Measuring Real-time Perceptions of Financial Market Stress

Christopher Gandrud, Mark Hallerberg

*Hertie School of Governance**

June 4, 2015

Incomplete Working Draft

Abstract

A wide range of political economy research on the causes, responses to, and effects of banking crisis needs an accurate and reliable measure of banking crises that is comparable across countries and ideally includes information on crisis severity. Most research to date uses one of two series of crisis data: Reinhart and Rogoff (2009) or Laeven and Valencia (2013). These measures are lacking in that they are simple dichotomous indicators of financial crisis and differ considerably in their start and end dates for many incidents. They are also constructed after the fact and so tend to be biased towards severe crises and away from those where government responses effectively calmed emerging trouble. Recent efforts, namely Jing et al. (2015), Rosas (2009), and Romer and Romer (2015) have attempted to develop more reliable measures of crises that also include continuous information on severity. Each of these approaches have important shortcomings. Jing et al.'s measure is based on central bank's policy responses, which researchers may want to examine as a dependent variable. Rosas relies on nationally reported banking system data, but this in formation is notoriously opaque (Gandrud and Hallerberg, 2015*a*) and can be subject to significant revisions. Romer and Romer's approach relies on very time intensive human coding of texts from the OECD and aggregates these codings using a simple summation method. Their approach, though it avoids the issues present in Jing et al. (2015) and Rosas (2009), is very laborious to construct, subjective, and equally weights each item in their coding scheme, which may not be reasonable. This paper describes the motivation and construction of our new measure of real-time perceptions of financial market stress based on kernel principal component analysis (PCA) of Economist Intelligence Unit monthly country reports. We refer to this measure as the EIU Perceptions of Financial Market Stress (EPFMS) Index. In doing so, we not only develop a novel indicator of financial market stress, but we also make a

*Please contact Christopher Gandrud (gandrud@hertie-school.org). Thank you to Ronen Palan for helpful comments. All data and replication material can be found at: https://github.com/christophergandrud/EIUCrisesMeasure.

contribution to the wider political science literature by demonstrating how kernel PCA can be used to summarize vast quantities of qualitative texts into useful cross-sectional time-series indicators.

Why and how do politicians respond to financial market stress? This question has attracted considerable attention recently following the 2007-2009 financial crisis and earlier following the late-1990s Asian financial crisis. However, virtually all of this research lacks a crucial variable: a real-time indication of the level of financial market stress that policy-makers believed that they faced. To understand why politicians made a given policy choice, we need to have a measure the conditions that they believed they were responding to.

Most research has used *post-hoc* assessments of banking crisis as a second-best alternative. However, this presents clear problems. Chiefly, using such measures creates clear selection bias as stress that politicians responded to effectively will not be selected. In addition, these measures are typically binary and so give no indication of stress intensity. The measures are also at gross intervals, typically yearly, prohibiting sub-annual analysis.

In this paper we aim to overcome these problems by develop a new index of real-time perceptions of financial market stress. The Index is created using a kernel principal component analysis (PCA) of monthly Economist Intelligence Unit (EIU) reports. We it the EIU Perceptions of Financial Market Stress (EPFMS) Index. This measure should supplant previous second-best measures of financial market stress by researchers aiming to understand why and how policy-makers respond to financial crisis. In so doing, we make a contribution to the wider political science literature by showing how kernel PCA can be used to summarize vast quantities of qualitative texts into cross-sectional time-series indicators.

We start the paper by detailing our motivation for creating a real-time index of perceptions of financial market stress. We then discuss the construction of the Index and compare it to widely used previous measures of financial market stress. [WOULD BE NICE TO HAVE A REPLICATION OF AN IMPORTANT PAPER].

1 Motivation

Researchers have tended to rely on two data sources for cross-country information on when a country is facing a financial crisis: Laeven and Valencia (2013) and Reinhart and Rogoff (2009). Knowing when crises started (and when they have ended) is crucial for research trying to understand issues such as how crises affect economic output, how governments choose to respond to financial market distress, and what the fiscal costs of financial crises are.

There are a number of problems with these indicators. Unlike economic recessions, financial crises are poorly defined in previous sources. This contributes to large inconsistencies between the timing of crises in the Laeven and Valencia (2013) and Reinhart and Rogoff (2009) data sets (Chaudron and de Haan, 2014). For example, Japan is labeled as having a crisis between 1997 and 2001 by the former, but 1992-1997 in the latter. Gandrud and Hallerberg (2015*b*) also find that there are significant difference in crisis timing between different versions of the Laeven and Valencia (2013) data. Crises are also identified by researchers who know what happened. Financial market stress that is addressed well by policymakers, preventing a major crisis, may therefore not be included. Similarly, stress that is temporarily dampened through unsustainable policy measures, only to flare up later, is not clearly recorded. This makes it difficult to adequately study why and how politicians respond to financial market stress. Related to this, current measures are dichotomous thus errors have large consequences for creating bias when used in econometric models. They also do not give any indication of how severe a crisis is.

Overall, we lack the continuous real-time measure of financial market stress that we need to be able to adequately examine why and how policy-makers respond to financial market problems.

There have been a number of recent attempts to create crisis measures that overcome these issues. Building on Von Hagen and Ho (2007), Jing et al. (2015) developed am index of money market pressure based on changes in short-term interest rates and stocks of central bank reserves. However, this measure conflates distress and policy responses, assuming central banks use the same reaction function to increased demand for liquidity. Rosas (2009) developed a dynamic latent trait model of banking system distress. However, his measure relies on nationally reported data to the IMF's International Financial Statistics, which Copelovitch, Gandrud, and Hallerberg (2015) show can be endogenous to financial market distress.

Romer and Romer (2015) aimed to address this issue by manually classifying 24 countries on a 15 point scale capturing the cost of credit intermediation. They code countries using information from OECD semi-annual *Economic Outlook* reports from 1967 to 2007. Relying on contemporaneous reports allows for the construction of a real-time measure of credit market distress. This would allow us to examine policy choices that head off trouble or unsustainably prolong brewing difficulties. Their, relatively, continuous measure gives an indication of market distress intensity.

Their approach could be improved in a number of key ways. First, they are necessarily limited to the relatively small sample of OECD countries. Second, their measure is laborious to create and update. Third, the scale is created by simply summing

[COMPLETE]

2 Creating the Perceptions of Financial Market Stress Index

We propose a new method of estimating a real-time measure of perceptions of financial market stress using kernel principle component analysis (Scholkopf, Smola and Muller, 1998; Lodhi et al., 2002; Spirling, 2012) of monthly country reports from the *Economist Intelligence Unit*.[1]

2.1 Why the EIU?

The EIU is the product of a an analysis of real-time, third-party assessments of financial market conditions reported monthly or quarterly (depending on the country). These reports contain both summaries of real-time information and forecasts of future economic conditions. They are a channel through which this information is disseminated to public and private actors. Together, the reports create a very large corpus (more than 20,000 texts from 1997 through 2011 [CHECK]) of monthly reports for more than 100 countries. As the texts generally follow the same format and style, they contain directly comparable assessments of economic conditions monthly across the globe for a significant time span. In contrast, the OECD *Economic Outlook* provides comparable reports for a very small number of wealthy countries on a bi-annual basis.

2.2 Summarizing Financial Market Stress in the EIU

Our aim is to create an index that classifies financial conditions on a continuous more-stressed/less stressed spectrum. So we clearly need an efficient way to summarize the vast quantity of information in the EIU reports. To do this we first collected and processed the texts. Then we used kernel principal component analysis to summarize the texts into a dimension of financial market stress. We rescaled the Index to ease interpretation. Finally, we used a number of strategies to examine the Index's validity.

2.2.1 Text selection

EIU reports contain assessments of a wide range of countries' economies, not just their financial system. So, our first step was to select the portions of the EIU texts that contained relevant information about countries' banking and financial systems. We collected the parsed reports–the reports were in HTML format. We then extracted the portions of the texts–headlines and paragraphs–that contained at least one of a number of keywords concerning banking and financial markets.[2] Due to a significant change in how the reports were

[1] See `http://www.eiu.com/`. Accessed May 2015.

[2] The keywords included: *bail-out*, *bailout*, *balance sheet*, *balance-sheet*, *bank*, *banks*, *banking*, *credit*, *crunch*, *default*, *finance*, *financial*, *lend*, *loan*, *squeeze* [MAKE SURE TO UPDATE]. These keywords were adapted from those used by Romer and Romer (2015) and are intended to select passages that discusses credit market conditions.

constructed in 2003, we also selected only texts from 2003 in order to maintain comparability across the time-series.

We then preprocessed these texts using standard techniques (see Grimmer and Stewart, 2013).[3] This involved removing common English words, such as 'was' and 'its'. The 'stopword' list we used was from Dhillon and Modha (2001). We also stemmed the words so that different variants of the same word are grouped together, removing extra whitespace between the words, removing punctuation and numbers. Finally, we dropped texts that included very few words (less than six). Including these texts prevented the estimation of the kernel PCA model.

2.2.2 Kernel Principal Component Analysis

Texts are frequently summarized using unordered 'bag-of-words' approaches, such as Latent Dirichlet Allocation, that do not retain word order. The result of these approaches is often clusters of 'topics' within speeches or speeches to clusters (see Grimmer and Stewart, 2013, for a review). We would like to accomplish something different. Ideally, we would like to preserve the order of the words in our texts and we would like to place the texts on a continuous scale that will be interpretable as a measure of perceived financial market stress. We would like to preserve the order of the words in the texts. Many financial terms such as 'credit growth' and 'borrowing costs' are used in completely different senses depending on the adjectives that modify them. For example, 'slowing credit growth' vs. 'expanding credit growth' or 'falling borrowing costs' vs. 'increasing borrowing costs'. A bag-of-words approach that treated each word as having meaning as an individual unit, rather than having meaning in ordered association with other words, would not adequately capture common and radically different meanings in the EIU documents.

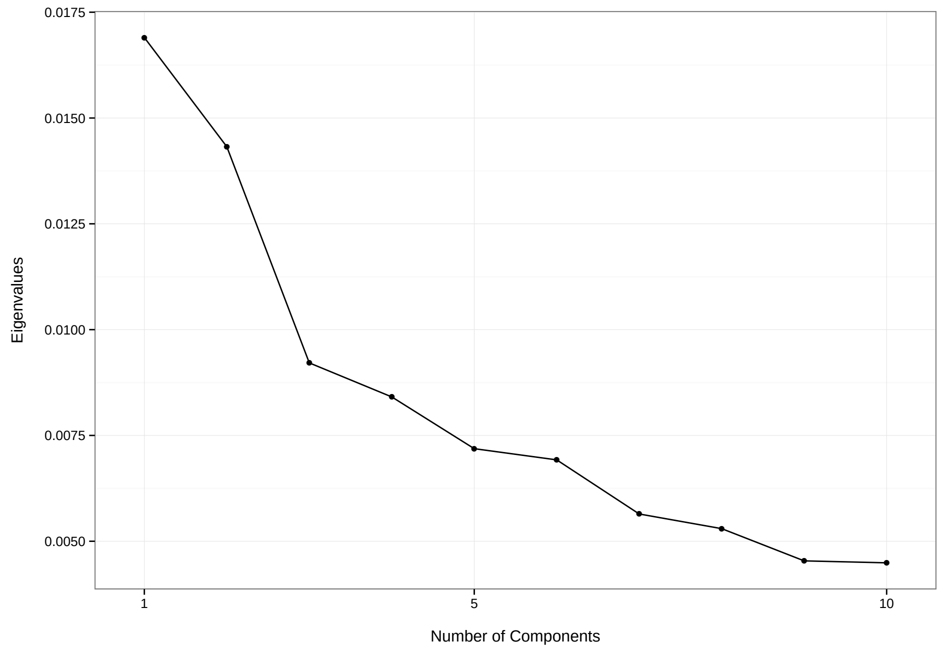
In order to address these issues we use kernel principal component analysis. This method was developed by Scholkopf, Smola and Muller (1998) and Lodhi et al. (2002) and introduced recently into political science by Spirling (2012).[4] Kernel PCA allows us to extract structure from this likely high-dimensional corpus (Zhang, Wang, and Ma 2010, 6531–37) while preserving word order. The unit of analysis is a sub-string kernel: in effect a short sequence of letters[5] that can be shared within and across words. Thus we can distinguish between two simple documents with the stemmed strings 'slow credit' and 'expand credit'. They share the five character kernels 'credit, but differ on 'slowc' and 'pandc' among others. Using Lodhi et al. (2002) we can summarize the similarity of these documents with the frequency distribution of five-length

[3] All preprocessing was done using the `tm` package (Feinerer and Hornik, 2015) in R (R Core Team, 2015).

[4] He used it to summarize changing trends in treaties between the US government and Native American groups.

[5] Following Spirling (2012), we used kernels with a length of 5, i.e. those that are five letters long. See also Lodhi et al. (2002) who demonstrate that in English strings lengths between four and seven are often optimal.

Figure 1: Assessing Model Fit: Eigenvalues for Kernel Principal Components



strings that they have in common–one–standardized by document length. We can find these pairs for all of the documents in our corpus to create a kernel matrix. Finally, we can scale the documents using principal component analysis.[6]

2.2.3 Dimensionality

To determine the number of dimensions that best describe the data, we conducted a scree test, the results of which are shown in Figure 1. There something of an 'elbow' in the plot at three components. This suggests that there is perhaps substantively meaningful variation in approximately the first three dimensions. The drop from the first to second component notable. We focus on the first dimension as the main dimension summarizing financial market conditions. We also examined a number of the other dimensions. However, these noticeably did not closely correspond to our priors about financial market stress based on previous indicators.

[6] We conducted kernel PCA with the `kpca` function from the R package **kernlab** (Karatzoglou et al. 2004).

3 Results

The lines in figures 3 and 4 show the results of the kernel PCA analysis for a selection of countries. We use the first principal component throughout the paper. Similar plots for all countries in the analysis are available in the Appendix. Before diving deeper into these results, it is important to note three simple transformations we conducted on the raw results. First, we flipped the scale. As we demonstrate when we compare the Index to other measures of crisis, this allows higher values of the EPFMS to be interpreted as 'more financial market stress'. Second, we rescaled the Index so that it would be between zero and one.[7] This eases interpretation and comparability to other measures. Henceforth we only use the rescaled version of the Index. Then we slightly smoothed the results by taking a two period–usually two months–moving average.

What does this dimension represent? We took a number of approaches to answer this question. First, following Spirling (2012) we used a random forests regression (Breiman, 2001; Jones and Linder, 2015) to examine the relationships between word stems from the texts and the Perceptions Index. Second, we compared the Index to previous indices using an 'interocular' test, e.g. looking a plots of the results and comparing them to our priors on financial market stress.

3.1 Random forests

Spirling (2012, 6–8) demonstrated the usefulness of using random forests "regressions" to explore what principal components from textual analyses represent. To use this tool to explore our data, we first created a document-term frequency matrix from the stemmed documents. Effectively this is a $k \times s$ matrix recording the frequency of each term in $\boldsymbol{S}$ for each document in $\boldsymbol{K}$. We removed sparse terms, i.e. kept only stems that were found in 90 percent of the documents. Random forests regressions, as opposed to ordinary least squares regressions, are useful for exploring this data's associations with the estimated principal components because it can handle many variables–in this case 958 stems–relative to the number of documents–12,473.

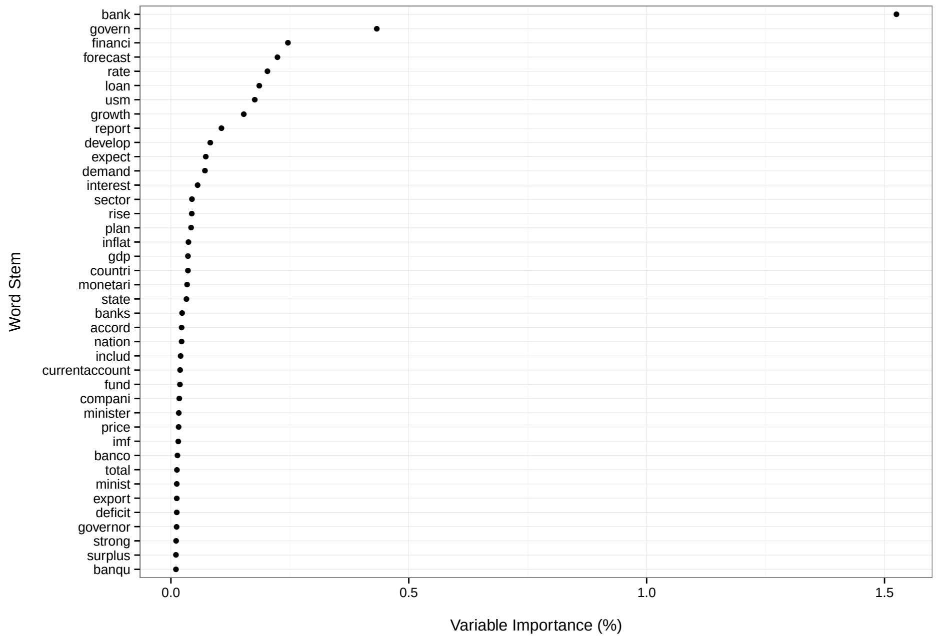
We focus on the variable importance from this analysis.[8] The results are shown in Figure 2. The logic behind variable importance in this context is as a measure of how well the frequency of a given stem in a text allows the model to predict the EPFMS score for that text.

Unsurprisingly, two of the three stems with the largest variable importance are 'bank' and 'financi'.

[7] $\frac{x-\min(\boldsymbol{X})}{\max(\boldsymbol{X})-\min(\boldsymbol{X})}$, where $\boldsymbol{X}$ is the vector of the first principal component and x is an individual value from this vector.

[8] We conducted the random forests regressions using the `rfsrc` function from the **randomForestSRC** R package (Ishwaran and Kogalur, 2015).

Figure 2: 40 Stems Estimated to be the Most Important for Predicting EIU Perception of Financial Market Stress Index



Terms with these stems were used to select the texts.

3.2 Comparison to other crisis measures

How does our measure compare to previous ways of measuring and timing financial market stress and crisis? We directly compare our measure to dichotomous measures in Reinhart and Rogoff (2009) and Laeven and Valencia (2013), as well as Romer and Romer's (2015) continuous measure.

There are some limitations in comparability based simply on the different coverage of the different indices. Romer and Romer (2015) in particular largely does not include the most recent crisis in their sample as they did not collect data past 2007. We had to make a number of transformations and assumptions to be able to compare the different data sets. First, the Laeven and Valencia and Reinhart and Rogoff data on recorded only at yearly intervals. So, we assumed that the crisis start and end dates they referred to were in the middle of the year, i.e. June. Second, we rescaled Romer and Romer's 16-point scale (in effect 13-points because they do not classify any country-quarter in their sample as being at the upper two positions on the scale) to be between 0 and 1 using the same method as above. Finally, it should be noted that Reinhart and Rogoff (2009) only cover 70 countries and they have updated their data least recently.

Table 1: Comparision of Crisis Measures' Definitions

Source	Measurement Level	Periodicity	Definition of Financial Market Distress/Crisis
Reinhart and Rogoff (2009, 11)	binary	annual	One of two types of events: (1) bank runs leading to closures, mergers, or public sector takeovers of one or more financial institution or (2) the closure, merger, takeover, or large-scale government assistant of an important financial institution marking the start of a string of similar events.
Laeven and Valencia (2013, 228)	binary	annual	Meets two conditions: (1) significant sign of financial distress in the banking system and (2) significant banking policy intervention measures in response to significant losses in the banking system.
Romer and Romer (2015, 3)	ordinal (0 to 15 scale)	bi-annual	Hand-coded perceptions of funding problems and rising loan defaults in *OECD Economic Outlook*

The solid lines in figures 3 and 4 show the EIU Perceptions of Financial Market Stress Index. The dashed lines show Romer and Romer's (rescaled) measure. Finally, the shaded boxes show the periods where Laeven and Valencia (2013) and Reinhart and Rogoff (2009) classify there as being a banking crisis.[9] It should be noted that Laeven and Valencia (2013) identify eight "borderline" crises in this period, in that the countries almost meet their systemic banking crisis definition because they only used two rather than three policy responses.[10] Some of these borderline cases are shown in the figures 3 and 4.

In many cases–given the time period limitations of each data series–, the indices overlap. Comparisons with Romer and Romer (2015) are limited, but we can see that in general, where comparable time series are available, that the EPFMS and their index are roughly similar. In particular, both indices increase in the US from early 2007. They both decline for Japan through 2004-2005. A notable difference is how Romer and Romer classify Japan as being without stress from mid-2005, while the EPFMS stays high relative to many other economically developed countries. While they both classify Iceland as being under stress in the late 2000s, the timing is different. Romer and Romer classify Iceland as in stress[11] in 2006-2007. This is earlier than not only a marked increase in the EPFMS Index, but also Reinhart and Rogoff and Laeven and Valencia's timing.

[9]We used Table 1 in Romer and Romer (2015) to recreate their data set. We downloaded Laeven and Valencia's data from: https://www.imf.org/external/pubs/cat/longres.aspx?sk=26015.0. Accessed May 2015. Reinhart and Rogoff's data was downloaded from: http://www.carmenreinhart.com/data/browse-by-topic/topics/7/. Accessed May 2015.

[10]The cases are: France, Hungary, Italy, Portugal, Russia, Slovenia, Sweden, and Switzerland.

[11]They classify Iceland as being in a "minor crisis" in the second half of 2006 and a "credit disruption" in the first half of 2007.

Reinhart and Rogoff (2009) sometimes start dating a crisis before Laeven and Valencia (2013)–particularly in Iceland and Ireland. This could reflect the slightly different definitions that they use. As summarized in Table 1, Reinhart and Rogoff (2009) date crises when bank runs occur. Laeven and Valencia (2013) begin the crisis clock when not only are there significant events in the financial system, but also when the government follows the distress with a policy response.

One very nice characteristic of the EPFMS is that we are able to follow progression of crises over time. (Laeven and Valencia, 2013, 227) comment that part of the problem with dating financial crises is that they develop differently:

> Some crises evolve gradually, gaining speed as the ripple effects from a seemingly small shock propagate forward in time . . . other episodes happen more abruptly and are often the result of sudden stops.

The real-time and relatively granular nature of the EPFMS allows to distinguish these types of crises. For example, we can see in Figure 4 that financial market difficulties in the United States crisis built over along period of time, with a few spikes during notable banking difficulties. Conversely, countries such as Germany, Hungary, and Iceland clearly have much more sudden periods of perceived financial distress. Using an binary definition of crises would no allow us to capture these trajectories.

We can use the EPMFS to identify periods where financial market conditions were perceived to be worsening, though for whatever reason these perceptions changed before other measures would record a financial crisis. Australia, Brazil, and the Czech Republic, among others, in about late-2008/2009 are notable examples. They all see noticeable spikes in perceptions of stress shortly after Lehman Brothers collapsed in the US. Fairly quickly thereafter, their EPMFS scores return to previous levels. Laeven and Valencia and Reinhart and Rogoff do not record these episodes as crises. The perceived stress likely experienced by policy-makers at this time would therefore be excluded from political science work using previous binary measures of crisis.

The advantages of the EPFMS are also apparent for timing the end of financial crises. This is a particularly difficult issue for the binary indicators. Though crisis onset is typically well defined, these measures rarely have a clear or non-ad hoc way of determining when a crisis has ended. In many cases Laeven and Valencia (2013) simply determine that a crisis has concluded five years after it began. Though we are limited in the range of EIU texts we have at our disposal, it is clear that some countries, notably then United Kingdom and the United States, were perceived to be having improved financial market conditions from about 2010. Other countries, particularly in Western and Souther Europe plateaued at a high level through the end of 2011. While still others go through ‘double dips’. Italy, for example, appeared to be improving in late 2009 through mid-2010. But perceptions worsened around 2011, likely in relation to the Eurozone crisis. Laeven and Valencia’s measure simply describes this entire period as a crisis. Not only does the EPMFS allow us to more accurately date when conditions were seen to have improved, but it also allows us to study this trajectory of these improvements.

Overall, the similarities between EPFMS scores and other measures of banking crises suggests that the EPFMS Index does capture aspects of financial market stress. In particular, higher values of the EPFMS are indicate higher levels of perceived financial market stress. At the same time, the differences between the measures also indicates that the EPFMS sheds unique light on processes not captured well by previous indices. One major difference that we will now look at in more detail is how having a continuous indicator allows us to consider how levels perceived financial market stress differ between developed and developing countries.

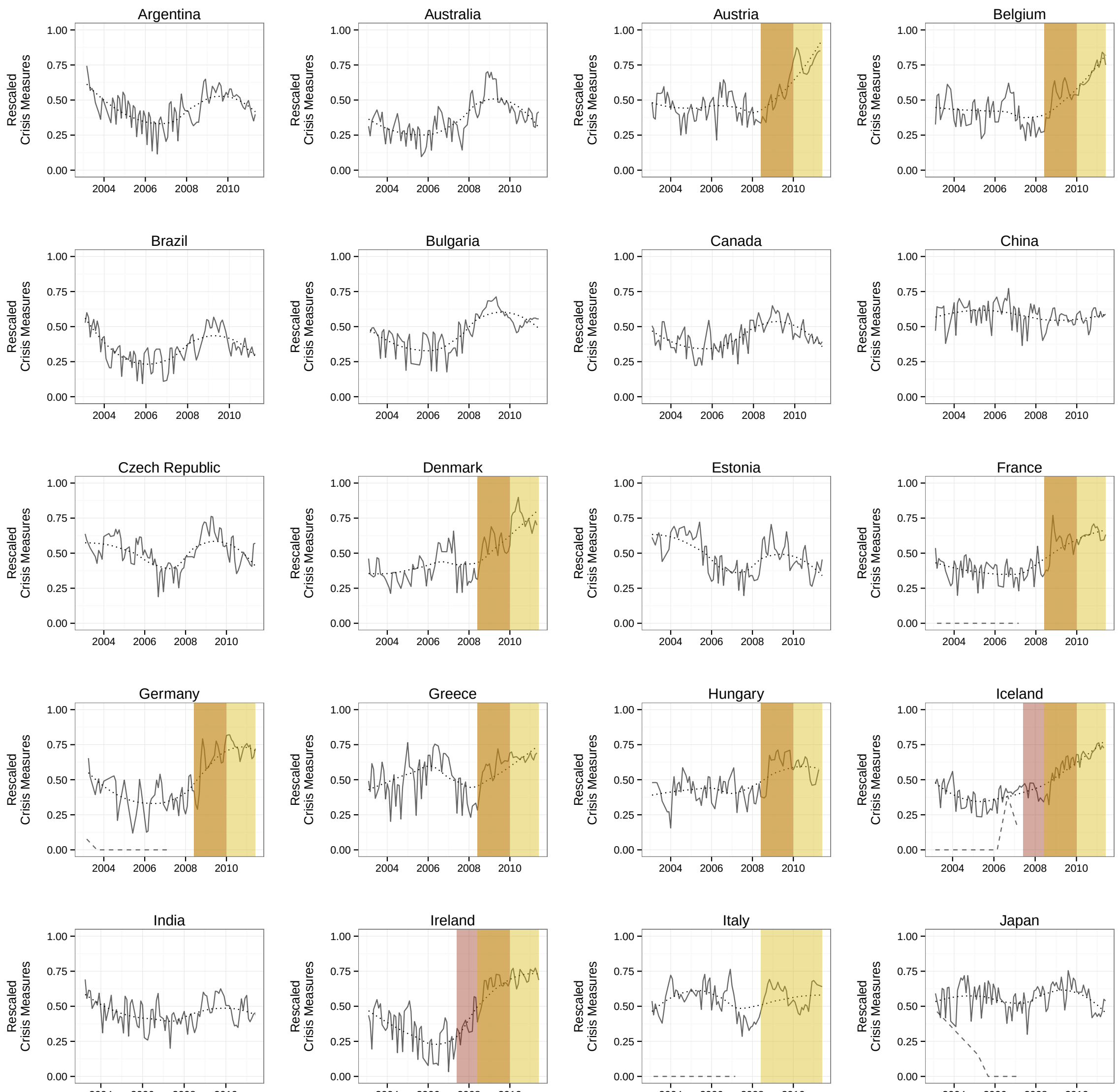
3.3 Developed vs. Developing countries

An important finding from examining the Index is that there is a clear difference in the level of perceived financial market stress in developed and developing countries. Notably, developing countries often have scores well above 0.5, while many developed countries only reach this level during financial crises. Developing countries often lack strong financial institutions and systems [CITE], so we should expect them to face generally tighter credit market conditions than developed countries. Formal financial markets are less important for developing countries’ economies [CITE].

These observations should lead to an important refinement to how the Index should be interpreted and how it should be used in empirical work. First, the Index measures banking market conditions, but not “crisis” directly. Instead, perceived crisis is likely the result of an interaction between the Index and the importance of financial markets for sustaining a country’s economy. Though policy-makers in developing economies face generally tight credit market conditions, these persistent conditions likely do not threaten the wider *status quo* economy. As such, we would not expect significant policy responses to address financial market stress in these places. Conversely, tightening of credit market conditions in a developed, financialized economy would likely have large negative implications for the wider economy. So, we would expect these politicians to respond to worsening credit market conditions.

Previous measures of financial market distress and crises have generally been unable to explore this

Figure 3: Comparing Perceptions of Financial Market Conditions to Laeven and Valencia (2013) and Reinhart and Rogoff (2009) (1)



Solid lines show the (rescaled) EIU Perceptions of Financial Market Stress indicator. Dotted lines represent a loess smooth of these series.

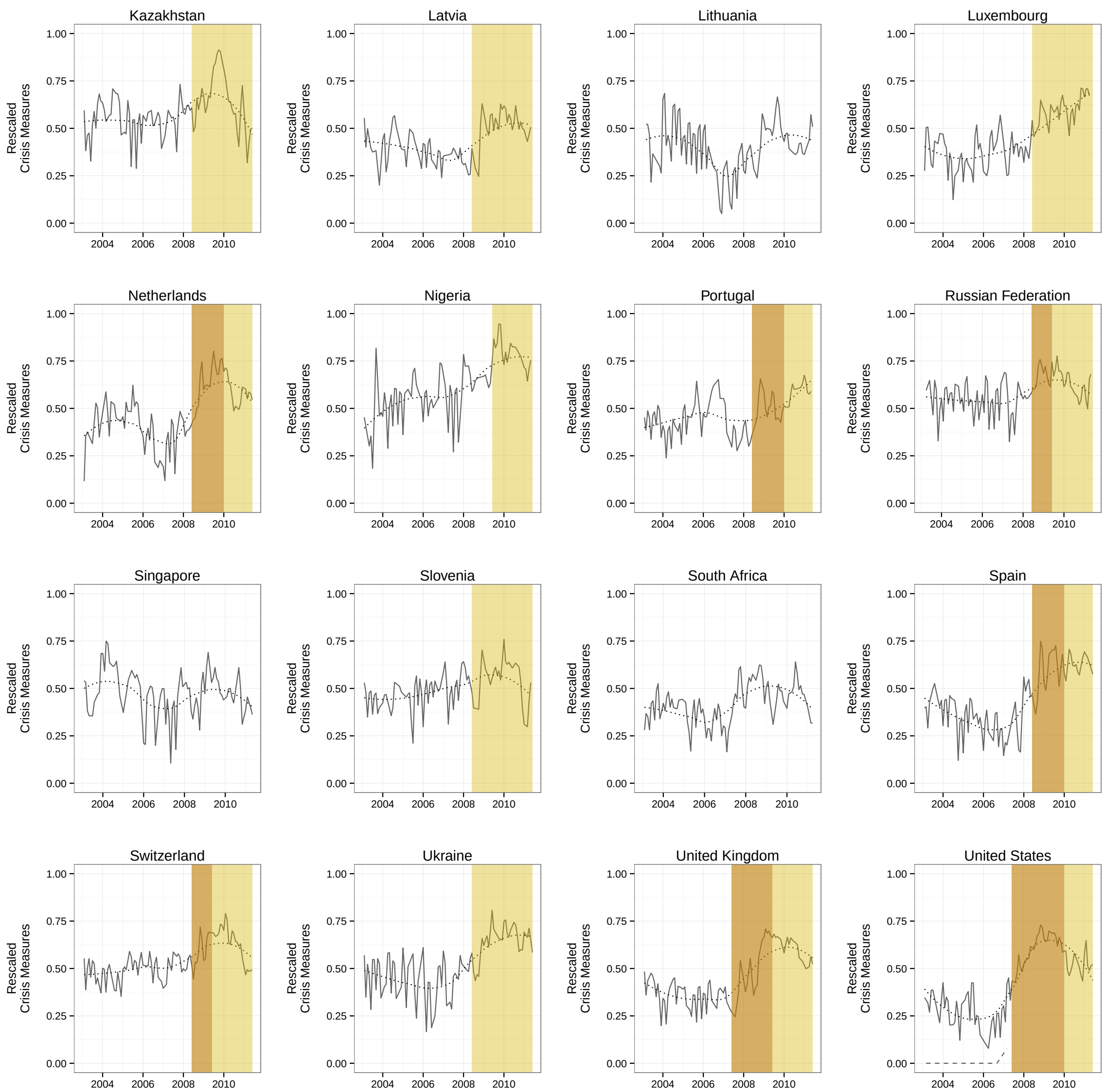
Dashed lines show Romer and Romer's (2015) rescaled index.

Yellow shaded areas indicate periods that Laeven and Valencia (2013) classify as systemic banking crises. Note that crises are automatically terminated at the end of 2011 due to the series not extending beyond this point, not necessarily because the crisis finished.

Red shaded areas indicate periods that Reinhart and Rogoff (2009) classify as banking crises. Note that crises are automatically terminated at the end of 2009 due to the series not extending beyond this point, not necessarily because the crisis finished.

Orange areas indicate periods where a crisis is recorded for both measures.

Figure 4: Comparing Perceptions of Financial Market Conditions to Laeven and Valencia (2013) and Reinhart and Rogoff (2009) (2)



Solid lines show the (rescaled) EIU Perceptions of Financial Market Stress indicator. Dotted lines represent a loess smooth of these series.

Yellow shaded areas indicate periods that Laeven and Valencia (2013) classify as systemic banking crises. Note that crises are automatically terminated at the end of 2011 due to the series not extending beyond this point, not necessarily because the crisis finished.

Red shaded areas indicate periods that Reinhart and Rogoff (2009) classify as banking crises. Note that crises are automatically terminated at the end of 2009 due to the series not extending beyond this point, not necessarily because the crisis finished.

Orange areas indicate periods where a crisis is recorded for both measures.

possible interaction. *Post-hoc* measures of crisis in particular capture the outcome of this process, rather than the process itself.

4 Summarizing Changes in the EPFMS

So far we have largely examined EPFMS score levels. Now we turn to examining changes in the EPFMS. To do this we use nonparametric drift-diffusion-jump models (DDJ) (Carpenter and Brock, 2011; Dakos et al., 2012). This approach allows us to draw more general conclusions about how perceptions of financial market stress change in more demanding and less demanding times.

This approach allow us to approximate processes of change in a time series without needing to make explicit assumptions about the underlying process that creates these changes.[12]

Drift is a measure of local rate of change. Diffusion is the small changes that happen at each time increment. Jumps are larger shocks that occur intermittently and are uncorrelated in time.

The approach we take to estimating the DDJ model is from Carpenter and Brock (2011). It approximates the unknown process generating the EPFMS scores:

$$dx_t = f(x_t,\ \theta_t)dt + g(x_t,\ \theta_t)dw + dJ_t \tag{1}$$

dx_t is the change in the EPFMS score x for a country at time t. θ_t is a critical transition parameter. The drift function is given by $f(x_t\theta_t)dt$. The diffusion function is given by $g(x_t\theta_t)dw$. J is a jump process. Please see Dakos et al. (2012, 7) for further details.[13] Note that we estimated the parameters for each country's time series separately.

In the abstract we would perhaps expect that jumps would be more common in countries' EPFMS scores during crisis periods because there would be large moves in the index. To test this we first graphically compared the distributions of jump and diffusion parameters across what Laeven and Valencia[14] classify as crisis and non-crisis periods. Figure 5 shows these densities. We have also included a measure of total variance, which is a summary of both jump and diffusion parameters.

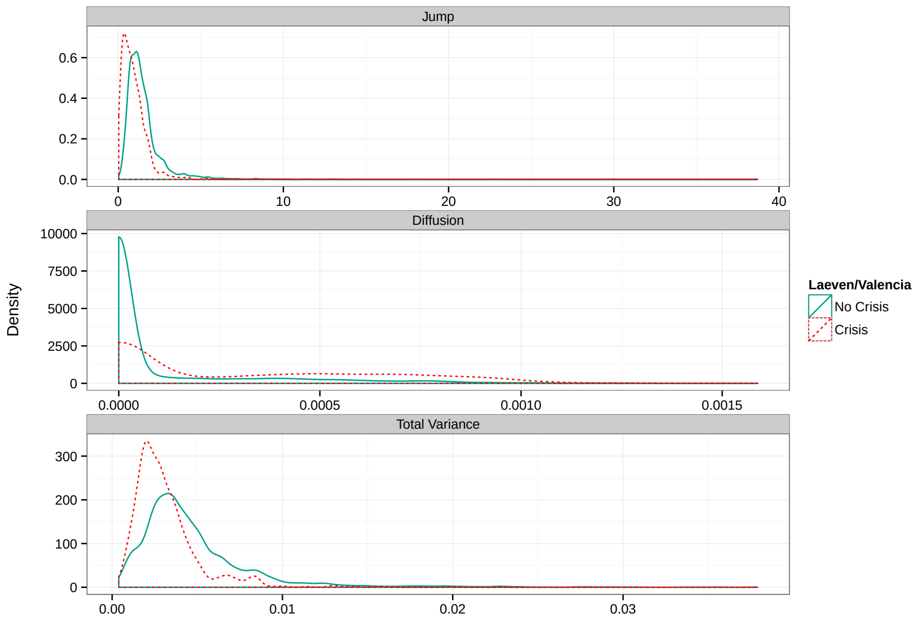
We can see that the distribution of estimated jump parameters in 'non-crisis' periods is shifted upward from the distribution of jump parameters in 'crisis' periods. Conversely, the distribution of diffusion param-

[12]It should be stressed that unlike in other applications of DDJ models, such as in ecology and related work in finance (Kou, 2008), that use them to predict future states, we are exclusively using this statistical approach to summarize changes and elucidate patterns in observed data.

[13]We estimated the model using the `ddjnonparam_ews` function from the **earlywarnings** R package (Dakos and Lahti, 2013).

[14]They are the most recently updated and comprehensive binary measure of crises.

Figure 5: Diffusion, Jump, and Total Variance Estimate Distributions Across Crisis and Non-Crisis Periods from Laeven and Valencia (2013)



eters in crisis periods is shifted upward from non-crisis periods. Finally, the distribution of total variance in crisis periods is lower than non-crisis periods. We found these distributions to be statistically significantly different in the described direction at all conventional levels using one-sided Kolmogorov–Smirnov tests.[15]

This is an interesting result considering our prior expectations. How can we make sense of it? It is useful to refer back to figures 3 and 4. Notice that many of there periods that are classified across measures as a crisis do indeed begin with a jump. Belgium, Denmark, and Germany are particularly illustrative of this. However, these changes are not unusually large relative to changes in previous years. What is different, however, is what happens after the jump. Before crisis periods there are relatively many jumps in both positive and negative directions. In crisis periods there are a few positive jumps followed by many smallish, often positive, changes in the EPFMS.

In non-crisis times there may effectively be more noise in economic events, causing relatively large positive and negative swings in perceptions of financial market conditions. When crises occur, the information used to create perceptions of financial market stress are clearer. Think for example of Lehman Brother's collapse and the continually bad news that followed. During a crisis initial shocks are followed by additional bad

[15] We ran the tests using the `ks.test function from base R.`

news. During non-crisis times a possible shock could be followed relatively quickly afterwards by good news.

Not all crises are the same. Most of the crises in the period for which we have data have been protracted. In some cases, however, crises came quickly and left almost as quickly. Kazakstan is a notable example. In late 2009 there was a prominent spike in perceptions of financial market stress. Within a few months, the EPFMS score returned to almost its previous–though still relatively elevated–trend level.

While the EPMFS is a fine-grained description of perceived stress, we should avoid using it as a predictive measure of when a crisis will begin or end.

5 Replication

6 Conclusions

References

Breiman, Leo. 2001. "Random Forests." *Machine Learning* 45(1):5–32.

Carpenter, SR and WA Brock. 2011. "Early warnings of unknown nonlinear shifts: a nonparametric approach." *Ecology* 92:2196–2201.

Chaudron, Raymond and Jakob de Haan. 2014. "Dating Banking Crises Using Incidence and Size of Bank Failures: Four Crises Reconsidered." *Journal of Financial Stability* pp. 1–34.

Dakos, Vasilis and Leo Lahti. 2013. "R Early Warning Signals Toolbox." *The R Project for Statistical Computing* . http://cran.r-project.org/web/packages/earlywarnings/index.html.

Dakos, Vasilis, Stephen R Carpenter, William A Brock, Aaron M Ellison, Vishwesha Guttal, Anthony R Ives, Sonia Kéfi, Valerie Livina, David A Seekell, Egbert H van Nes and Marten Scheffer. 2012. "Methods for Detecting Early Warnings of Critical Transitions in Time Series Illustrated Using Simulated Ecological Data." *PLoS ONE* 7(7):e41010–20.

Dhillon, I. S. and D. S. Modha. 2001. "Concept decompositions for large sparse text data using clustering." *Machine Learning* 42(1):143–175.

Feinerer, Ingo and Kurt Hornik. 2015. *tm: Text Mining Package*. R package version 0.6-1.
URL: *http://CRAN.R-project.org/package=tm*

Gandrud, Christopher and Mark Hallerberg. 2015*a*. "Does Banking Union Worsen the EU's Democratic Deficit? The Need for Greater Supervisory Data Transparency." *JCMS: Journal of Common Market Studies* .

Gandrud, Christopher and Mark Hallerberg. 2015*b*. "When All is Said and Done: Updating 'Elections, Special Interests, and Financial Crisis'." *Research and Politics* .

Grimmer, Justin and Brandon M Stewart. 2013. "Text as Data: The Promise and Pitfalls of Automatic Content Analysis Methods for Political Texts." *Political Analysis* 21(3):267–297.

Ishwaran, H. and U.B. Kogalur. 2015. *Random Forests for Survival, Regression and Classification (RF-SRC)*. R package version 1.6.1.
URL: *http://cran.r-project.org/web/packages/randomForestSRC/*

Jing, Zhongbo, Jakob de Haan, Jan Jacobs and Haizhen Yang. 2015. "Identifying banking crises using money market pressure: New evidence for a large set of countries." *Journal of Macroeconomics* 43(C):1–20.

Jones, Zachary and Fridolin Linder. 2015. "Exploratory Data Analysis using Random Forests." *Paper presented at the Annual MPSA Conference* .

Kou, S.G. 2008. *Jump-Diffusion Models for Asset pricing in financial engineering*. Vol. 15 Elsevier pp. 72–116.

Laeven, Luc and Fabián Valencia. 2013. "Systemic Banking Crisis Database." *IMF Economic Review* 61(2):225–270.

Lodhi, Huma, Craig Saunders, John Shawe-Taylor, Nello Cristianini and Chris Watkins. 2002. "Text classification using string kernels." *The Journal of Machine Learning Research* 2:419–444.

R Core Team. 2015. *R: A Language and Environment for Statistical Computing*. Vienna, Austria: R Foundation for Statistical Computing.
URL: *http://www.R-project.org/*

Reinhart, Carmen and Kenneth Rogoff. 2009. *This Time is Different: Eight Centuries of Financial Folly*. Princeton: Princeton University Press.

Romer, Christina and David Romer. 2015. "New Evidence on the Impact of Financial Crises in Advanced Countries." pp. 1–65. http://eml.berkeley.edu//~cromer/RomerandRomerFinancialCrises.pdf. Accessed April 2015.

Rosas, Guillermo. 2009. "Dynamic Latent Trait Models: An application to Latin American Banking Crises." *Electoral Studies* 28:375–387.

Scholkopf, B., A. Smola and K. Muller. 1998. "Nonlinear Component Analysis as a Kernel Eigenvalue Problem." *Neural Computation* 10:1299–1319.

Spirling, Arthur. 2012. "U.S. Treaty Making with American Indians: Institutional Change and Relative Power, 1784-1911." *American Journal of Political Science* 56(1):84–97.

Von Hagen, Jorgen and T. Ho. 2007. "Money market pressure and the determinants of banking crises." *Journal of Money, Credit, and Banking* 39:1037–1066.