Measuring Real-time Perceptions of Financial Market Stress

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Abstract

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) and its predecessors. These measures are lacking in that they are constructed post-hoc and so tend to be biased towards severe crises and away from circumstances where governments effectively calmed emerging trouble. This creates clear selection bias. In addition, they are simple dichotomous indicators of financial crisis and do so do not indicate crisis severity. We use a kernel principal component analysis (PCA) of Economist Intelligence Unit monthly country reports to develop a new real-time and continuous measure of perceived banking system stress. 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 also make a contribution to the wider political science literature on measurement 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 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 perceived. To understand why politicians made a given policy choice, we need to have a measure of the conditions that they believed they were responding to.

*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.

Most recent research on the political responses to and effects of financial crises has relied on one of two measures of financial crisis–Reinhart and Rogoff (2009) or Laeven and Valencia (2013) and its predecessors. These measures are post-hoc binary assessments of crisis occurrence and therefore are particularly lacking for studying political responses to financial crisis.

In this paper we aim to develop a new index of real-time perceptions of financial market stress that will be useful for researchers studying the political responses and consequences of financial crises. 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.

Plan to include at least one replication.

1 Motivation

Knowing when crises started, when they ended, and how severe they were over their course is crucial for research trying to understand how governments choose to respond to financial market distress, the fiscal costs of these responses, and the political outcomes. Researchers working on these issues have tended to rely on two data sources of cross-country information on when a country is facing a financial crisis–Reinhart and Rogoff (2009) or Laeven and Valencia (2013) and its predecessor versions. For a literature review see Gandrud and Hallerberg (2015), as well as tables 2 and 3 in the Online Appendix.

There are a number of problems with these indicators. Chiefly, crises are identified *post hoc* by researchers who know what happened after the fact. Financial market stress that is addressed well by policymakers, thus 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.

The measures are dichotomous. So, they do not give any indication of how severe a crisis was. Having a

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*

dichotomous measure also means that measurement errors–incorrectly timing the start or end of a crisis–can have large consequences for creating bias in econometric models where they are used. Measurement error is a significant problem in this data. Unlike economic recessions, financial crises are poorly defined in previous sources. There are 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) find that there are significant difference in crisis timing between different versions of the Laeven and Valencia (2013) data. The measures are at gross intervals, typically yearly, prohibiting sub-annual analysis. Finally, while the measures use fairly precise definitions of when a crisis started (see Table 1 for a summary), reasons for dating the end of a crisis are either unstated as in the case of Reinhart and Rogoff (2009) or ad hoc. Laeven and Valencia (2013, footnote 19) determine that a crisis has concluded when real GDP and real credit growth are positive for two years, or five years after the crisis began.

Overall, we lack a 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.

Romer and Romer (2015) attempted to solve many of the problems in the Reinhart and Rogoff (2009) and Laeven and Valencia (2013) data sets by manually classifying 24 countries on a 16 point scale of 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 is limited in a number of key ways. First, they are necessarily confined to the relatively small sample of OECD countries. Second, their measure is laborious to create and update. If there was a more encompassing corpus of texts than the OECD *Economic Outlook*, actually applying the method would be very costly. Third, relying on human coders introduces well-known problems of inter-coder reliability.

Others have attempted to create measures of national banking system fragility and crisis using using quantitative accounting and economic data. The finance literature widely uses a statistical quantity know as 'Z-Scores', originally developed to assess firm solvency Roy (1952), to measure national financial system fragility when examining how banking system structure and policies affect the probability of bank-specific and financial system difficulties (e.g. Beck, De Jonghe and Schepens, 2013; Čihák and Hesse, 2010; Laeven and Levine, 2009; Uhde and Heimeshoff, 2009). Though there are various ways to calculate this measure (Lepetit and Strobel, 2013, 73), in general uses bank accounting information–assets, equity, and return on assets–to create an inverse measure the probability of a country's 'banking system insolvency'.

There have been a number of recent innovations to measuring banking system stability using quantitative data. Building on Von Hagen and Ho (2007), Jing et al. (2015) developed an 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. His measure relies on nationally reported data to the IMF's International Financial Statistics (IFS). Copelovitch, Gandrud and Hallerberg (2015) show that data reporting to the IFS is very uneven across countries and time. They indicate that decisions to report data to the IFS could be endogenous to political events, complicating attempts to use IFS data to date crisis occurrence and severity. Furthermore, as Kayser and Leininger (2005) show, people make decisions based contemporaneously available data, but researchers often use data that has been updated after the fact. Using revised IFS data will give an inaccurate impression of the conditions that politicians believed they were in at the time. Apart from Z-Scores, one version of which is available from the World Bank's Global Financial Development Database (World Bank, 2013), these various quantitative measures have not been made publicly available to researchers.

2 Creating the EIU Perceptions of Financial Market Stress Index

We overcome many of the problems that plague previous measures by using a new approach to estimating real-time perceptions of financial market stress. Our method uses kernel principle component analysis (Scholkopf, Smola and Muller, 1998; Lodhi et al., 2002; Spirling, 2012) of country reports from the *Economist Intelligence Unit*[1] to create a monthly index for almost all countries from 2003 through 2011.

2.1 Why the EIU?

The EIU is the compilation of real-time, third-party assessments of financial market conditions reported monthly or, for a subset of countries, quarterly. These reports contain both summaries of present and future economic conditions. They are also 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) of reports for more than 100 countries. As the texts generally follow the same format and style, they contain directly comparable assessments of economic conditions 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. As such, the EIU is preferable for creating a cross-country indicator of perceived financial market stress.

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 for as many country-months as possible. Therefore, we clearly need an efficient way to summarize the vast quantity of information in the EIU reports along such a spectrum. To do this we first collected and processed the texts. We then used kernel principal component analysis to summarize the texts into a dimension of financial market stress. We rescaled the Index to ease interpretation.

2.2.1 Text selection

EIU reports assess many economic sectors within a country, not just the financial sector. So, our first step was to select the portions of the EIU texts that contained relevant information about countries' financial systems. We automatically collected and 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

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

keywords concerning banking and financial markets.[2] 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).[3] This involved removing common English words, such as 'was' and 'its'. The 'stopword' list we used was from Dhillon and Modha (2001). We stemmed the words so that different variants of the same word are grouped together. We removed extra whitespace between the words, as well as removed punctuation and numbers. Finally, we dropped texts that included very few words (less than six). In practice, including these texts had prevented the estimation of the kernel PCA model.

2.2.2 Kernel Principal Component Analysis

Texts are frequently summarized using unordered 'bags-of-words' approaches, such as Latent Dirichlet Allocation, that do not retain word order. The result of these approaches is often clusters (bags) of 'topics' within speeches or clusters of speeches around topics (for a review see Grimmer and Stewart, 2013). 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'. Likewise, adjectives can have very different implications for describing market conditions depending on the nouns that they modify. For example, 'increasing' can indicate worsening conditions as in 'increasing non-perfomring loans' or improving conditions as in 'increasing lending'. A bags-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). Spirling (2012) introduced it into political science. He used it to summarize changing trends in treaties between the US government and Native American groups. Kernel PCA allows us to extract structure from our likely high-dimensional EIU corpus

[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 discuss credit market conditions.

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

(Zhang, Wang, and Ma 2010, 6531–37) while preserving word order.

Our unit of analysis is a sub-string kernel: in effect a short sequence of letters[4] 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 strings that they have in common–i.e. 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.[5]

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 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 is notable. In the rest of the article 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.

3 Results, Validation, and Description

The lines in figures 3 and 4 show the results of the kernel PCA analysis–the first principal compenent–for a selection of countries. 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.[6] 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.

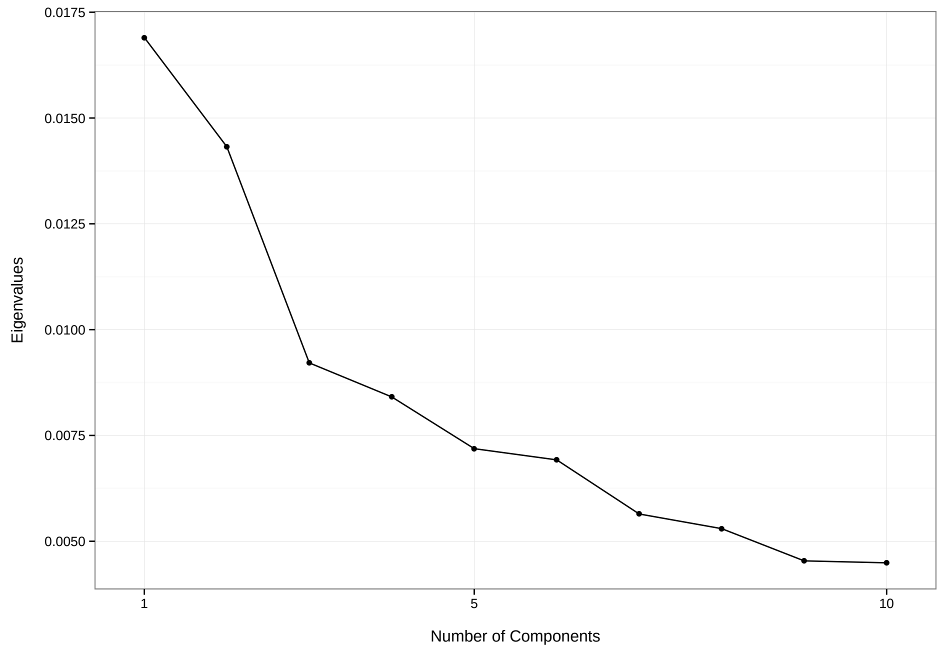
What does this dimension represent? We took a number of approaches to answer this question. First,

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

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

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

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



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, i.e. looking at plots of the results and comparing them to our priors on financial market stress.

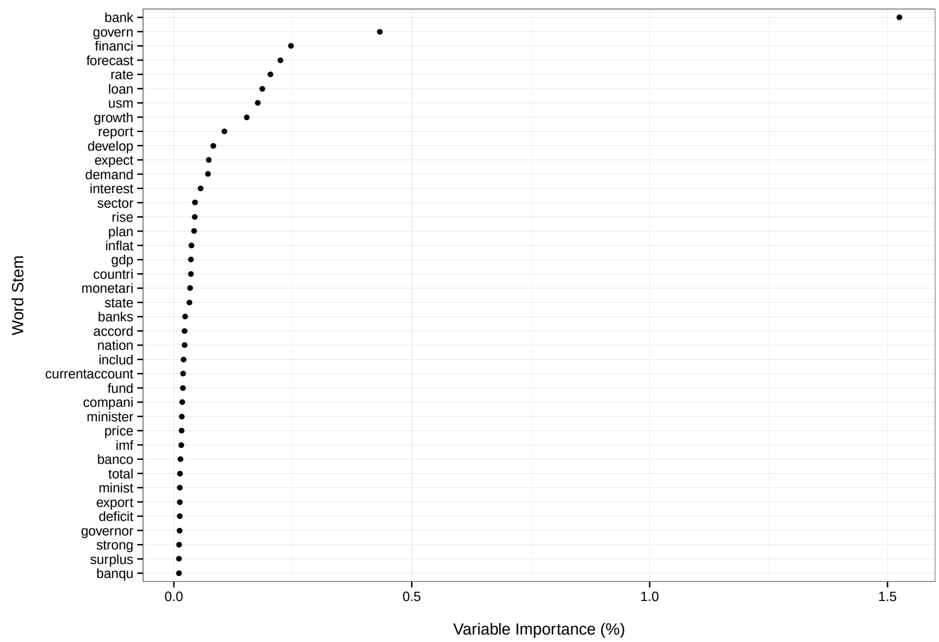
3.1 Random forests

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.[7] The results are shown in Figure 2. The logic

[7] 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



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'. 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 14-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.[8] 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.[9] 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[10] 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.

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

[8] 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.

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

[10] 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.

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. 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 Southern 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 Comparision to Accounting Measures of Banking System Fragility

How does the EPFMS compare to the widely used Z-Score measure of banking system fragility? Though they measure different quantities–perceptions for the former, bank accounting quantities for the latter–both potentially provide indications of national banking market stress. We might expect them to be related to one another, either being positively correlated and/or one acting as a leading indicator of the other.

We compare the EPFMS to the Bank Z-Score measure compiled from Bankscope data by the World Bank's Global Financial Development Database project (World Bank, 2013).[11] The measure is interpretable as the inverse of the upper bound of the probability of the banking system's insolvency.[12] Figure 5 shows a comparison of the two measures for selected countries. Note that to ease visual comparability we rescaled the Z-Score to be within zero and one as before, and also reversed the scale so that larger values indicate a higher probability of banking system insolvency.[13] We also converted the EPFMS to yearly averages for comparability.

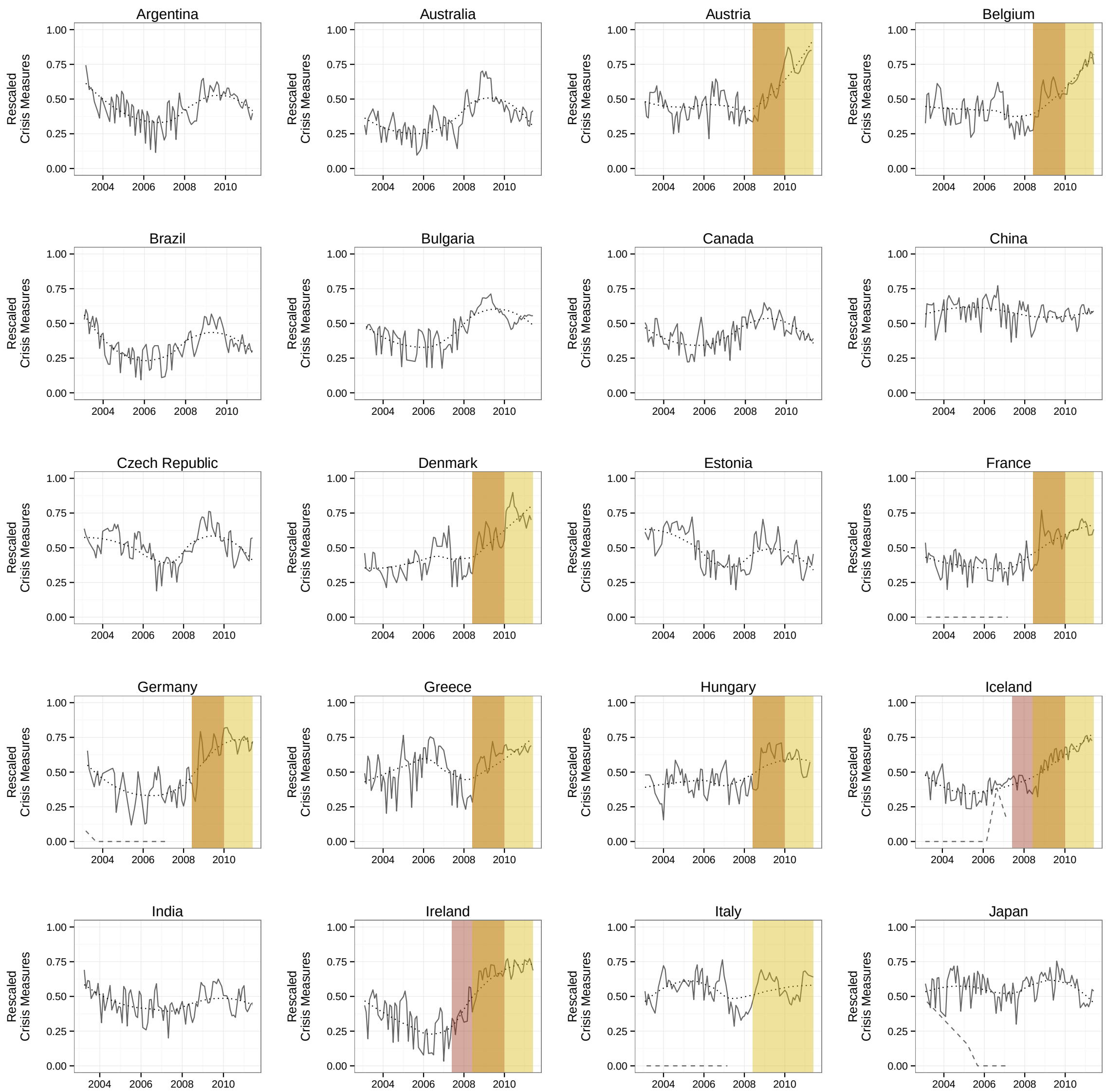
There appears to be very little relationship between Z-Scores and the EPFMS Index. The rescaled Z-Score is positively correlated with the EPFMS, as we would expect, but this is very weak with a correlation coefficient of 0.07 (significant at the 5% level). Interestingly, the Z-Score does not vary significantly within countries over time, especially compared to the EPFMS. There is very little difference between Z-Scores for countries during the financial crisis (however measured) and during more stable times. Thus Z-Scores may not be useful indicators of financial crisis. Z-Scores also do not appear to predict perceptions of financial market stress. In a simple dynamic linear regression that had EPFMS as the dependent variable and included lagged EPFMS, lagged Z-Scores, and country fixed-effects, Z-Scores were not statistically significantly associated with perceptions of financial market stress. It is beyond the scope of our article to determine why the Z-Score is a sub-optimal measure of financial market stress. However, the measure's peculiar aspects found here are important to note for future researchers: the indicator has weak time-variance, it does not distinguish between periods of significant know financial market stress and less stressful times, and it has poor power predicting perceived financial market stress.

[11] Indicator ID: GFDD.SI.01. Accessed June 2015.

[12] Formally: $\frac{\mathrm{ROA}_t + \frac{\mathrm{equity}_t}{\mathrm{assets}_t}}{\sigma_{\mathrm{ROA}}}$. ROA is return on equity. σ_{ROA} is presumably for the entire period for which data is available, though the World Bank's documentation does not explicitly specify this. It is common in other work for the σ_{ROA} to be based on a three year rolling window (Beck, De Jonghe and Schepens, 2013, 225). All quantities are in country aggregates.

[13] It is also common to log-transform the Z-Scores (Beck, De Jonghe and Schepens, 2013, 225). However, it is unclear how this is done as there are negative values in the Z-score that create undefined values when logged.

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.

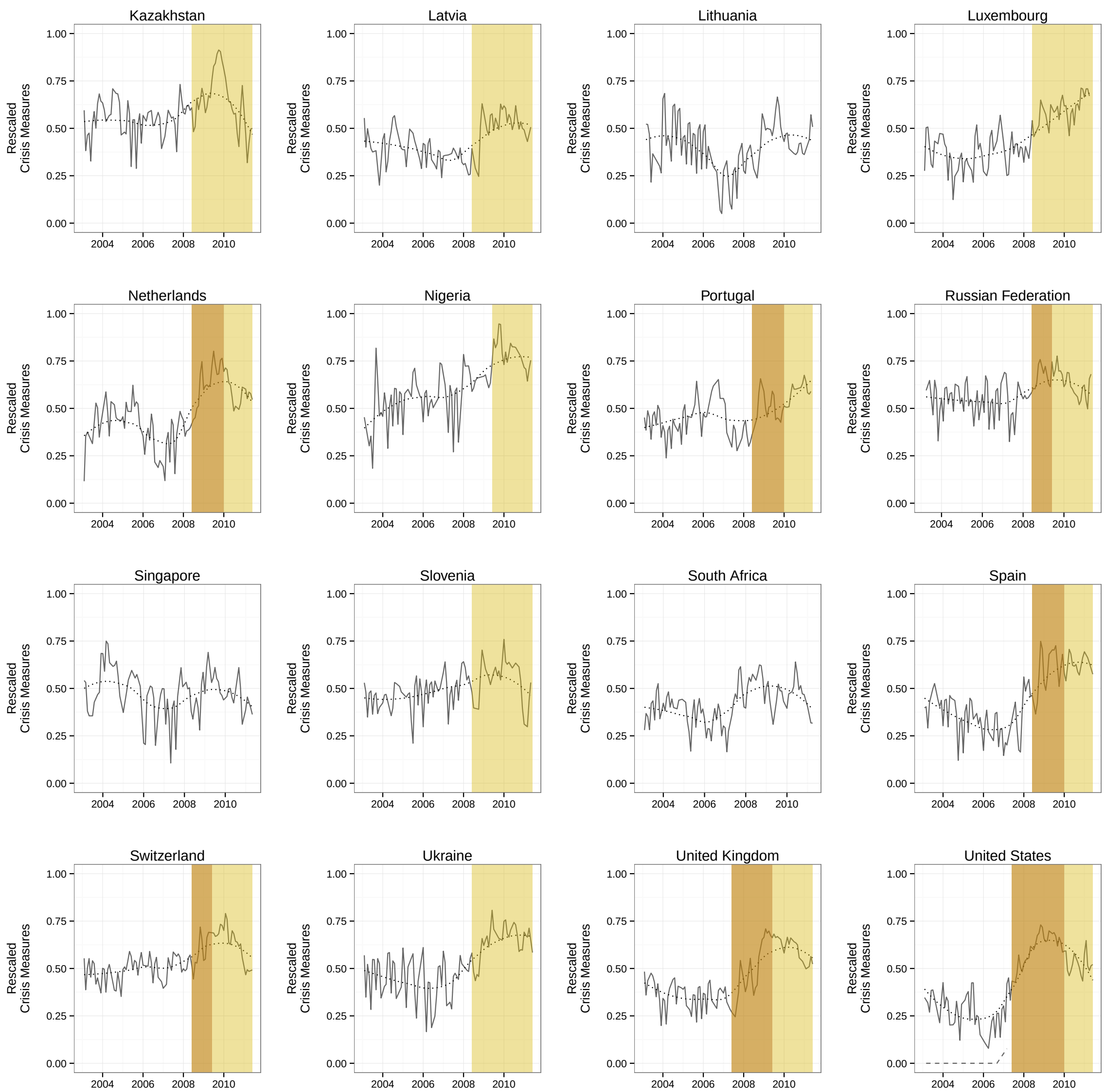
Dashed lines show Romer and Romer's (2015) rescaled index.

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)



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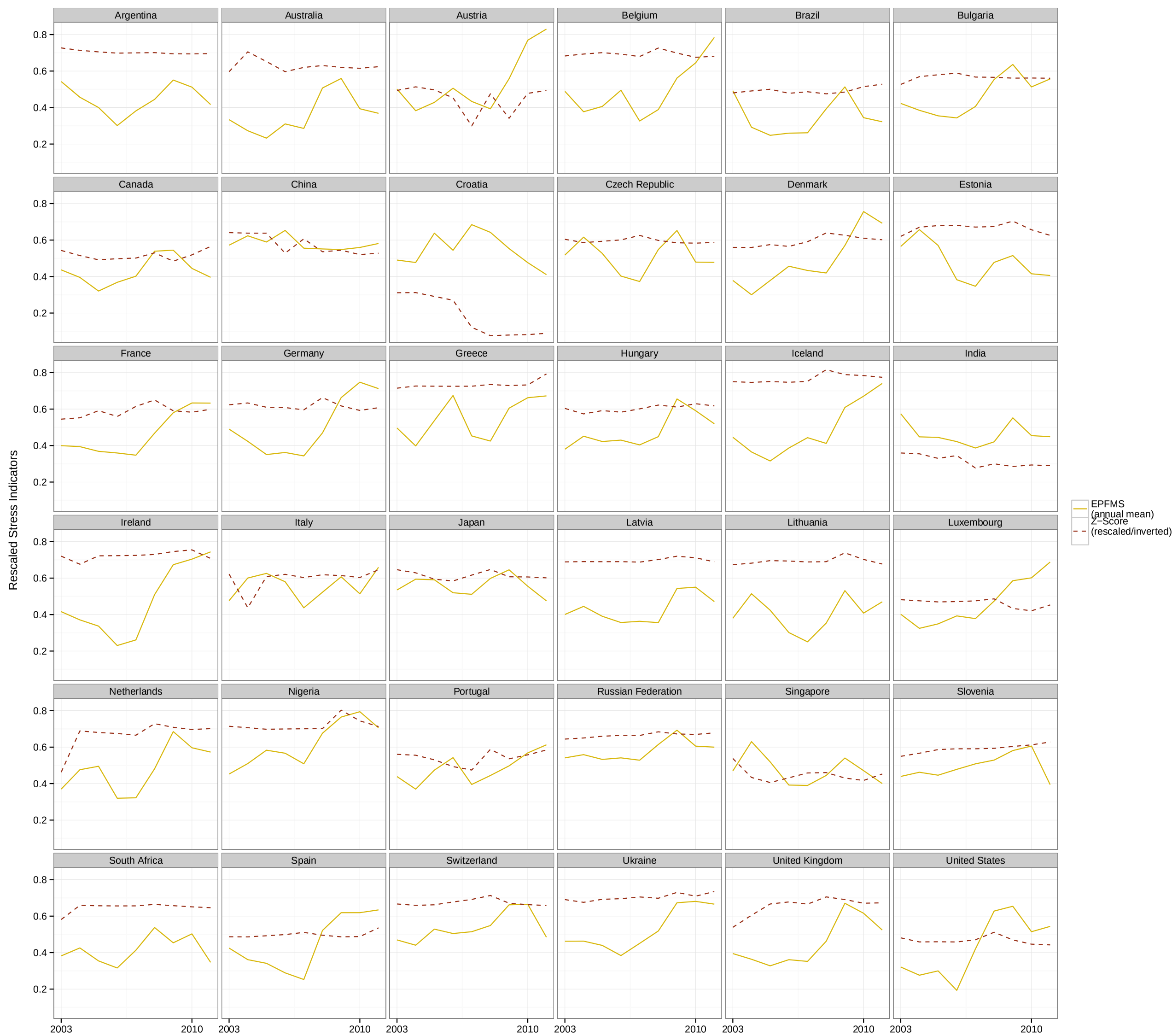
Orange areas indicate periods where a crisis is recorded for both measures.

Figure 5: Annual Mean EPFMS Compared to Country-level Z-Scores



3.4 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 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.[14]

Drift is a measure of local rate of change. Diffusion is the small changes that happen at each time

[14]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.

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.[15] 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[16] classify as crisis and non-crisis periods. Figure 6 shows these densities. We have also included a measure of total variance, which is a summary of both jump and diffusion parameters.

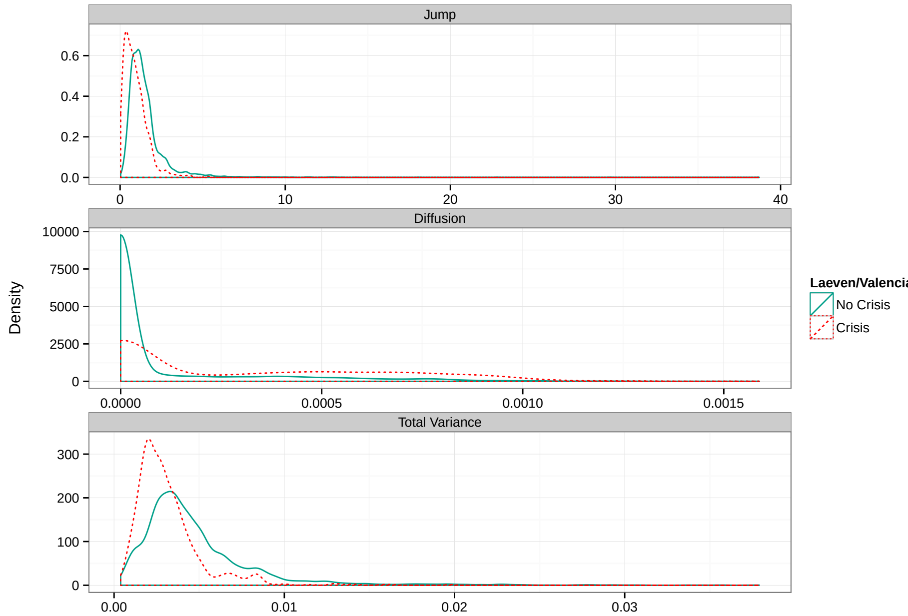
We can see that the distribution of estimated jump parameters in 'non-crisis' periods is shifted upward from the distribution of jump parameters in 'crisis' periods. Conversely, the distribution of diffusion parameters in crisis periods is shifted upward from non-crisis periods. Finally, the distribution 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.[17]

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

[15]We estimated the model using the `ddjnonparam_ews` function from the **earlywarnings** R package (Dakos and Lahti, 2013).
[16]They are the most recently updated and comprehensive binary measure of crises.
[17]We ran the tests using the `ks.test` function from base R.

Figure 6: Diffusion, Jump, and Total Variance Estimate Distributions Across Crisis and Non-Crisis Periods from Laeven and Valencia (2013)



and the continually bad news that followed. During a crisis initial shocks are followed by additional bad 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

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Online Appendix

Make tables more relevant for paper

Table 2: Selected Literature Review of Political Institutions and Financial Crisis (Crisis Occurrence, Policy Choices/Policy Outcomes)

Work	Crisis Type	Key Arguments/Findings	Crisis Data Sources	Observation Period
Gandrud (2013, 2014)	Banking crises	- Best practice financial governance institutional designs are more likely to be adopted during crises when there is high uncertainty about policy choices and outcomes.	Laeven & Valencia (2008), Reinhart & Rogoff (2010)	Late 1980s-2007
Hallerberg & Scartascini (2013)	Banking, debt crises	- Banking crises reduce the probability of fiscal reforms, but the longer a crisis lasts and if it becomes a sovereign debt crisis the the probability of reform increases. - Countries with more personalistic voting are more likely to reform.	Laeven & Valencia (2012) for Latin American countries	1975-2005
Hallerberg & Wehner (2013)	Banking, currency, debt crises	- Some evidence that more technically competent ministers of finance are appointed during debt crises. Not much robust evidence for other effects of crisis on the technical competency of economic policy-makers.	Laeven & Valencia (2012)	1975-2010
Hicken, Satyanath, & Sergenti (2005)	Growth shocks	- The size of the winning coalition is positively associated with growth recoveries following forced devaluations.	Own data aggregated from multiple sources	1990s-2002
Keefer (2007)	Banking crises	- Higher electoral competitiveness leads to faster and less costly crisis responses. - Checks and balances not associated with crisis policy choices or outcomes.	Modified Honohan & Klingebiel (2003)	1975-2000
Kleibl (2013)	Banking crisis	- Responses to regulatory failures are conditioned by the level of public ownership in the banking sector.	Laeven & Valencia (2010), Reinhart & Rogoff (2009) for OECD countries	1975-2010
MacIntyre (2001)	Financial crises	- U-shaped relationship between veto players and crisis outcomes	Own data aggregated from multiple sources	1997-1998
Rodrick (1991)	Growth shock	- Many veto players, if organized to manage conflicts, will result in more appropriate and quickly implemented crisis management policies.	Own data aggregated from multiple sources	1960-1975 & 1975-1989
Rosas (2006, 2009)	Banking crisis	- Democratic regimes have fewer bailouts. - Central bank independence and transparency lead to fewer bailouts.	Modified Honohan & Klingebiel (2000)	1980-1998
Satyanath (2006)	Banking crises	- Executives without 'banking cronies' and that are not prevented from appointing their own bureaucrats by many veto players are more likely to have stringent financial regulation that prevents crises.	Case studies of 7 East Asian countries	1997 Asian Financial Crisis
Wibbels & Roberts (2010)	Currency, growth, & fiscal crises	- Unions and strong left parties are more associated with crises, though combined strong unions-left parties may alleviate inflationary crises.	Own data aggregated from multiple sources for 17 Latin American countries	1980-2006

Table 3: Selected Literature Review of Political Institutions and Financial Crisis (Political Outcomes)

Work	Crisis Type	Key Arguments/Findings	Crisis Data Sources	Observation Period
Bernhard & Leblang (2008)	Currency crisis	- Changes in the probability that cabinets will collapse condition the probability of speculative attacks. - Higher probability of a speculative attack decreases the probability of calling strategic elections.	Own data aggregated from multiple sources	1957-2005
Chwieroth & Walter (2013)	Banking crises	- Probability of government survival during crises changed over time as expectations changed about what governments should do to respond. - Governments with more veto players after the inter-war period are treated more harshly by voters.	Reinhart & Rogoff (2010)	1813-2008
Crespo-Tenorio, Jensen, & Rosas (Forthcoming)	Banking crisis	- Increasing globalization weakens the accountability link between politicians and voters. - Incumbents in open capital economies are more likely to survive a crisis, than those in closed economies.	Own data aggregated from multiple sources.	1975-2005
Montinola (2003)	Banking crisis	- IMF credits decrease the probability of resolving banking crises. - The decisiveness of a political regime significantly influences the probability of emerging from systemic distress, though this depends on whether the crisis is moderate or severe.	Own data aggregated from multiple sources	1980-1995
Pepinsky (2012)	Banking crisis	- Two factors–incumbent governments' responsibility for the current crisis and their responsiveness to its domestic economic effects–shape the political effects of the global economic crisis.	Laeven & Valencia (2010)	2007-2009