Online Appendix for The Measurement of Real-Time Perceptions of Financial Stress: Implications for Political Science

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April 7, 2017

*Please contact Christopher Gandrud (gandrud@iq.harvard.edu). Thank you to Nicole Rae Baerg, Vincent Arel-Bundock, Ronen Palan, Stefano Pagliari, David Singer, participants at the 2015 American Political Science Association Annual Conference, the 2015 International Political Economy Society Conference, and City, University of London, and two anonymous reviewers for helpful comments. We also thank Sahil Deo and Christian Franz for early research assistance. Our research is generously supported by the Deutsche Forschungsgemeinschaft (No. HA5996/2-1). All data and replication material can be found at: https://github.com/christophergandrud/EIUCrisesMeasure.

Online Appendix

Table A-1: Comparison of Binary Crisis Measures' Definitions

Source	Measurement Level	Periodicity	Definition of Financial Market Distress/Crisis
Reinhart and Rogoff (2009; 2010, 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–at least three measures–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.

Laeven and Valencia define "significant intervention" as at least three of the following six policies being used: deposit freezes/banking holidays, significant bank nationalizations, bank restructuring gross costs, extensive liquidity support, significant guarantees, and significant asset purchases (2013, 229).

Selection of Literature Including Binary Cross-Country Measures of Financial or Banking Market Crisis

Table A-2: Selected Literature Review of Political Institutions and Financial Crisis (Binary Crisis Occurrence, Political Outcomes)

Work	Crisis Type	Key Arguments/Findings	Crisis Data Sources
Bernhard and 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
Chwieroth and Walter (2015)	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 and Rogoff (2010)
Crespo-Tenorio, Jensen and Rosas (2014)	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.	Laeven and Valencia (2010)
Funke, Schularick and Trebesch (2015)	Banking crisis	- Policy uncertainty rises as government majorities and polarization increases following crises. - Crises increase support for extreme-right parties.	Laeven and Valencia (2013)
Hernández and Kriesi (2015)	Financial crisis	- During crises established Western European parties faced electoral losses and extreme parties increased their vote shares.	A dummy = 1 after November 2008.
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
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 and Valencia (2010)

Table A-3: Selected Literature Review of Political Institutions and Financial Crisis (Binary Crisis Occurrence, Policy Choices/Policy Outcomes)

Work	Crisis Type	Key Arguments/Findings	Crisis Data Sources
Broz (2013)	Banking crisis	- In OECD countries right-wing governments pursue policies that lead to financial instability. Voters respond to resulting crises by voting in left-wing governments.	Reinhart and Rogoff (2009); Laeven and Valencia (2012)
Galasso (2012)	Financial and economic crises	- Governments respond to financial crises by increasing regulation.	Dummy based on OECD output gap below -3.4%
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 and Valencia (2008); Reinhart and Rogoff (2010)
Ha and Kang (2015)	- Banking crisis	Developing countries respond to crises with fiscal and monetary tightening, which was moderated by political constraints, left ideology governing parties, and up coming elections.	Laeven and Valencia (2008).
Hallerberg and Scartascini (2015)	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 and Valencia (2012) for Latin American countries
Hallerberg and 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 and Valencia (2012)
Hicken, Satyanath and Sergenti (2005) (2005)	Growth shocks	- The size of the winning coalition is positively associated with growth recoveries following forced devaluations.	Own data aggregated from multiple sources
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 and Klingebiel (2003)
Kleibl (2013)	Banking crisis	- Responses to regulatory failures are conditioned by the level of public ownership in the banking sector.	Laeven and Valencia (2010); Reinhart and Rogoff (2009) for OECD countries
MacIntyre (2001)	Financial crises	- U-shaped relationship between veto players and crisis outcomes	Own data aggregated from multiple sources
Reischmann (2016)	Banking crises	- Creative accounting as measured by changes in the stock flow adjustment occurs more during financial crises, though effect may be swallowed up by the period fixed effects in his regressions as crises are highly correlated with time in his sample.	Laeven and Valencia (2012)
Rodrik (1999)	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
Rosas (2006, 2009*a*)	Banking crisis	- Democratic regimes have fewer bailouts. - Central bank independence and transparency lead to fewer bailouts.	Modified Honohan and Klingebiel (2000)
Seiferling and Tareq (2015)	Banking crisis	- Find advanced economies governments extend more loans and purchase more equities in temporarily insolvent firms during financial crisis than emerging market governments.	Laeven and Valencia (2010) via Weber (2012)
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 using own data
Wibbels and 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

Further discussion of continuous financial market stress measures

Another approach is to measure stress and crisis using nationally aggregated quantitative accounting data. The finance literature relies on a statistical quantity known as Z-Scores. The concept was originally developed to assess firm solvency (see Roy, 1952). In the banking context, it is often used to measure national financial system fragility, which allows researchers to examine how banking system structures and policies affect the probability of 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), bank accounting information–assets, equity, and return on assets–is typically used to create an inverse measure of the probability that a country's banking system will become "insolvent".

Similarly, the CAMELS system uses accounting data to rate bank soundness. The CAMELS indicators include a bank's capital adequacy, asset quality, management capacity, earnings, the liquidity of its assets, and its sensitivity to market risks. Andrianova et al. (2015) gathered individual bank data from the Bankscope service on these quantities for 128 countries, created annual national aggregates, and released the components in a "database on financial fragility".

Research looking at longer time spans has been limited by what data is available at the bank-level for measuring banking system health. Danielsson, Valenzuela and Zer (2015) examine the Minskian (1982) hypothesis that stable conditions in the present induce increased risk-taking behavior and thus crises in the future with annual stock market volatility. This data allows them to cover a period of 211 years. It seems plausible that stock market volatility is positively associated with broader financial market volatility. Nonetheless, it is well understood in political economy (seminally Hall and Soskice, 2001) that the importance of equity markets for financing banks and the "real" economy varies considerably by country and over time.

There have been a number of further innovations to the measurement of banking system stability using quantitative data. Though they make interesting contributions to measuring financial market stress, these indicators have not been used in applied research as frequently as Z-Scores or CAMELS components. Building on Von Hagen and Ho (2007), Jing et al. (2015) develop an index of money market pressure based on changes in short-term interest rates and stocks of central bank reserves. Problematically for the study of policy responses, it assumes that central banks use the same reaction function to increased demand for liquidity. Rosas (2009*b*) 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).

Most simply, we could perhaps use individual indicators from the IFS or the broader Global Financial

Development Database (GFDD, World Bank, 2015), such as the provision of private sector credit by deposit banks as an indicator of credit conditions or non-performing loan ratios as an indicator of bank balance sheet health. However, there are a number of issues.

First, as mentioned before, the importance of each individual measure varies depending on the context. Second, how these indicators are measured can vary significantly across countries. Many of the GFDD indicators have a note attached that "due to differences in national accounting, taxation, and supervisory regimes, these data are not strictly comparable across countries". Third, Copelovitch, Gandrud and Hallerberg (2015) show that national reporting to the IFS and GFDD is highly uneven across countries and time. As such, they indicate that decisions to report data could be endogenous to economic and political events, complicating attempts to use these data. They find that reporting on credit market conditions declined significantly in the European Union in the lead up to and during the crisis beginning in 2007. Further indicating the pervasiveness of the missingness problem with quantitative data, Andrianova et al. (2015) extensively discuss problems of missingness in their privately gathered database on financial fragility and caution users of the database about the effects it might have on their analysis. Fourth, as Kayser and Leininger (2015) show, people make decisions based on contemporaneously available information, but researchers attempting to understand this behavior use data that has been significantly updated after the fact. Similar to the binary crisis indicators' *post hoc* measurement problem, using revised IFS and GFDD data gives an inaccurate impression of the conditions that politicians believed they faced at the time.

KPCA comparison with Minhas, Ulfelder and Ward (2015)

Our approach is broadly similar to Minhas, Ulfelder and Ward (2015) who use a supervised machine learning approach called support vector machines and United States State Department Country Reports on Human Rights Practices to classify countries according to dichotomous regime types. Our work is distinct in that KPCA of EIU reports allows us to develop a continuous measure of perceived financial market stress. Perhaps more importantly, their supervised learning approach assumes that countries have been well classified by previous indicators, which they use to train their model. As discussed above, we are not confident that previous measures do well classify high and low stress periods. Therefore, we use the unsupervised KPCA approach to establish new estimates.

Text selection and pre-processing

EIU reports assess many economic sectors within a country, not just the financial sector. Our first step was to select the portions of the EIU texts that contained relevant information about countries' financial systems. We automatically collected and parsed the reports from their original HTML format. We then extracted the portions of the texts–headers and paragraphs–that contained at least one of a number of keywords concerning financial markets.[1] Due to a significant change in the reports formatted in 2003, we selected only texts from 2003 in order to maintain comparability across the time-series. The texts from 2003 follow the same format and style and contain directly comparable assessments of economic conditions across the globe over a significant time span.

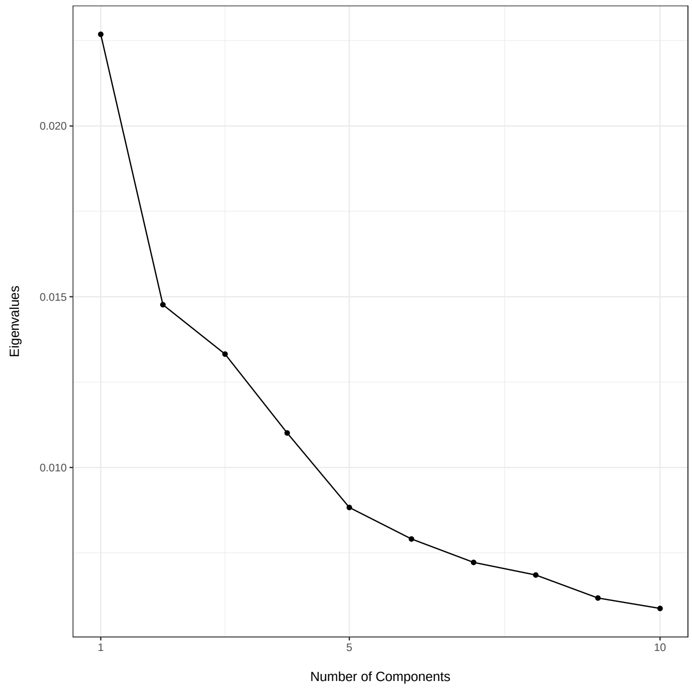
We also pre-processed the selected texts using standard techniques (see Grimmer and Stewart, 2013). This involved removing common English words, such as 'was' and 'its'. The 'stopword' list we used to do this was from Dhillon and Modha (2001). We stemmed the words so that different variants of the same word are represented by a common 'stem'. This allowed us to work with a more manageable number of kernels. We removed extra white space between the words, as well as punctuation–with the exception of apostrophes indicating possession–and numbers. Finally, we dropped texts that included very few words (less than six). In practice, including these texts hindered the estimation of the KPCA model. All pre-processing was done using the `quanteda` package (Benoit and Nulty, 2017) in R (R Core Team, 2016).

Dimensionality

To determine the number of dimensions from the KPCA that best describe the data, we conducted a scree test, with results in Figure A-1. There is a clear "elbow" in the plot at component two. This suggests that the first component explains the most variation in the data. As such, FinStress is created from the first dimension as it is the main dimension summarizing financial market stress. We examined a number of the other dimensions. However, these did not correspond to our priors about financial market stress based on previous indicators. For example, Figure A-2 compares FinStress to the second component, which has been transformed using the same procedures. It is difficult to discern consistent substantive meaning–at least for financial market stress–from the second component. Strikingly for Spain and the United Kingdom it does

[1] The keywords included: *bail-out*, *bailout*, *balance sheet*, *balance-sheet*, *bank*, *banks*, *banking*, *credit*, *crunch*, *default*, *finance*, *financial*, *lend*, *loan*, *squeeze*. These keywords are adapted from those used by Romer and Romer (2015) and are intended to select passages that discuss credit market conditions. Note that a small number of the words, primarily *bank* and *financial* are by far the most selective.

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



not reflect widely reported financial market stress in these countries in the latter part of the sample.

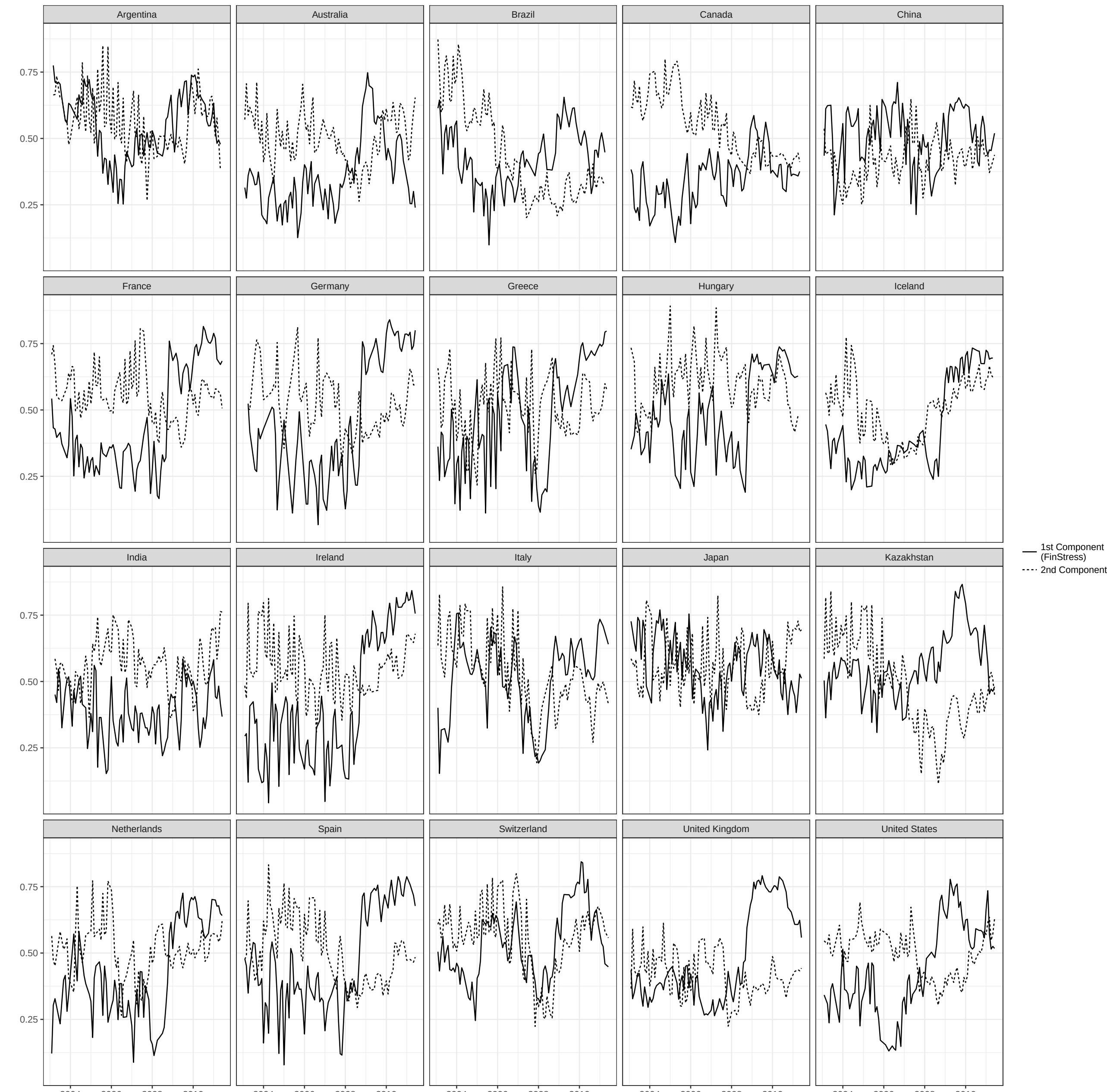
Given that components other than the first component do not appear to be substantively meaningful, we focus on the most parsimonious output of the KPCA analysis–the first component.

FinStress validity: random forests

Spirling (2012, 88-90) demonstrated the usefulness of using random forests regressions (Breiman, 2001; Jones and Linder, 2015) 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 stem in $\boldsymbol{S}$ for each document in $\boldsymbol{K}$. *The document-term matrix clearly does not preserve word order, so should only be thought of as a partial method of assessing validity.* 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 921 stems–relative to the number of documents–12,373.

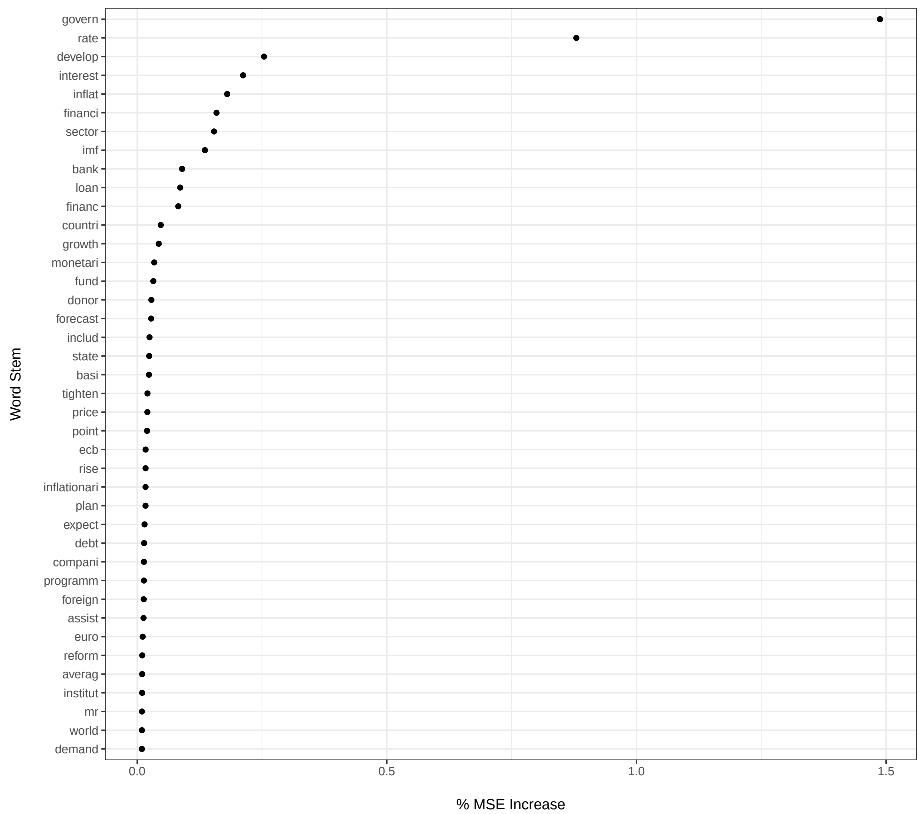
We focus on estimated variable importance. Variable importance in this context functions as a measure

Figure A-2: KPCA First Component (FinStress) vs KPCA Second Component (select countries)



Both components were transformed using the same procedures discussed in the text.

Figure A-3: 40 Stems Estimated to be the Most Important for Predicting EIU Perception of Financial Market Stress Index



of how well the frequency of a given stem in a text allows the model to predict the FinStress score for that text.[2] Key results are shown in Figure A-3.

Unsurprisingly, a number of the stems with the largest variable importance are "bank", "financi", and "loan". Terms with these stems were used to select the texts. The prevalence of these terms and others that are clearly related to the financial sector, such as "interest", "rate", and "fund", indicate that FinStress is indeed about financial sector conditions and not some other topic. Words relating to the direction of financial conditions are important including, "growth" and "tighten". Words relating to the macro-political economic environment of finance are also important, including "govern" and "imf".

[2]Specifically, importance is measured in terms of the percentage increase in mean squared error (MSE) after permuting the variable. If a variable is important, then permuting it will decrease predictive performance, i.e. increase MSE. We conducted the random forests regressions using the `rfsrc` function from the **randomForestSRC** R package (Ishwaran and Kogalur, 2015).

FinStress validity: word-stem component correlations

Table A-4 shows a selection of correlations to provide a sense of the general directions of the relationships between the stems and the Index not provided by the random forest variable importance estimates. A number of terms related to debt, financial assistance, the International Monetary Fund (IMF), and aid are positively related to FinStress. This suggests that the positive direction of the scale is in fact capturing periods where policymakers perceive higher financial market stress. Words that are generally about positive credit conditions, such as "growth", "surplus", and "boom" are negatively associated with the Index. This suggests that the lower end of the scale indeed indicates more positive financial market conditions. Finally, we can see that adjectives that have seemingly opposite meanings–"stronger" and "weaker"–are both negatively associated with the Index. Such findings indicate that a KPCA approach is useful compared to context-less bag-of-words sentiment analysis approaches based on individual word stems.

Table A-4: Selection of Word Stems and Correlations with FinStress

Stems	Correlations
imf	0.36
assist	0.35
debt	0.33
aid	0.27
paid	0.18
strain	0.12
rise	-0.02
surplus	-0.02
boom	-0.02
growth	-0.03
weaker	-0.03
stronger	-0.05

FinStress compared to a bag-of-words principal components analysis

KPCA allows us to utilize word order information, which we argued in the main paper is particularly important for gaining an accurate understanding of the perceived stress levels communicated in the EIU corpus. However, KPCA achieves this at non-trivial computational expense.[3] Perhaps a simpler method that did not preserve word order would be less computationally expensive with little loss in validity? To test this we conducted a traditional "bag-of-words" principal components analysis (PCA) on the texts and compared the results to FinStress.

[3]The scores with 5-character kernels were estimated using KPCA a 2014 iMac with 16GB of RAM and a 2.93 GHz Intel Core i7 processor. On this system the analysis took 3.68 days (318,316.2 seconds).

We started this analysis with the same preprocessed corpus as the KPCA we used to create FinStress. We converted this corpus into a document-term matrix that did not preserve term order within the documents. Due to the large number of unique words, even after stemming and other preprocessing was conducted on the EIU corpus for the KPCA analysis, we were unable to run PCA on this document-term matrix. The number of terms exceeded the number of documents and so violated a key constraint of PCA. As such we removed sparse terms from the corpus, keeping only those that were present in 90 percent of the texts. We then ran the PCA analysis and selected the first component, rescaled it using the same procedures as for the FinStress Index. Finally we smoothed it with a two-period moving average, again as we did with FinStress.

The computation time for the bag-of-words PCA was trivial–under eight seconds–and the resulting estimates are positively and statistically significantly correlated with FinStress at all standard significance levels. However, with a correlation coefficient of 0.22, the magnitude of the relationship is not large. To examine the relative validity of the two measures, we directly compared the two sets of estimates for a diverse set of countries. These are shown in figures A-4 and A-5. While there are some similarities, overall the bag-of-words created PCA estimates miss significant known crisis points that are accurately captured by FinStress. For example, the Irish 2008 crisis is accurately captured as starting in late 2008–when the government instituted large bank guarantees in response to imminent bank collapses (Gandrud and O'Keeffe, forthcoming)–by a dramatic increase in FinStress in late 2008. Ireland's PCA results also increase dramatically, but not until much later in 2010. Increased financial market stress is completely missed by the bag-of-words PCA estimates for a number of countries including Austria, Belgium, Denmark, Greece, Hungary, Iceland, and Spain.

While estimating the bag-of-words PCA was computationally much less intensive than using KPCA, it produced much less valid results. As such, the added computational effort involved in using KPCA is an appropriate cost for creating a more valid index of perceptions of financial market stress.

FinStress validity: sensitivity to sub-string kernel length

Previous work using KPCA on English-language texts suggests that sub-string kernel lengths of four to seven characters long are ideal (Lodhi et al., 2002). Following this finding, as well as precedent set by Spirling (2012), we estimated FinStress using five character kernels. We also ran models with three, four, and six character length kernels to examine how sensitive FinStress was to this choice. Note that all aspects of the analysis, e.g. pre- and post-processing were the same across all of these estimations. The first three panels from the top-left in Figure A-6 compare the alternative estimations. There are not meaningful differences

Figure A-4: FinStress Estimates Compared to PCA Bag-of-words Estimates (1)

Figure A-5: FinStress Estimates Compared to PCA Bag-of-words Estimates (2)

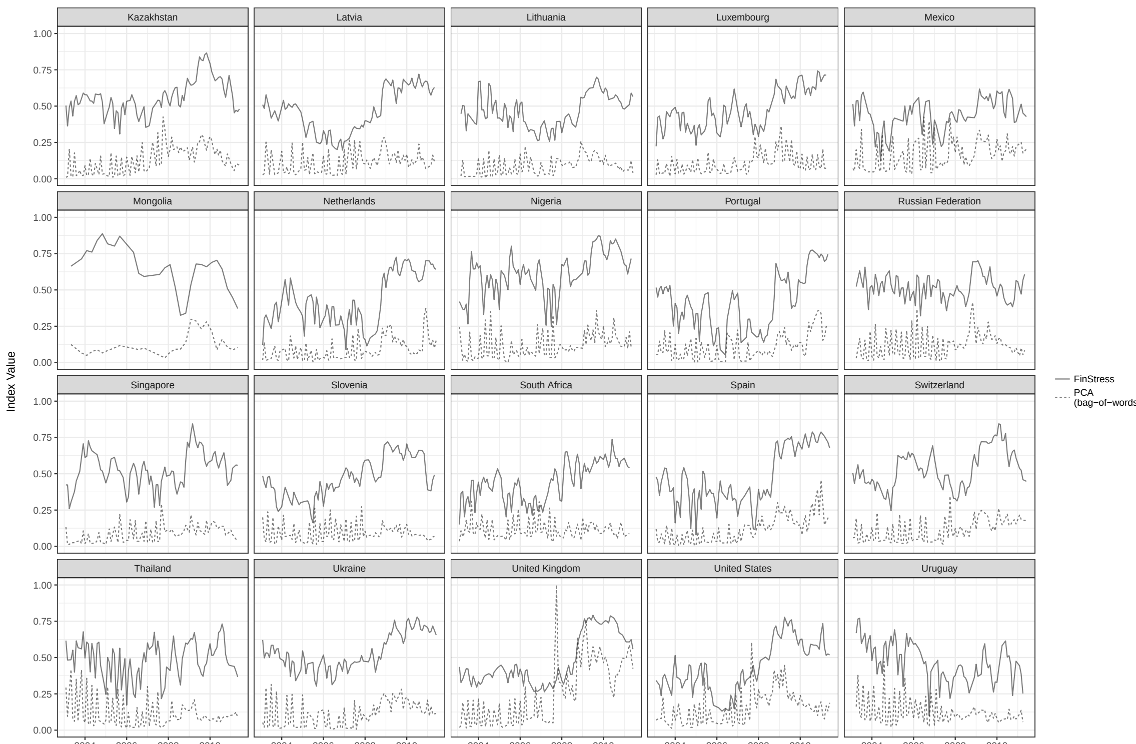
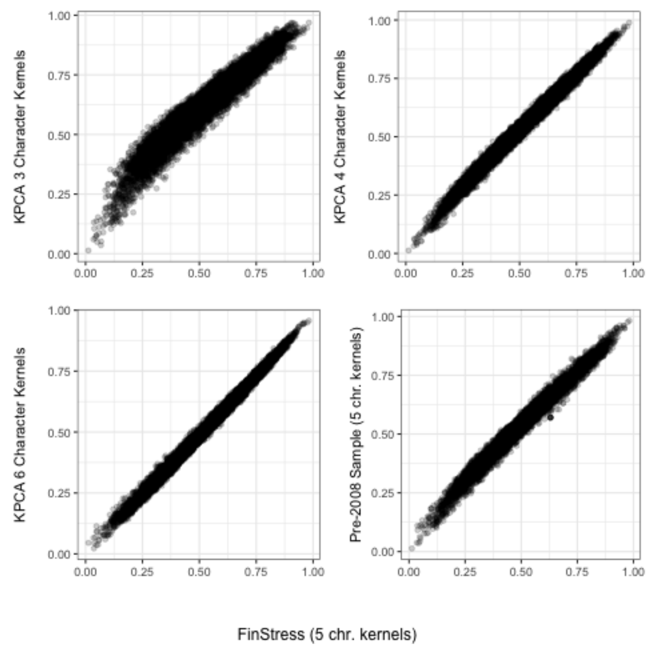


Figure A-6: FinStress–Five Character Kernel PCA–Compared to Alternative KPCA Specifications



between estimates made with four, five, and six character kernels. The estimates using three string kernels–a length below the range suggested by Lodhi et al. (2002)–are somewhat different from FinStress. Nonetheless, the estimates are similar overall. We have no reason to believe that kernels shorter than those suggested by the literature are more accurate than our 5 character kernels. It appears from this analysis, that FinStress estimates are not being unduly influenced by our choice to use five character sub-strings rather than other specifications within the range suggested by the literature.

FinStress validity: sensitivity to sample period

How sensitive are the FinStress estimates to the particular time period included? We discussed in the text how large changes in document style can affect the results. This is why we use only EIU documents from 2003; they follow a consistent style. Similarly are the FinStress results driven by a particular time period due to certain words or types of events in those periods? Do descriptions of future events, such as bursting housing bubbles from 2008 affect how these topics shape FinStress for earlier periods in ways that would not reflect how actors at these earlier times viewed them?

To assess these issues we re-ran KPCA using exactly the same procedures, but only including documents from the 2003 through 2007 period before the start of the Global Financial Crisis. The bottom-right panel of Figure A-6 compares these to the original FinStress results for the same period. They are very similar. This indicates that future events are not unduly influencing past perceptions and that it would be possible to use the KPCA method to extend the analysis using similarly formatted documents from the EIU.

FinStress validity: additional qualitative examinations of texts

To get a qualitative sense of FinStress' wider qualitative validity, we examined texts associated with minimum and maximum FinStress scores for a number of other countries. Figure A-5 shows maximum scores for Brazil, Latvia, and Ireland. Brazil had a maximum FinStress score in the sample of 0.65 in 2009. The score reflects the EIU's assessment that the global financial crisis presents risks for banks and lenders "will find it increasingly difficult to roll over credit lines". Latvia had a similar maximum FinStress score–0.65 in 2010–and the text this score is generated from clearly describes a troubled financial sector as it notes that the Bank of Latvia "appears worried that commercial banks are reluctant to extend new loans". Ireland had an even higher maximum FinStress score–0.84 in 2011. The text this score is estimated from describes a highly troubled banking system that is going through a painful restructuring process and is reducing the supply of credit to the economy.

The texts that created country-minimum FinStress scores–shown in Table A-6–describe "confidence in financial markets" in Brazil (2005), "lending continues to expand" in Latvia (2006), and stable currency conditions in Ireland (2004). Importantly, in the Brazilian case the text is not without concerns that the conditions may not continue into the future. All of them (apart from Ireland which was in the Euro and so had monetary policy set by the European Central Bank), mention monetary policy moves to curb overheating. So, while low FinStress scores appear to be reflecting financial markets with strong credit provision, embedded in these texts is a concern that the boom may be peaking. This is an important finding to keep in mind when interpreting the substantive meaning of low FinStress scores. It is an issue that [WITHHELD FOR BLIND REVIEW] formally model in separate work and are able to empirically test using FinStress.

Developed vs. developing countries

Developing countries often lack strong financial institutions and systems. Facing a very risky pool of borrowers, banks tend to make fewer loans (Andrianova et al., 2014). So we should expect them to face generally tighter credit market conditions than developed countries.

The left panel of Figure A-7 shows average stress levels in developed vs. developing countries that Laeven and Valencia code as not being in crisis–indicates that there is a difference in the level of perceived financial

Table A-5: Portions of Texts EIU Reports with Country-**Maximum** FinStress values (selected countries)

Country	Month-Year	FinStress	Text Selection
Brazil	April 2009	0.65	Brazil's terms of trade will weaken significantly and Brazilian banks, along with major corporate borrowers, will find it increasingly difficult to roll over credit lines as lenders around the world rebuild their balance sheets.
Ireland	April 2011	0.84	Irish households are highly indebted. Private consumption will therefore be constrained as households rebalance their balance sheets and as credit conditions remain tight in 2011-13. Investment will continue to shrink in 2012 as the collapse of the construction industry maintains momentum ... [the] most recent stress tests reveal the complete failure of earlier attempts to assess the impairment of the banks' balance sheets. Of particular note is the fact that no serious provision had previously been made for losses on the banks' mortgage lending, despite a massive collapse in the residential property market that has been ongoing for some years.
Latvia	August 2010	0.65	Domestic demand in 2010 will be squeezed by higher unemployment, falling real and nominal wages, and pressure on firms' and households' balance sheets from their high level of debt. ... One area that is proving slow to stabilise is bank borrowing. The stock of borrowing continues to fall: total bank credit was down by 7.6% year on year in June. There are signs that in month-on-month terms, borrowing may be stabilising. Nevertheless, the [Bank of Latvia] appears worried that commercial banks are reluctant to extend new loans, preferring to deposit excess funds with the central bank.

Table A-6: Portions of Texts EIU Reports with Country-**Minimum** FinStress Values (selected countries)

Country	Month-Year	FinStress	Text Selection
Brazil	August 2005	0.1	By continuing to meet the target for the primary fiscal surplus despite strong political pressure to increase spending on social programmes, and by increasing the benchmark Selic overnight rate until inflation began to subside in June, the government has confirmed its cautious stance. Apart from keeping a rein on inflation, this has helped to maintain confidence in the financial markets.
Ireland	April 2004	0.04	...we still expect short-term euro area interest rates to rise in 2005, as the euro stabilises and the recovery gathers pace.
Latvia	December 2006	0.2	We expect growth of bank lending to begin to slow in 2007, but if lending continues to expand more rapidly than expected, the [Bank of Latvia] may raise rates further.

market stress in developed and developing countries from 2003 to 2008. Developing countries on average have higher FinStress scores. For example, the mean score in middle and low income countries (as classified by the World Bank) is 0.55 in 2005, a level developed countries only reached after the collapse of Lehman Brothers in 2008.[4] The mean levels across the two groups converge in the Global Financial Crisis. The distribution of FinStress scores in these two groups of countries across the sample is significantly different in the expected direction in the sample using one-sided Kolmogorov-Smirnov tests.[5]

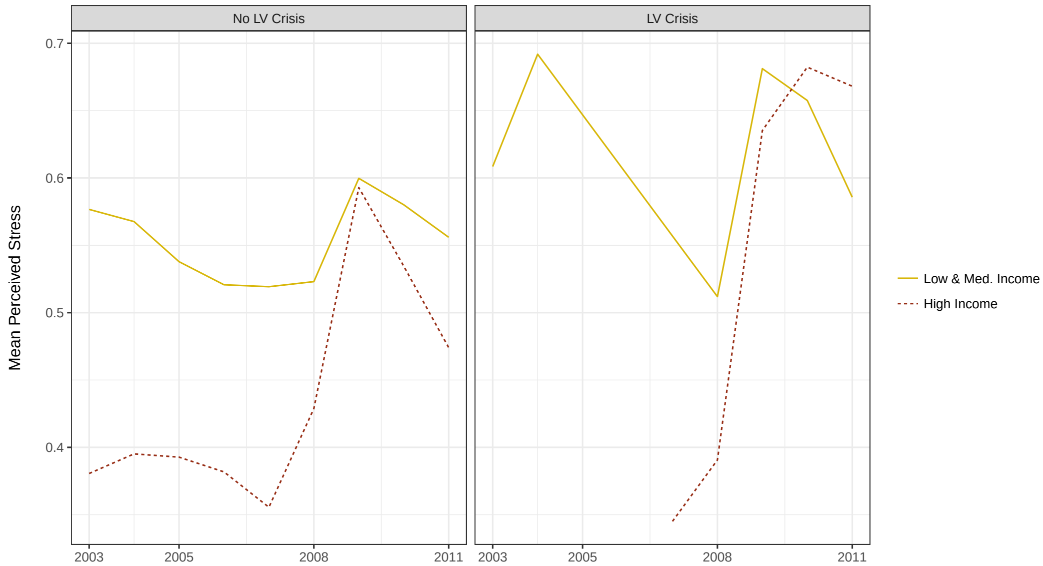
Nonetheless, during periods that the binary Laeven and Valencia measure codes as being a crisis, i.e. implement policy responses to financial market stress,the two sets of scores are very similar (see the right-panel of Figure A-7). Apart from 2007 and 2008 where the binary measures have significant "annual rounding error",[6] on average countries in crisis have FinStress scores above about 0.55. It appears that while developed countries have more stressed financial markets than developed countries that on average, developed and developing countries have clear policy responses to financial market stress when their FinStress scores are well above about 0.55.

[4]The 2005 mean for high income countries is 0.47

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

[6]Remember that the binary measure can include both less and more stressed portions of a year as all being in crisis.

Figure A-7: Comparison of Mean FinStress Scores in High vs. Low and Medium Income Countries



Plot excludes Uruguay, which was a substantial outlier with a much lower average FinStress score during what Laeven and Valencia classify as a crisis than all other developing countries.

Correlations Between FinStress and Camel Variables

How does FinStress correlate with the components of the CAMELS system of bank soundness? We used annual FinStress means to compare it to annual national aggregates of the CAMELS variables in Andrianova et al. (2015). Figure A-8 shows the bi-variate relationships between FinStress and these variables. FinStress is statistically significantly associated with six of the seven CAMELS variables at the 5 percent level.[7] FinStress is strongly associated with three of the CAMELS variables in that there is a correlation coefficient greater than 0.2 or less than -0.2. These variables are impaired assets to gross loans, net loans to total assets, and liquid assets to total assets. See also Figure A-9 for the full correlation matrix. FinStress is most strongly positively associated with impaired assets.[8]

[7]It is not significantly associated with Return on Average Assets.

[8]The log of impaired assets–it is a highly skewed variable–is associated with FinStress with a correlation coefficient of 0.45, significant at all standard levels

Figure A-8: Comparing Annual Mean Perceptions of Financial Market Conditions with Components of the CAMELS System from Andrianova et al. (2015)

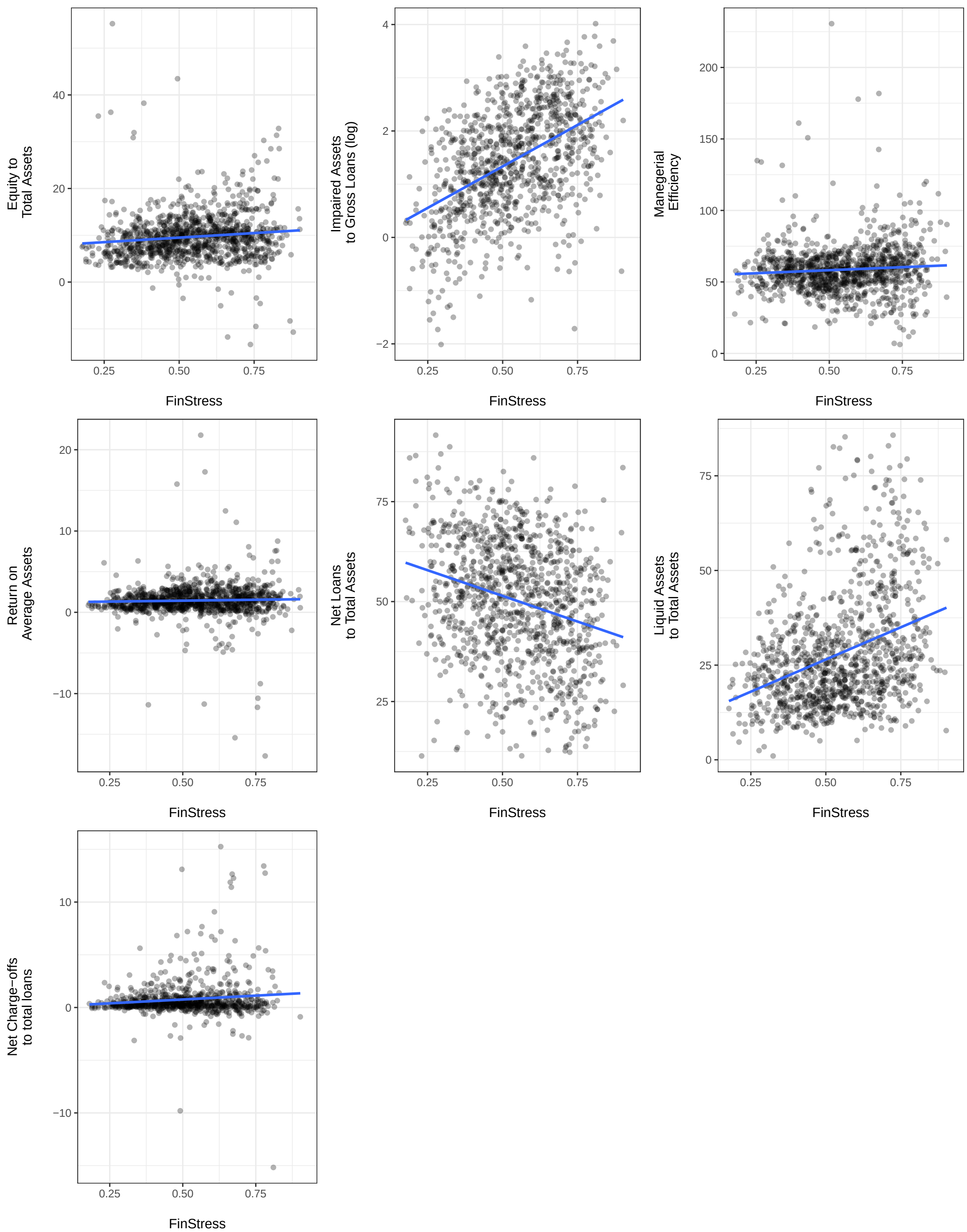


Figure A-9: Correlation between Annual FinStress Mean Scores and CAMELS Variables from Andrianova et al. (2015)

Global comparison to accounting measures of banking system fragility

Moving beyond simple correlations, to assess the relationships between the various quantitative measures of bank and banking system stress and FinStress we use a random forest regression. We include in the regression CAMELS indicators from Andrianova et al. (2015) and a number of other indicators from the Global Financial Development Database that the World Bank classified as being related to banking system stability (World Bank, 2015), including Z-Scores.[9] Our main reason for using random forest regressions is

[9] Variables from the GFDD include: provisions to NPLs, stock price volatility, regulatory capital to assets, capital to assets, credit to deposits, stock market returns, and private sector credit provided by banks and other financial institutions. The last two are not classified by the GFDD as banking "stability" indicators, but we included them as they may be substantively

that we are examining the relationships between many highly correlated variables and FinStress. As all of the right-hand side variables are country-year aggregates, we examine their relationship with country-year mean FinStress levels.

The random forest regressions are based on a slim sub-sample for which we have FinStress scores. There are 1,677 country-years for which we have average FinStress scores, but due to missingness issues discussed above, only 425 of these have complete information across the included indicators and thus are included in the random forest regression.

Figure A-10 shows the importance each variable plays on average for predicting FinStress levels. Impaired loans are found to be the most important variable for predicting FinStress levels in this sub-sample.[10] The third most important is highly related to impaired assets–return on average assets. When there are more non-performing loans the average return on all loans is lower. Z-Scores are a fairly poor predictor of FinStress. Please see below for a detailed exploration of the relationship between FinStress and Z-Scores. The main conclusion of this work is that Z-Scores, at least as measured by the World Bank, are a poor measure for examining how banking stress changes over time and should be avoided in research on this.

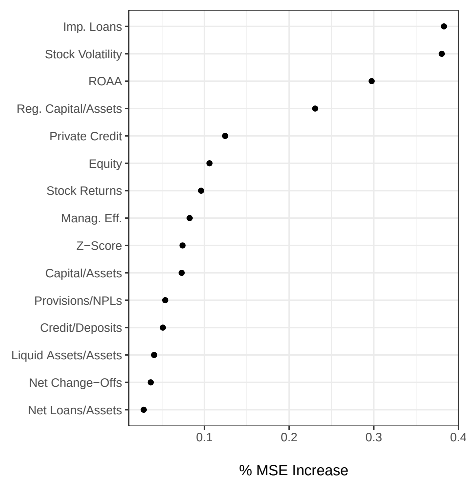
Figure A-11 shows the predicted values from repeated draws of FinStress averaged within the values of the other variables included in the random forest regressions (see Jones and Linder, 2015, 14). This gives us a window into the nature of the estimated relationship between the predictor variables and FinStress. Impaired loans (log) have an almost linear 45 degree positive relationship with FinStress. Higher impaired loan ratios are strongly associated with higher FinStress scores. Impaired assets are otherwise often known as non-performing loans. Banks are solvent when their assets (e.g. loans and the income they generate) can cover their liabilities (e.g. deposit withdrawals). Impaired assets greatly threaten banks' ability to meet their obligations and so threaten their solvency. As such, it seems as though FinStress is closely related to bank balance sheet health.

Greater stock price volatility also appears to have a strong linear relationship with FinStress, where more volatility is related to higher FinStress scores. While most of the other variables appear to have less linear relationships with FinStress, they are generally in the expected direction. For example, the higher banks' return on average assets, the higher their equity, and the higher their provisioning, the lower the FinStress

important.

[10] In a sample of all countries, exchange rate change is also relatively important, though when the sample is subsetted to look only at high income countries, it has no impact on reducing predictive error. This makes substantive sense as in the period under examination exchange rates in high income countries were relatively stable, even during crises. Stress in developing countries is closely related to foreign exchange disruptions and the currency asset-liability mismatches banks face in these situations.

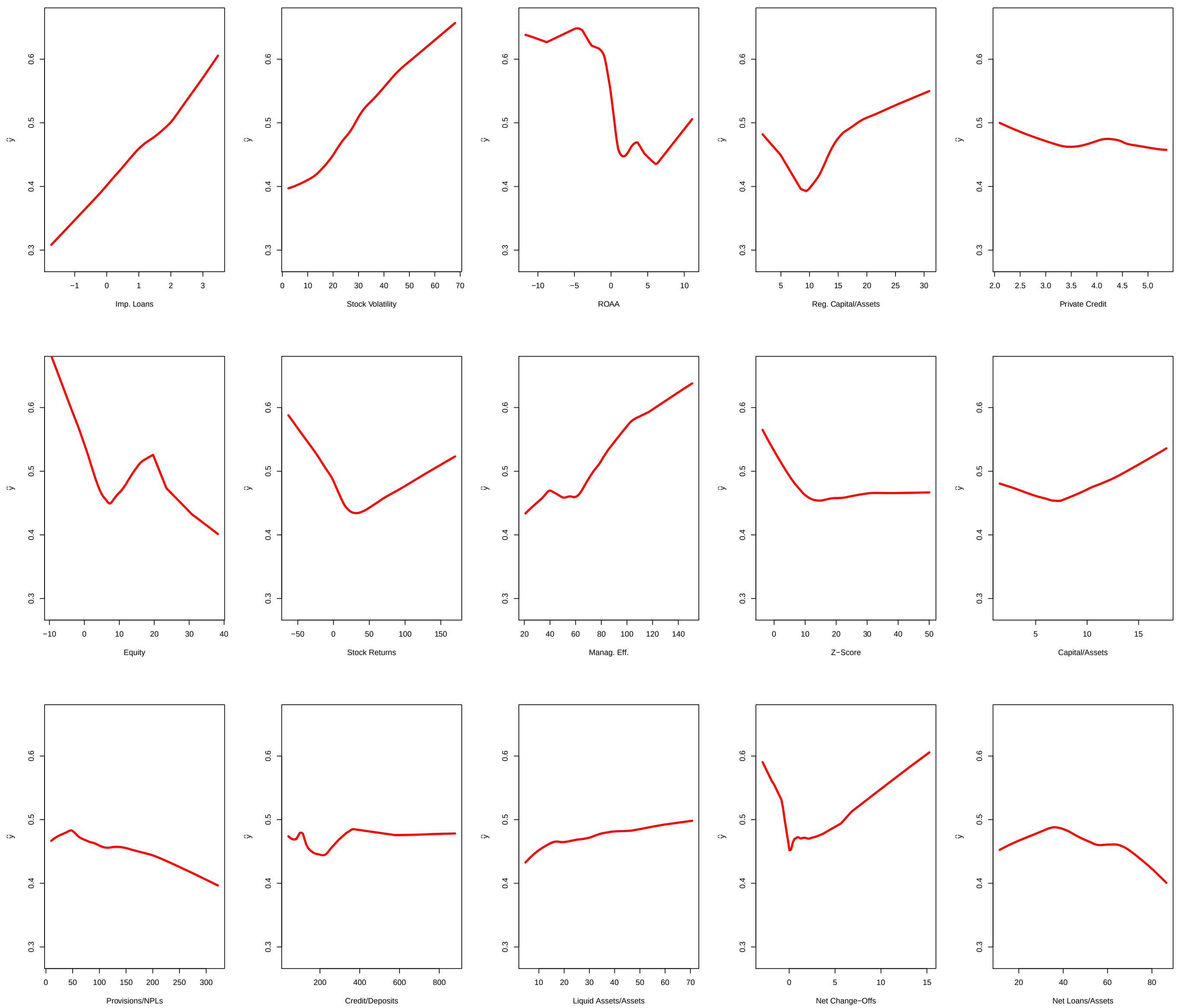
Figure A-10: Importance of Various Quantitative Financial System Stability Measures for Predicting EIU Perceptions of Financial Market Stress Index



scores. These findings further corroborate the proposition that FinStress is a valid indicator of financial market stress, specifically in banking, and give more definition to specifically what the Index measures.

Finally, it is important to examine the perhaps initially counter-intuitive finding that FinStress is positively associated with liquid (e.g. cash) asset ratios. Banks with more liquid assets are less likely to become insolvent because they can use these assets to meet their liabilities. However, high liquid asset ratios can be a manifestation of a stressed financial system as banks create large liquid asset stockpiles when they are reluctant to lend–take on less liquid assets. This behavior restricts credit to the wider financial system and economy. Following the Lehman Brothers collapse in 2008 an extreme version of this occurred, becoming known as a “credit crunch”. Andrianova et al. (2014) find that African banks have very high liquid asset ratios because lending risks are high, so banks are reluctant to make new loans. This may explain why developing countries often have persistently high FinStress scores (see above). To a large extent net loans and liquid assets are inversely related. As such we find a negative relationship between net loans and FinStress–banks in countries with higher FinStress scores are making fewer loans and instead are hoarding liquid assets.

Figure A-11: Partial Dependence of Each Predictor in the Random Forest Regression on FinStress ($\hat{y}$)



FinStress compared to Z-Scores

How does FinStress compare to the widely used Z-Score measure of banking system fragility? We saw in the main text that the global random forest regression indicates that Z-Scores are not very predictive of FinStress. Given the prominence of the Z-Score measure in the finance literature, we wanted to further explore this (null) relationship.

It is important to note that the two quantities do measure different phenomena–perceptions for the former and bank accounting relationships for the latter–, but both potentially provide indications of stress. As was the case for the dichotomous measures of financial crises, we would expect them to be positively correlated with one another. Another interesting question would be whether one would precede the other. Does weakness in accounting quantities proceed perceived stress?

To explore these possibilities, we compare FinStress to the easily accessible Bank Z-Score measure compiled from Bankscope data in the World Bank's Global Financial Development Database (GFDD) 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 A-12 shows a comparison of the two measures for selected countries. Note that to ease visual comparability we rescaled the Z-Scores to be within zero and one as before, and reversed the scale so that larger values indicate a higher probability of banking system insolvency.[13] As before, we converted FinStress to yearly averages for comparability.

There does not appear to be much of a relationship between Z-Scores and FinStress. The rescaled World Bank Z-Scores are positively correlated with FinStress, but this is not significant at the 10% level.[14] Interestingly, the World Bank's Z-Scores do not vary significantly within countries over time, especially compared to FinStress. There is little difference between Z-Scores for countries during periods of heightened financial stress (however measured) and more stable times. Thus Z-Scores, at least those provided by the World Bank, are not a useful indicator of financial crisis states. Z-Scores do not appear to predict perceptions of financial market stress. In a simple partial correction linear regression that had FinStress as

[11] Indicator ID: GFDD.SI.01. Accessed January 2017.

[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 country aggregates.

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

[14] We also examined an alternative data source compiled by Andrianova et al. (2015), which transformed Bankscope data as well. In this case there was a weak positive association significant at the 5% level. However, again there was little cross-time variation in the Z-Score.

the dependent variable and included lagged FinStress, lagged Z-Scores, and country fixed-effects, Z-Scores were not statistically significantly associated with perceptions of financial market stress (see Table A-7).

The simplicity with which Z-Scores can be calculated with readily available data likely contributes to their wide use in the literature, especially relative to other quantitative measures of financial system fragility that are often difficult to obtain. However, it is clear that Z-Scores–at least the version available through the World Bank's GFDD–are a sub-optimal cross-time measure of financial market stress. It is beyond the scope of our article to determine the source of the measure's peculiar characteristics, but they are important to note here: the indicator has weak time-variance, it does not distinguish between periods of significant known financial market stress and less stressful times, and it does not help us predict perceived financial market stress. FinStress, in contrast, is much notably time-variant in ways that correspond closely to prior information on financial market stress.

Table A-7: Do Z-Scores Predict Perceived Financial Market Stress?

	Dependent variable:
	Annual Mean FinStress
Annual Mean FinStress (lag)	0.582^{***}
	(0.026)
Z-Score (lag)	-0.001^{*}
	(0.001)
Fixed effects?	Yes
Observations	1,332
R^2	0.308
Adjusted R^2	0.204
F Statistic	257.133^{***} (df = 2; 1157)
Note:	*p<0.1; **p<0.05; ***p<0.01

Compare model fit: FinStress vs. Laeven and Valencia (2013)

Table A-8 presents full parameter estimate results for models discussed in Section 4.2 in the paper. Note that in models with cumulative debt revisions as the dependent variable, FinStress is the annual average. We used the annual average because the dependent variable is measured on an annual basis.

Figure A-12: Annual Mean FinStress Compared to Country-level Z-Scores (rescaled)

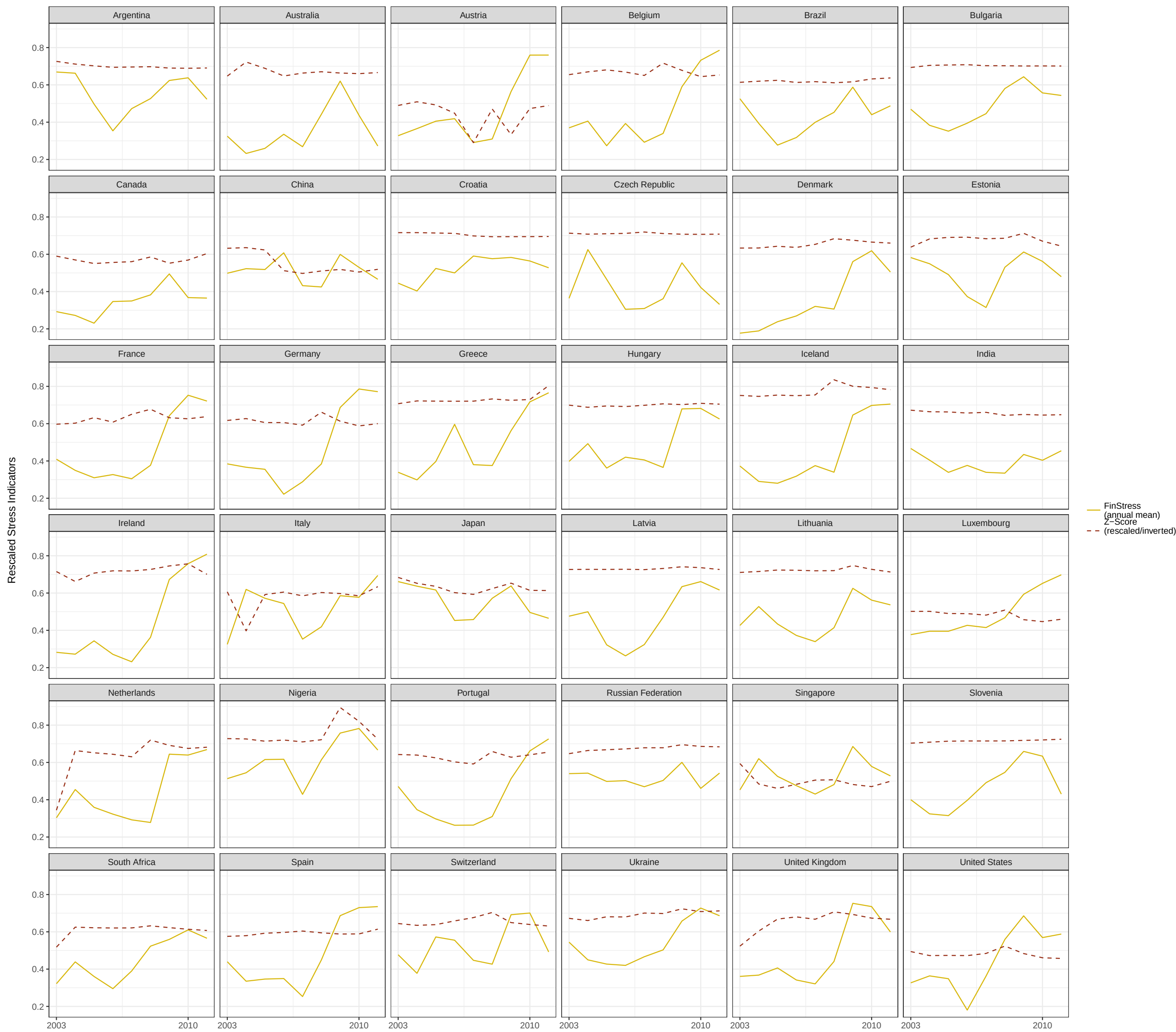


Table A-8: Comparing FinStress and LV Binary Measure Model Fit

	Dependent variable:			
	Electoral Volatility		Cum. Debt Revisions	
	(1)	(2)	(3)	(4)
FinStress	−41.914*		0.020	
	(21.568)		(0.013)	
FinStress^2	57.473**			
	(23.276)			
Laeven/Valencia Crisis		4.396**		0.841**
		(1.955)		(0.356)
Unscheduled Elec.			−6.676***	0.463
			(2.101)	(0.783)
Scheduled Elec.			0.204	−0.106
			(1.297)	(0.367)
FinStress * Unscheduled			0.170***	
			(0.042)	
FinStress * Scheduled			−0.005	
			(0.028)	
LV * Unscheduled				1.942*
				(1.069)
LV * Scheduled				0.110
				(0.776)
Constant	17.233***	10.009***	2.270**	2.715***
	(4.600)	(1.112)	(0.949)	(0.660)
Fixed Effects?	No	No	Yes	Yes
Observations	34	34	245	245
R^2	0.242	0.136	0.483	0.457
Adjusted R^2	0.193	0.109	0.405	0.375
Residual Std. Error	5.077 (df = 31)	5.333 (df = 32)	1.869 (df = 212)	1.915 (df = 212)
F Statistic	4.943** (df = 2; 31)	5.056** (df = 1; 32)	6.185*** (df = 32; 212)	5.580*** (df = 32; 212)

Note: *p<0.1; **p<0.05; ***p<0.01

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