Measuring Real-time Perceptions of Financial Market Stress

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Note: This work is in the early stages of development. It will be updated significantly.

Abstract[1]

> 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. Not only do we develop a novel indicator of financial market stress, but we also make a 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. 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.

[1] 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.

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 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) 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.

C. 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

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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. The index is created with kernel principle component analysis (Scholkopf, Smola, and Muller 1998; Lodhi et al. 2002; Spirling 2012) of monthly country reports from the *Economist Intelligence Unit*.[2]

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 are both a summary of real-time information and forecasts on counties' economic conditions as well as 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]See http://www.eiu.com/. Accessed May 2015.

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.[3] Due to a significant change in how the reports were 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).[4] This involved removing common English words, such as 'was' and 'its', stemming 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).[5] The unit of analysis is a sub-string kernel: in effect a short sequence of letters[6] that can be shared within and across words. Thus we can distinguish between two simple documents with the stemmed

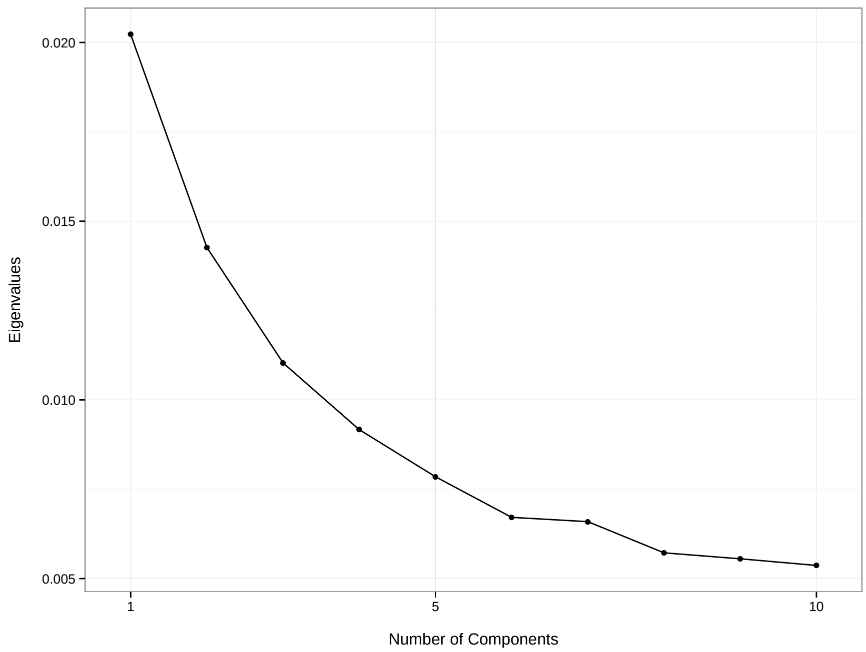
[3]The keywords included: *bail-out*, *bailout*, *balance sheet*, *balance-sheet*, *bank*, *banks*, *banking*, *credit*, *crunch*, *default*, *finance*, *financial*, *lend*, *loan*, *squeeze* [MAKE SURE TO UPDATE]. These keywords were adapted from those used by C. Romer and Romer (2015) and are intended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

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

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

[6]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 ‘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 using with the frequency distribution of five-length 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.[7]

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 is an ‘elbow’ in the plot at about six topics. This suggests that there is perhaps substantively meaningful variation approximately the first six dimensions. The drop from the first to second component is clear. We focus on the first dimension as the main dimension summarizing financial market conditions.[8]

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

[8] 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.

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 discussing diving deeper into these results, it's important to note two simple transformations we conducted on the raw results. First, we rescaled the index so that it would be between zero and one.[9] 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 forest 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 forest

Spirling (2012, 6–8) demonstrated the usefulness of using random forest "regressions" to explore what principal components from textual analyses represent. To do this 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 forest regressions as opposed to ordinary least squares regressions are useful in this context because there are many variables–in this case [GET] stems–relative to the number of documents–12,486 [UPATE]. The result of this analysis[10] that we focus on is variable importance shown in Figure 2.

3.2 Comparison to other crisis measures

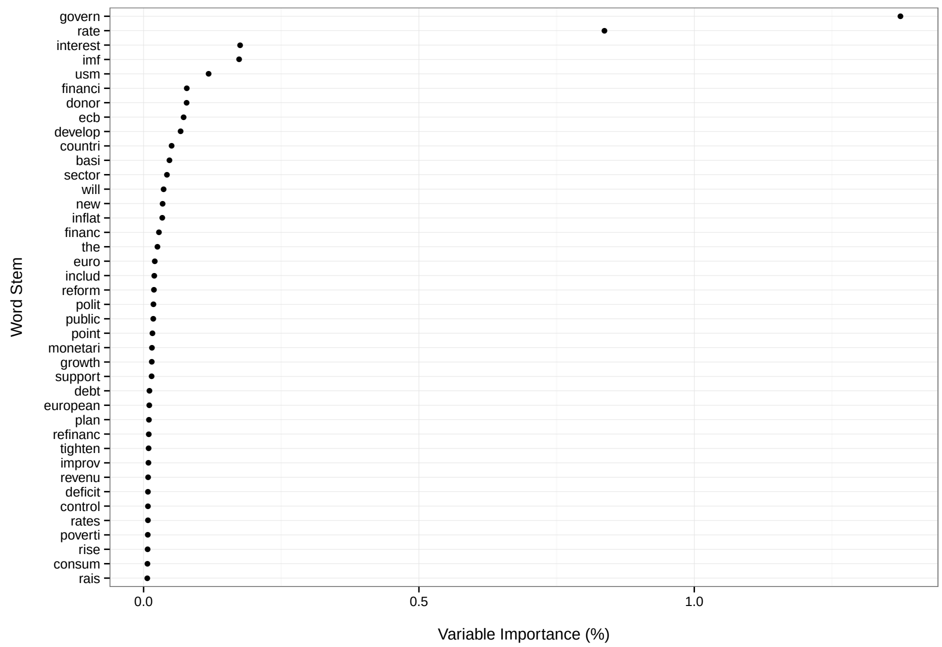
How does our measure compare to previous ways of measuring and timing financial market stress and crisis? We directly compare our measure to dichotomous measures in Reinhart and Rogoff (2009) and Laeven and Valencia (2013) as well as Romer and Romer's (2015) continuous measure.

There are some limitations in comparability based simply on the different coverage of the different indices. C. 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

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

[10] We conducted the random forest 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



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 15-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.

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.[11]

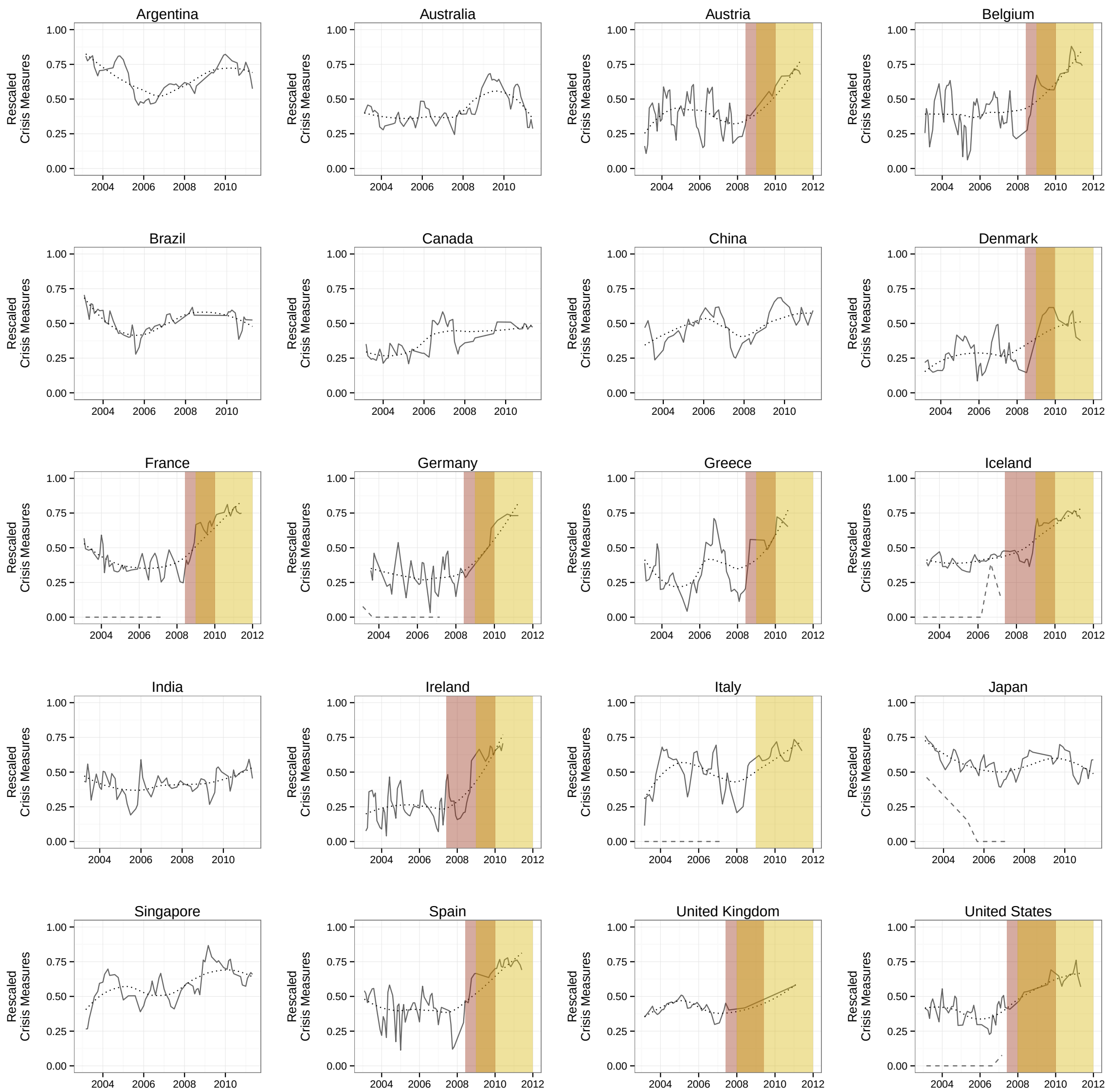
In many cases, the three indices

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

[11] We used Table 1 from the April 2015 version of C. 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.

Figure 3: Comparing Perceptions of Financial Market Conditions to Laeven & Valencia (2012) and Reinhart & Rogoff (2009) (1)



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

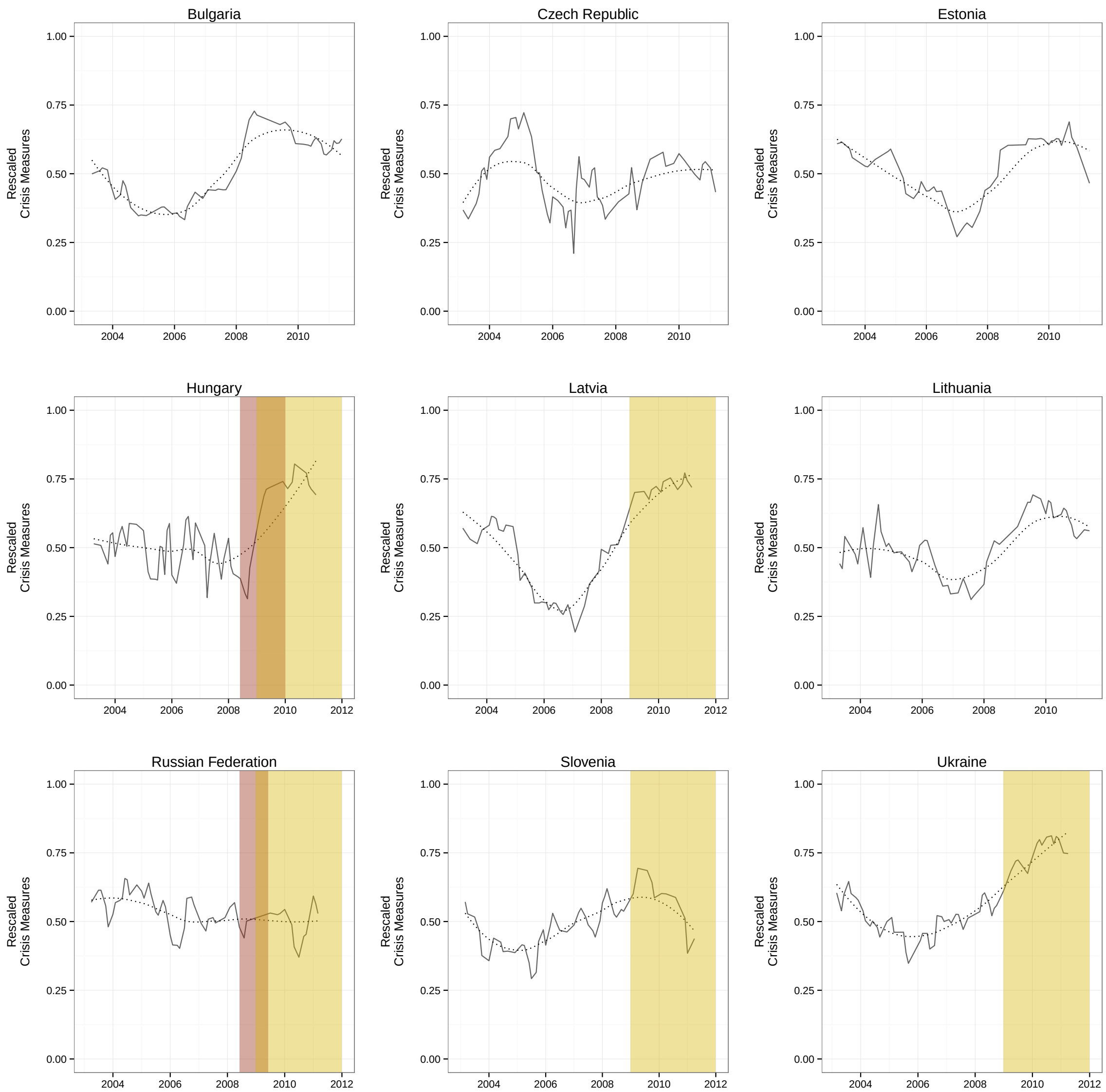
Dashed lines show Romer and Romer's (2015) rescaled index.

Yellow shaded areas indicate periods that Laeven and Valencia (2012) 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 & Valencia (2012) and Reinhart & 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 (2012) 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.

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

4 Replication

5 Conclusions and Possible Future Work

6 Appendix

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