smaller than the 0.87 estimated with the CGG, but not statistically significantly different.

In Table 3, we also conduct ROC analysis for subsamples of countries; one sample includes countries that experienced a systemic crisis in the 2007-08 period only (the GFC crisis only countries) and another includes countries that experienced a banking crisis in other periods as well (the non-GFC crisis countries). We find similar results, but the CGG outperforms the LPS Index in nearer horizons for countries that also experienced a banking crisis outside the GFC period and this outperformance is statistically significant starting at the 3-quarter horizon. In general, both the LPS Index and the CGG perform relatively better in predicting systemic crises for the non-GFC crisis countries compared to predicting systemic crises in countries that only experienced a systemic crisis in the GFC period.

Finally, the aggregate LPS Index outperforms the total debt service ratio for all horizons in our sample based on a more limited set of publicly available data since 1999. The systemic crisis episodes are predominantly from the GFC in this comparison by definition. The results for the debt service ratio differs greatly from Drehmann and Juselius (2014), where they detrend the debt service ratio using 15-year rolling windows using privately estimated data for a far longer time series. Publicly available data from the BIS statistics is only available from 1999. Therefore, we cannot detrend the debt service ratio, which accounts for the difference in its predictive power of crises from Drehmann and Juselius (2014).

Our main set of results for predicting the onset of banking crises according to Laeven and Valencia (2013) are described in Table 4 for 27 countries. Again, we compare each vulnerability index to the CGG. The results are qualitatively the same; they consistently show that sector-specific vulnerability indexes rarely outperforms the CGG in predicting banking crises, with the exception of the Risk Appetite Vulnerability Index and External Sector Vulnerability Index, especially at longer horizons. The aggregate LPS Index also shows consistency and stability across all the different horizons ranging from 12 to 1 quarter prior to a banking crisis when predicting a systemic crisis. In particular, the LPS Index outperforms the CGG beginning 5 quarters prior to a crisis, and this outperformance is statistically significant. The LPS + Sovereign Vulnerability Index outperforms the CGG starting 8 quarters prior to a systemic crisis. These results are similar to Table 3, but the AUC levels are somewhat lower, mostly due to the differences in the dependent variable. In essence, it is more difficult to predict banking crises than systemic crises. When it comes to banking crises, the AUC from using the LPS Indexes also peak at a horizon of one quarter, but now is slightly higher than the 0.77 estimated with the CGG.

In Table 4, the results for the subsample of countries which experienced a banking crisis only in the GFC period are similar to those when predicting systemic crises. The LPS Index outperforms the CGG in predicting banking crises in longer horizons. However, when it comes to predicting banking crises for countries that also experienced banking crises outside the GFC period, the results between the LPS Index and the CGG are generally not statistically distinguishable. This is partly because the CGG is far better at predicting banking crises for countries experiencing banking crises also outside the GFC period than at predicting banking crises for countries experiencing banking crises only during the GFC period.

Finally, the aggregate LPS Index outperforms the total debt service ratio in predicting banking crises for all horizons in our sample as in the case for predicting systemic crises.

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 in predicting both systemic and banking crises 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. For example, 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-focused 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, many of our more granular data are not available going that far back in time. Indeed this is one of the primary advantages of looking at the CGG; one can consider credit trends over a longer 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 5 shows the ROC results for our analysis in real time. For comparison with the results in Drehmann and Juselius (2014), we start off with trying to predict systemic crises for the 26 countries used in Drehmann and Juselius (2014) using the same nonparametric methodology. We get close to their published AUC results in the first row, which differ by a few percentage points. Using a parametric approach, the AUC metric decreases slightly. When we subsample the period to start in 1996, the AUC decreases slightly again across all horizons. Finally, the fourth and fifth rows show how the LPS Index and the CGG compare in predicting systemic crises in real time for the sample of 20 countries that overlap with our sample. Although the LPS Index is consistently associated with a higher AUC value across all horizons, only at the horizon of 12 quarters is the value statistically different from using the CGG. When we do the same analysis to predict banking crises, we have similar results, but the AUC values for both the LPS Index and CGG are considerably lower, implying that it is harder to predict banking crises than systemic crises with our aggregate measures of financial vulnerability. Overall, even with the disadvantages of trying to predict banking crises in real time using the LPS Index, this Index does not perform worse than the CGG.

Finally, we also look at moving averages of the LPS Index and the CGG to account for the fact that there may be sharp increases or decreases that explain the performance of these measures at different horizons. For example, an ideal index for an early warning indicator would presumably have persistent and steady characteristics prior to a crisis. Therefore, we consider 4-quarter, 12-quarter, and 20-quarter moving averages of the LPS Index and the CGG to see if our results for the full sample hold. Table 6 shows our results for all of these indicators. Indeed, the LPS Index outperforms the CGG in predicting banking crises at most horizons in our sample, indicating that the LPS Index is more stable leading up to 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. However, the fact that the LPS Index outperforms 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 drawdowns in revolving credit (as seen in the recent financial crisis) may temporarily elevate the gap measure as well (but stemming 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). 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 may be better as 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.[15]

Severity of Banking Crises Next, we look at how elevated vulnerability indexes are associated with losses 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 Corporate Vulnerability Index, a subcomponent of the Nonfinancial Vulnerability Index. This is interesting because

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

Nonfinancial Vulnerability Index 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 subindex 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 have a limited number of banking crisis observations, in order to show this relationship econometrically, we use the following regression model:

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

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 7 describes our results. Consistent with the scatter plots in Figure 7, the Corporate Vulnerability Index in column (2) explains the variation in output loss the best. After that, the two aggregate indexes, the LPS + Sovereign Index and the LPS Index (columns (5) and (4), respectively) both explain about 16 to 18 percent of the variation. The coefficient on the External Sector Vulnerability Index is also significant, but the index explains only about 14 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 about 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 40 percent of the variation (not shown). The CGG and the LPS Index explains about 30 percent each. Likewise, the output loss results are sensitive to outliers and the number of observations due to the small sample size.

In sum, the aggregate LPS Indexes, which by definition accounts for imbalances in multiple sectors in the financial system, is superior to the CGG, especially in predicting their onset 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 a 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 can include country fixed effects, $\alpha_{k,i}$.

Table 8 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 Index level of somewhere in the vicinity of the 25th percentile of its 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 quarters. Whereas the External Sector Vulnerability Index and the LPS Index have minimal 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 7.

Finally, to see if banking crisis episodes drive these results, we only look at the length of recessions when they are not associated with a banking crisis. As this shrinks the sample by a third, we drop country fixed effects. Table 9 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 8 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. First, 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 variation in 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 in explaining some of the variation in 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 and our results are robust to subsampling countries that also experienced banking crises outside the 2007-2008 period. Second, 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 monitor 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 that are not in our sample. 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. Our holistic framework may still have 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.

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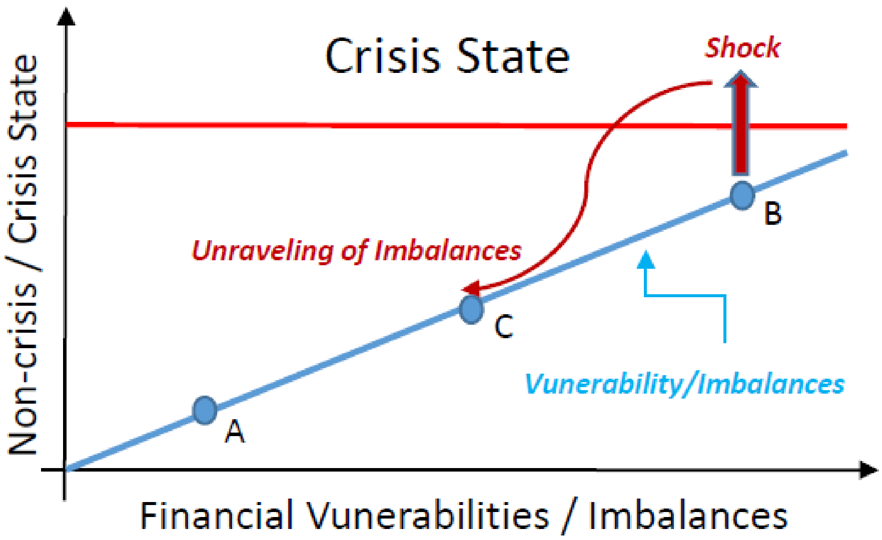

Figure 1: **Understanding Financial Crises**

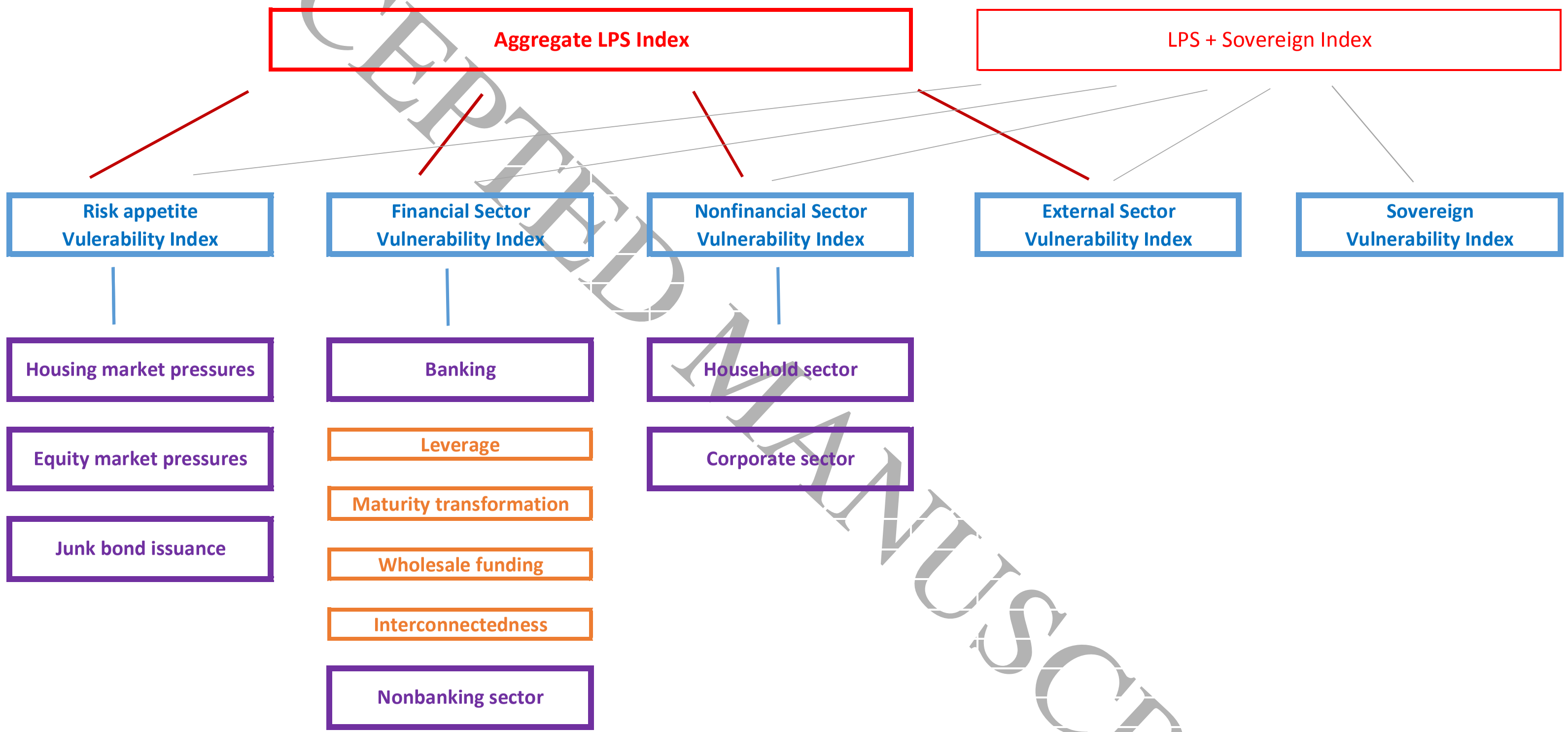

Figure 2: **Categorization of Vulnerabilities Schematic**

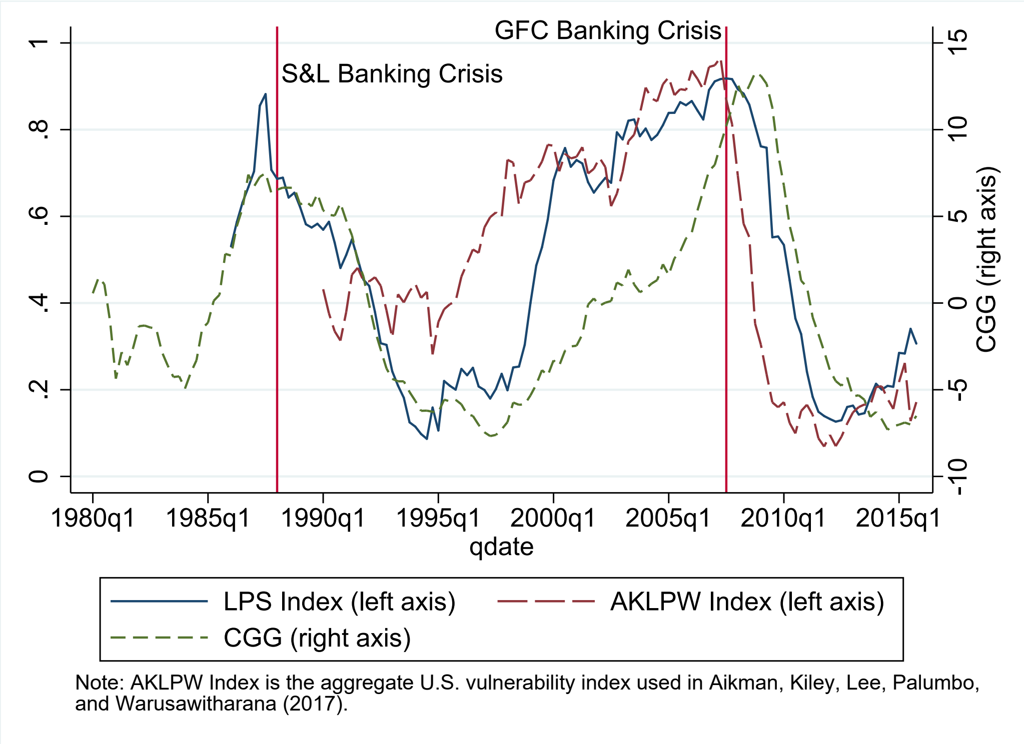

Figure 3: **Comparison of Vulnerability Measures for the United States**

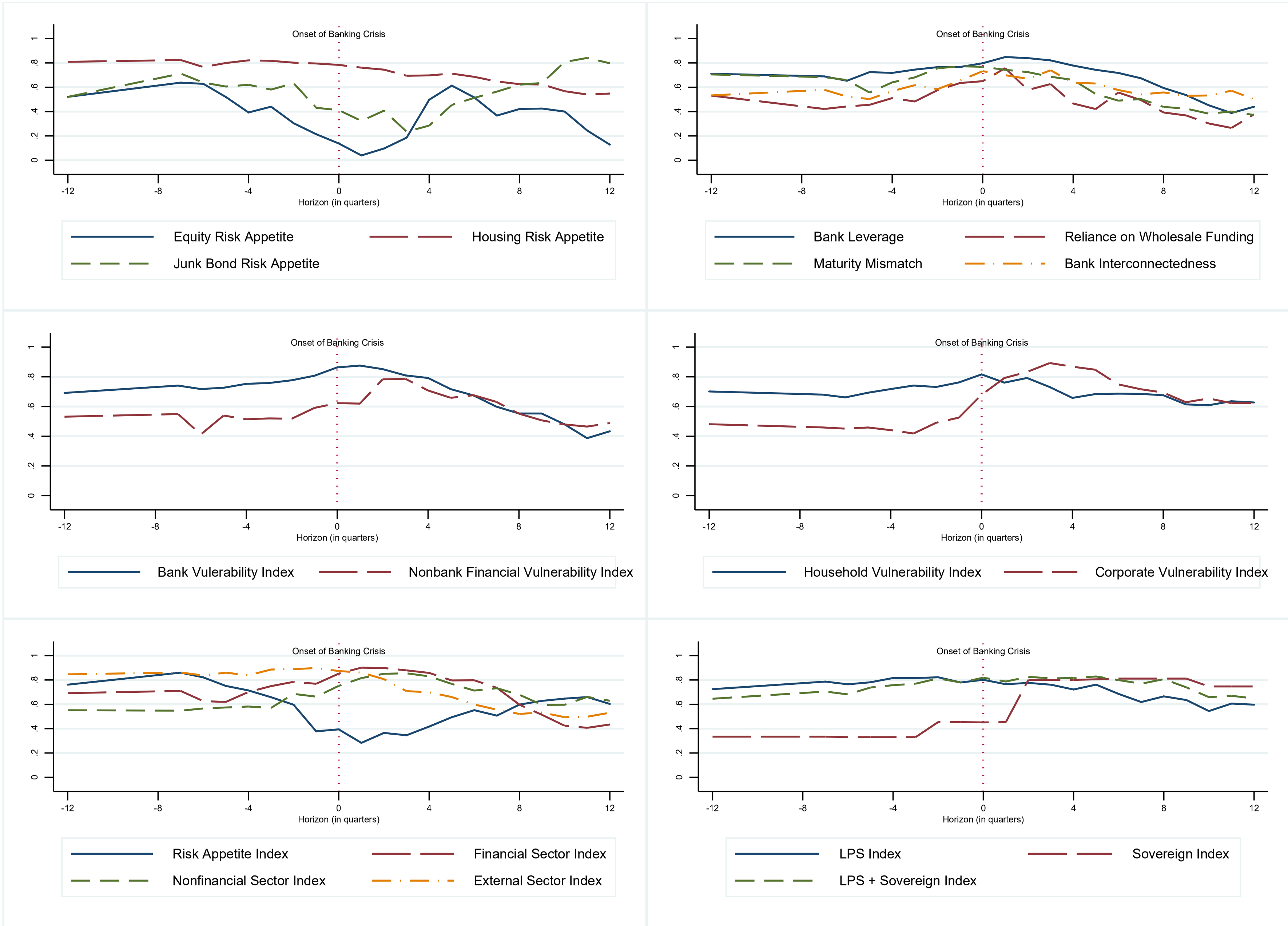

Figure 4: **Various Vulnerability Indexes around Banking Crises**

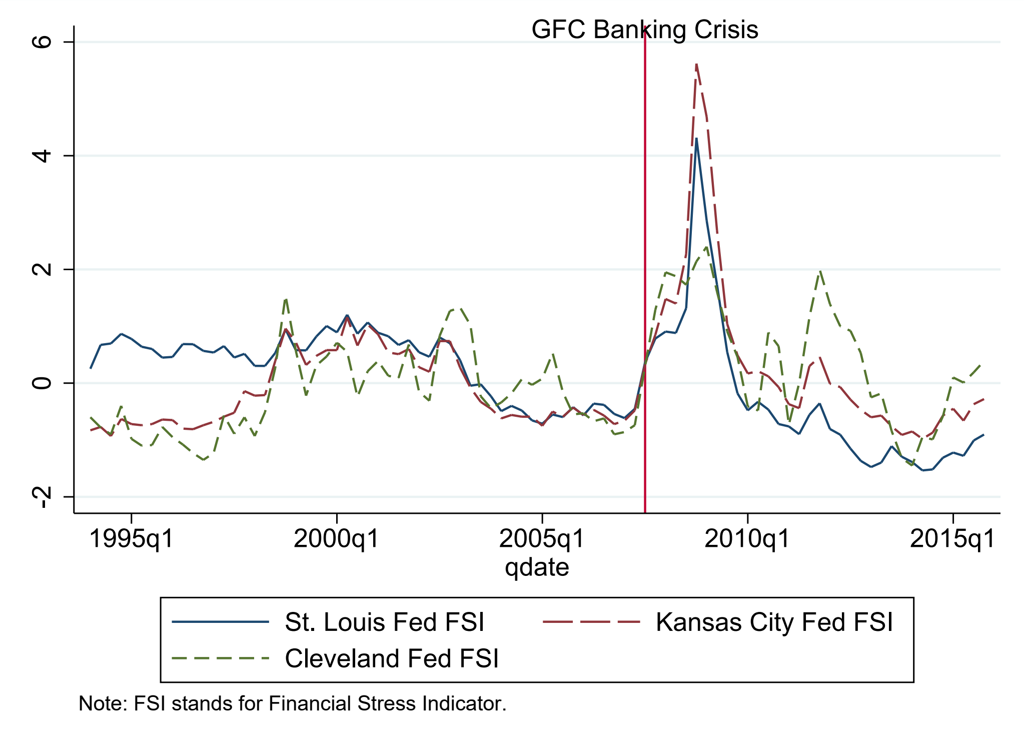

Figure 5: **Financial Stress Indicators for the United States**

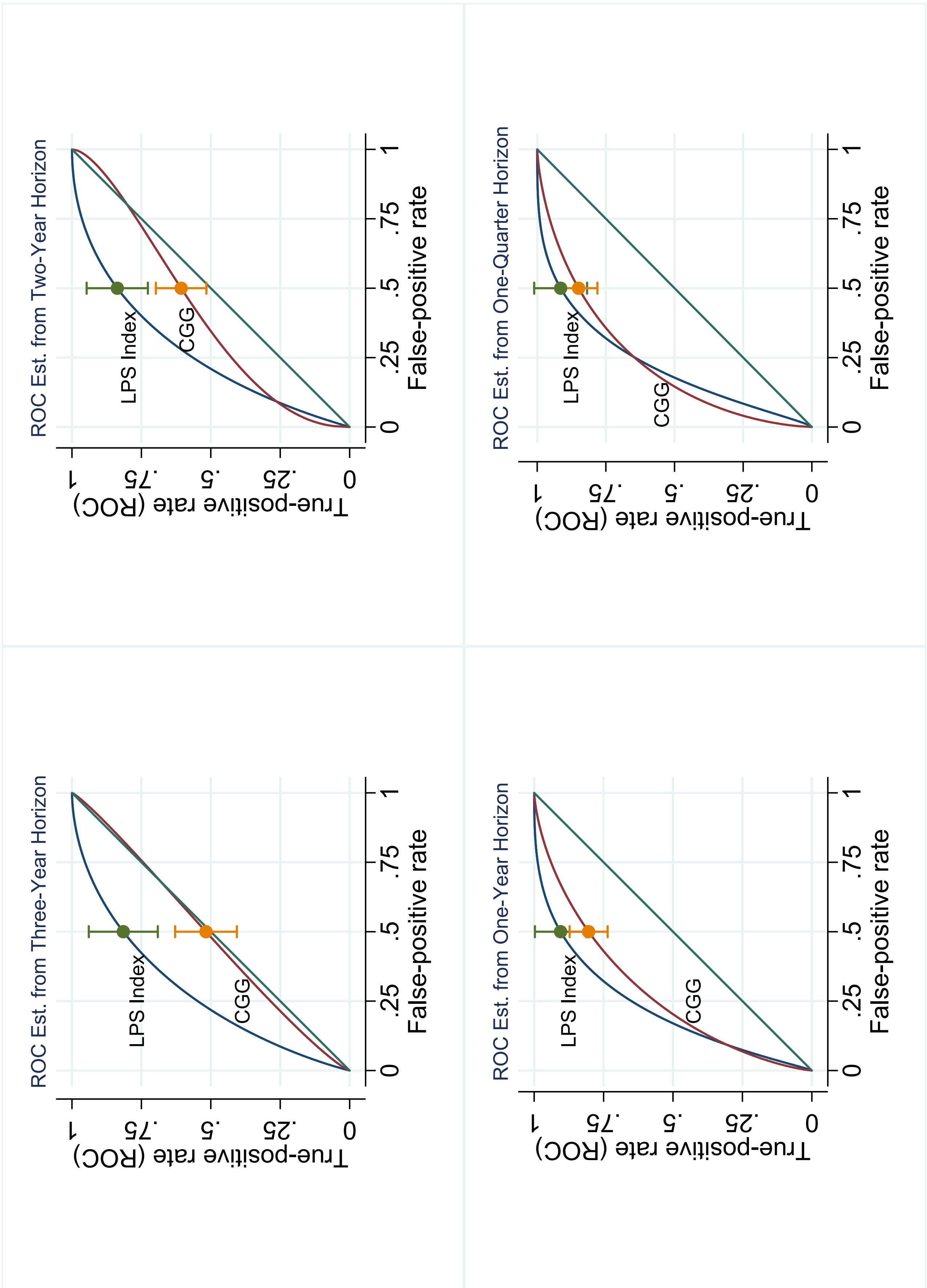

Figure 6: **Estimated ROC Curves and True-Positive Rate Confidence Intervals (given False-Positive Rate = 0.5)**

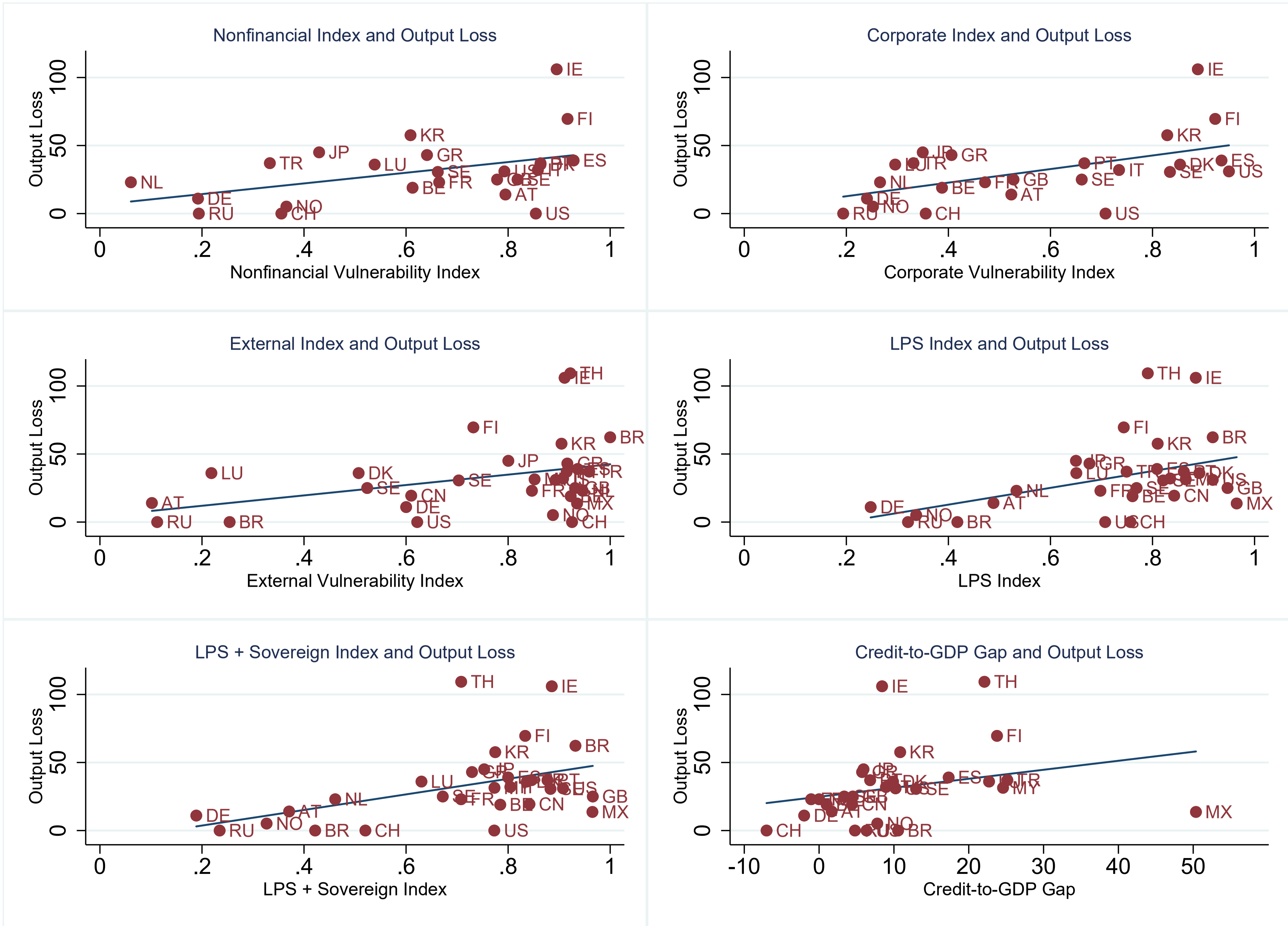

Figure 7: **Measures of Vulnerabilities and Output Loss**

Table 1: Systemic Crises, Banking Crises, and Output Losses

Country	Systemic Crisis	Banking Crisis	Output Loss (pct.)	GFC
Austria	NA	2008:Q3	14.0	✓
Belgium	2008:Q4	2008:Q3	19.0	✓
Brazil	NA	1990:Q1	62.3	
	NA	1994:Q4	0.0	
China	NA	1998:Q3	19.4	
Denmark	2008:Q4	2008:Q3	36.0	✓
Finland	1991:Q3	1991:Q3	69.6	
France	2008:Q4	2008:Q3	23.0	✓
Germany	NO SYS. CRISIS	2008:Q3	11.0	✓
Greece	2008:Q4	2008:Q3	43.0	✓
Ireland	2008:Q4	2008:Q3	106.0	✓
Italy	1992:Q3	NO CRISIS		
	2008:Q4	2008:Q3	32.0	✓
Japan	1992:Q4	1997:Q4	45.0	
Luxembourg	NA	2008:Q3	36.0	✓
Malaysia	1997:Q3	1997:Q3	32.4	
Mexico	NA	1994:Q4	13.7	
Netherlands	2008:Q4	2008:Q3	23.0	✓
Norway	1990:Q4	1991:Q4	5.2	
Portugal	2008:Q4	2008:Q3	37.0	✓
Russia	NA	1998:Q3	NA	
	NA	2008:Q3	0.0	✓
South Korea	1997:Q3	1997:Q3	57.6	
Spain	2008:Q4	2008:Q3	39.0	✓
Sweden	1991:Q3	1991:Q3	30.6	
	NO SYS. CRISIS	2008:Q3	25.0	✓
Switzerland	1991:Q3	NO CRISIS		
	NO SYS. CRISIS	2008:Q3	0.0	✓
Thailand	1997:Q3	1997:Q3	109.3	
Turkey	NA	2000:Q4	37.0	
United Kingdom	1990:Q2	NO CRISIS		
	2007:Q3	2007:Q3	25.0	✓
United States	1990:Q2	1988:Q1	0.0	
	2007:Q3	2007:Q3	31.0	✓

Note. Systemic crisis beginning period from Drehmann and Juselius (2014). Countries with "NA" (not available) are countries not in Drehmann and Juselius (2014). Countries with "NO SYS. CRISIS" are countries that did not have a systemic crisis stemming from domestic financial vulnerabilities according to Drehmann and Juselius (2014). Banking crisis beginning period and output loss from Laeven and Valencia (2013). Countries with "NO CRISIS" are countries with no banking crisis associated with a given time period according to Laeven and Valencia (2013). Output loss from Laeven and Valencia (2013) 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. "NA" in this column means data is not available because the country is not part of the sample of countries in Drehmann and Juselius (2014).

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 Systemic Crises across Different Horizons

	-12	-11	-10	-9	-8	-7	-6	-5	-4	-3	-2	-1
Subindexes and CGG												
Risk App. Index	0.80***	0.79***	0.72**	0.76**	0.78	0.76	0.74	0.73	0.65	0.60	0.52	0.47
CGG	0.53	0.56	0.58	0.62	0.68	0.70	0.71	0.77	0.80**	0.84***	0.87***	0.89***
Fin. Index	0.64	0.63	0.61	0.64	0.65	0.72	0.71	0.77	0.77	0.80	0.82	0.84
CGG	0.55	0.58	0.59	0.63	0.68	0.71	0.72	0.78	0.80	0.84	0.86	0.89
Nonfin. Index	0.58	0.58	0.58	0.62	0.64	0.68	0.65	0.71	0.73	0.77	0.79	0.80
CGG	0.58	0.60	0.60	0.63	0.68	0.69	0.69	0.76	0.79	0.84	0.86	0.89*
External Index	0.73***	0.76***	0.78***	0.78**	0.79*	0.79	0.81**	0.80	0.78	0.78	0.80	0.81
CGG	0.52	0.55	0.57	0.61	0.66	0.68	0.69	0.75	0.78	0.82	0.85	0.87
Agg. Indexes and CGG												
LPS Index	0.79***	0.79***	0.76***	0.79**	0.81***	0.83**	0.83**	0.86**	0.84	0.84	0.84	0.85
CGG	0.52	0.55	0.57	0.61	0.66	0.68	0.69	0.75	0.78	0.82	0.85	0.87
LPS + Sovereign	0.73***	0.72***	0.69**	0.73**	0.75	0.77	0.77	0.81	0.79	0.81	0.84	0.85
CGG	0.52	0.55	0.57	0.61	0.66	0.68	0.69	0.75	0.78	0.82	0.85	0.87
Subsample of countries												
LPS (GFC crisis only)	0.72***	0.72**	0.69**	0.74**	0.77**	0.82**	0.82**	0.86**	0.84*	0.83	0.83	0.86
CGG (GFC crisis only)	0.49	0.50	0.52	0.56	0.60	0.62	0.63	0.69	0.69	0.75	0.78	0.82
LPS (non-GFC crisis)	0.90***	0.90***	0.87***	0.88**	0.88**	0.85	0.83	0.86	0.84	0.87	0.87	0.83
CGG (non-GFC crisis)	0.56	0.60	0.62	0.66	0.73	0.77	0.78	0.83	0.89	0.92**	0.94***	0.93***
Debt Service Ratio												
LPS Index	0.85***	0.87***	0.80**	0.83**	0.85**	0.85**	0.89***	0.89**	0.91**	0.91**	0.87*	0.91**
Debt Service Ratio	0.48	0.49	0.51	0.53	0.56	0.58	0.60	0.63	0.66	0.67	0.68	0.69

Note. Each column signifies the horizon in which systemic crises according to Drehmann and Juselius (2014) are predicted, which ranges from 12 quarters ahead to 1 quarter before the onset of systemic crises beginning with a sample of 20 countries from 1986 to 2012. Each set of two columns looks at how the AUCs compare between two different indicators. "GFC crisis only" includes a sample of 12 countries with a crisis only in the 2007-08 period. "non-GFC crisis" includes a sample of 8 countries which have also experienced a crisis outside the 2007-2008 period. Debt serice ratios are available for only 21 countries mostly from 1999. 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

	-12	-11	-10	-9	-8	-7	-6	-5	-4	-3	-2	-1
Subindexes and CGG												
Risk App. Index	0.73***	0.72***	0.79***	0.71***	0.67	0.72	0.68	0.69	0.66	0.61	0.54	0.44
CGG	0.47	0.48	0.46	0.50	0.57	0.60	0.63	0.69	0.74	0.75**	0.78***	0.79***
Fin. Index	0.67***	0.67	0.64	0.66	0.68	0.67	0.65	0.67	0.73	0.72	0.76	0.80
CGG	0.51	0.58	0.58	0.58	0.60	0.63	0.65	0.70	0.74	0.75	0.77	0.78
Nonfin. Index	0.50	0.51	0.51	0.51	0.55	0.56	0.57	0.58	0.63	0.63	0.66	0.67
CGG	0.51	0.58	0.57	0.57	0.58	0.60	0.62	0.67*	0.73*	0.74*	0.76*	0.78**
External Index	0.74***	0.78***	0.76**	0.79***	0.77***	0.74**	0.77***	0.78**	0.77	0.77	0.75	0.77
CGG	0.52	0.58	0.57	0.58	0.59	0.61	0.63	0.69	0.73	0.74	0.76	0.77
Agg. Indexes and CGG												
LPS Index	0.73***	0.74**	0.76***	0.75**	0.74**	0.74*	0.74*	0.77*	0.78	0.78	0.77	0.78
CGG	0.52	0.58	0.57	0.58	0.59	0.61	0.63	0.69	0.73	0.74	0.76	0.77
LPS + Sovereign	0.70***	0.72**	0.69*	0.69*	0.69*	0.70	0.69	0.72	0.73	0.73	0.76	0.76
CGG	0.52	0.58	0.57	0.58	0.59	0.61	0.63	0.69	0.73	0.74	0.76	0.77
Subsample of countries												
LPS (GFC crisis only)	0.71***	0.74***	0.78***	0.75***	0.79***	0.74***	0.74***	0.76**	0.78*	0.78	0.75	0.75
CGG (GFC crisis only)	0.42	0.42	0.41	0.43	0.45	0.47	0.50	0.57	0.64	0.65	0.67	0.71
LPS (non-GFC crisis)	0.75*	0.75	0.74	0.75	0.70	0.74	0.73	0.78	0.78	0.78	0.79	0.80
CGG (non-GFC crisis)	0.59	0.65	0.65	0.67	0.67	0.70	0.72	0.76	0.79	0.81	0.83	0.83
Debt Service Ratio												
LPS Index	0.66**	0.65*	0.71***	0.67*	0.68*	0.74***	0.71**	0.76***	0.77**	0.78***	0.76**	0.77**
Debt Service Ratio	0.48	0.49	0.49	0.50	0.52	0.53	0.55	0.56	0.58	0.59	0.61	0.62

Note. Each column signifies the horizon in which banking crises according to Laeven and Valencia (2013) are predicted, which ranges from 12 quarters ahead to 1 quarter before the onset of banking crises beginning with a sample of 27 countries from 1986 to 2012. Each set of two columns looks at how the AUCs compare between two different indicators. “GFC crisis only” includes a sample of 14 countries with a crisis only in the 2007-08 period. “non-GFC crisis” includes a sample of 13 countries which have also experienced a crisis outside the 2007-2008 period. Debt serice ratios are available for only 21 countries mostly from 1999. 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 5: Area Under the ROC Curve (AUC) prior to Systemic and Banking Crises across Different Horizons - Real Time Analysis

	-12	-11	-10	-9	-8	-7	-6	-5	-4	-3	-2	-1
Systemic Crises (26 countries)												
CGG (nonparametric)	0.78	0.78	0.77	0.78	0.78	0.80	0.80	0.81	0.82	0.82	0.82	0.82
CGG (parametric)	0.77	0.76	0.76	0.77	0.77	0.78	0.78	0.78	0.79	0.79	0.79	0.78
CGG (from 1996)	0.73	0.72	0.72	0.73	0.74	0.74	0.73	0.74	0.75	0.76	0.77	0.77
Subsample of 20 countries												
LPS Index	0.80*	0.76	0.77	0.77	0.79	0.78	0.75	0.78	0.76	0.75	0.78	0.77
CGG	0.73	0.71	0.71	0.72	0.73	0.73	0.72	0.72	0.73	0.74	0.75	0.74
Banking Crises (27 countries)												
LPS Index	0.69**	0.66	0.65	0.67	0.62	0.62	0.61	0.65	0.67	0.65	0.64	0.65
CGG	0.61	0.61	0.60	0.61	0.62	0.61	0.62	0.64	0.65	0.66	0.66	0.66

Note. Each column signifies the horizon in which systemic or banking crises, according to Drehmann and Juselius (2014) and Laeven and Valencia (2013), respectively, are predicted, which ranges from 12 quarters ahead to 1 quarter before the onset of systemic or banking crises beginning with the 1980-2012 period. All results are in quasi-real time as we take only the data up to a given period in calculating the LPS Index or CGG. However, data may be revised after release. The first three rows illustrate how the AUC decreases from a nonparametric estimation (as used in Drehmann and Juselius (2014)) to a parametric estimation, then cutting the sample by sixteen years to include only 1996-2012. The AUC results fall slightly after each of these changes. The AUC falls the most when we switch from looking at the onset of systemic crises to banking crises keeping the time period of 1996-2012. The increase in the number of countries does not affect the level of AUC estimates, so we omit the results for keeping the number of countries constant at 20 countries when evaluating the AUC for banking crises. Each set of two columns looks at 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 6: Area Under the ROC Curve (AUC) prior to Banking Crises across Different Horizons - Moving Average Analysis

	-12	-11	-10	-9	-8	-7	-6	-5	-4	-3	-2	-1
4 qtr mov. average												
LPS Index	0.72***	0.73***	0.75***	0.76***	0.76***	0.76**	0.75**	0.76*	0.77*	0.78	0.78	0.78
CGG	0.46	0.47	0.53	0.54	0.59	0.60	0.61	0.64	0.68	0.72	0.75	0.77
12 qtr mov. average												
LPS Index	0.67***	0.68***	0.70***	0.71***	0.73***	0.75***	0.77***	0.77***	0.78***	0.79***	0.80***	0.80***
CGG	0.47	0.47	0.48	0.48	0.49	0.49	0.51	0.54	0.57	0.60	0.65	0.68
20 qtr mov. average												
LPS Index	0.65***	0.66***	0.67***	0.67***	0.68***	0.71***	0.71***	0.72***	0.74***	0.75***	0.76***	0.77***
CGG	0.45	0.45	0.46	0.47	0.46	0.47	0.48	0.53	0.56	0.58	0.58	0.60

Note. Each column signifies the horizon in which banking crises, according to Laeven and Valencia (2013), are predicted, which ranges from 12 quarters ahead to 1 quarter before the onset of systemic or banking crises beginning with the 1980-2012 period. The main independent variables are 4-quarter, 12-quarter, and 20-quarter moving averages for the LPS Index and the Credit-to-GDP gap, respectively. 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 7: Output Loss and Financial Vulnerability Measures

	(1)	(2)	(3)	(4)	(5)	(6)
Nonfinancial Index	39.92**					
	(2.23)					
Corporate Index		49.9***				
		(3.03)				
External Index			38.1**			
			(2.13)			
LPS Index				61.7**		
				(2.58)		
LPS + Sov. Index					57.2**	
					(2.72)	
CGG						0.66
						(1.51)
Constant	6.50	2.79	4.35	−11.8	−7.75	24.8***
	(0.55)	(0.27)	(0.31)	(−0.66)	(−0.50)	(3.72)
Obs.	24	24	30	30	30	29
R-sq. adj.	0.15	0.26	0.14	0.16	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 8: Length of Recession and Financial Vulnerability Measures

	(1)	(2)	(3)	(4)	(5)	(6)
Risk Appetite Index	3.77**					
	(2.65)					
House Price Index		4.38**				
		(2.42)				
External Index			1.58			
			(1.23)			
LPS Index				2.39		
				(1.53)		
LPS + Sov. Index					2.77**	
					(2.18)	
CGG						0.00
						(0.14)
Fixed effects	✓	✓	✓	✓	✓	✓
Obs.	83	74	89	91	93	85
R-sq. adj.	0.21	0.20	0.16	0.26	0.22	0.21

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 9: Length of Recessions (not associated with banking crises)

	(1)	(2)	(3)	(4)	(5)	(6)
Risk Appetite Index	2.96***					
	(3.10)					
House Price Index		3.21***				
		(2.86)				
External Index			−0.17			
			(−0.18)			
LPS Index				2.00*		
				(1.91)		
LPS + Sov. Index					1.92**	
					(2.24)	
CGG						0.01
						(0.43)
Constant	2.31***	2.17***	3.97***	2.75***	2.79***	3.85***
	(4.15)	(3.41)	(7.20)	(4.43)	(5.41)	(13.4)
Obs.	56	52	59	61	63	56
R-sq. adj.	0.14	0.12	−0.02	0.04	0.06	−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. * $p < .1$, ** $p < .05$, *** $p < .01$