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

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Responding to financial market disruptions is a defining challenge for policymakers and a central topic of political research. Yet established measures of financial conditions have significant shortcomings. Annual binary crisis variables limit our ability to explore non-linear relationships and the political effects of rapidly changing conditions. Continuous indicators have their own flaws in operationalization and reproducability. We create a continuous measure of real-time perceived stress using a kernel principal component analysis (KPCA) of *Economist* monthly country reports. We demonstrate the usefulness of our measure by showing that it more accurately captures the effect of financial market stress levels on electoral volatility. We also show how KPCA can be used to efficiently summarize large quantities of texts into cross-sectional time-series variables.

Keywords: financial crisis, economic policymaking, banking, electoral volatility, natural language processing

How do politicians and voters respond to financial market stress and with what political effects? Previous research addressing these questions lacks a crucial variable: a continuous indicator of the level of financial market stress that policymakers and voters perceived in real-time. We need a measure of actors' contemporary perceptions of financial market conditions to understand why they made a given choice and with what effects.

Previous binary crisis measures are constructed *post hoc*, so tend to be biased towards severe crises and away from circumstances where governments effectively responded to emerging trouble. As such, they suffer from clear selection bias. Annual *post hoc* measures do not necessarily capture conditions as they were perceived at the time of events such as elections. As dichotomous indicators, they neither measure crisis severity nor how it varies over time. They use *ad hoc* methods to determine when crises have ended. Previous continuous measures of financial market stress are less common and suffer from other problems. They capture quantities whose importance, measurement, and reporting varies significantly across countries and over time.

To overcome these issues, we develop a continuous measure of real-time perceptions of financial market stress with a kernel principal component analysis (KPCA) of detailed qualitative data, namely monthly *Economist Intelligence Unit* (EIU) reports. We call it the EIU Perceptions of Financial Market Stress Index: *FinStress* for short. FinStress enables new political research possibilities. As a continuous measure, FinStress could be used to examine which policies are effective at preventing or reducing extreme stress and which political conditions are conducive to

implementing these policies. As a comparable continuous monthly indicator, FinStress could be used to test hypotheses that rely on sub-annual data and follow the intensity of stress over time.

Here we provide examples for studying the impact that financial market stress has on voters' choices and on revisions to European Union government budget figures.

Not only do we create and demonstrate the usefulness of this measure, we contribute to the wider methodological toolkit by showing how KPCA can be used to summarize vast quantities of similarly formatted qualitative texts into continuous cross-sectional time-series indicators.

PREVIOUS MEASURES AND THEIR USE IN RESEARCH

Binary measures

Researchers studying the politics of financial crises mostly rely on two sources of cross-country information about crises. The first is from Reinhart and Rogoff.[1] The second is from Laeven and Valencia.[2]

Reinhart and Rogoff classify countries in crisis when they experience at least one type of event: (1) one or more bank run, closure, merger, or public sector takeover and/or (2) closure, merger, takeover or large-scale public assistance of an important financial institution that marks the start of a string of similar events.[3]

Laeven and Valencia take a similar approach that emphasizes public interventions. A country-year is in crisis when there is both significant distress in the banking system and policymakers respond with significant interventions.[4]

These binary crisis indicators come from detailed comparative work that identifies key features of crises. Yet, they have a number of problems for studying political behavior. Crises are identified *post hoc* by researchers who know what happened after the fact. Financial market stress that policymakers successfully address, which prevents a crisis, is not included. Similarly, stress that a government temporarily dampens through unsustainable policy measures, only to flare up later, is not recorded. The measures are dichotomous. They do not indicate crisis severity nor how it changes over time. Having an annual dichotomous measure also means that measurement errors–incorrectly timing the start or end of a crisis–can bias statistical model estimates.

There are large inconsistencies between the timing of crises in the Laeven and Valencia and Reinhart and Rogoff data sets.[5] Moreover, there are significant differences in crisis timing between different versions of the Laeven and Valencia data.[6] While the measures use precise definitions of when a crisis started, reasons for dating the end of a crisis are either unstated, as in the case of Reinhart and Rogoff, or are *ad hoc*. Laeven and Valencia[7] determine that a crisis has concluded when real GDP and real credit growth are positive for two years, or five years have elapsed from the crisis start year.

Despite these shortcomings, the indicators have been widely employed in the literature. Fielding and Rewilak and Herrera, Ordoñez, and Trebesch use Laeven and Valencia's indicator as a dependent variable to understand how capital flow bonanzas affect the probability of crises

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[1]Reinhart and Rogoff 2009, 2010.

[2]Laeven and Valencia 2013, along with their predecessors.

[3]Reinhart and Rogoff 2009; 2010, 10.

[4]Laeven and Valencia 2013, 228. Please see the Online Appendix for more details.

[5]Chaudron and Haan 2014.

[6]Gandrud and Hallerberg 2015.

[7]Laeven and Valencia 2013, footnote 19.

occurring.[8] Danielsson, Valenzuela, and Zer use Reinhart and Rogoff to understand how stock price volatility predicts crises.[9] Keefer and Rosas use earlier versions of the Laeven and Valencia data set to identify periods of crisis and to argue that electoral competitiveness affected policy responses.[10] Reischmann employs the Laeven and Valencia measure to examine electoral effects on "creative public budget accounting" during crises.[11] Ha and Kang use Laeven and Valencia to find that developing country governments respond to crises with fiscal and monetary tightening, though this is moderated by political constraints.[12] Gandrud and Kleibl combine the two data sources to understand how financial regulatory structures are changed after crises.[13] Broz integrates the data sets to find a "partisan financial cycle".[14] Crespo-Tenorio, Jensen, and Rosas, Chwieroth and Walter, and Pepinsky use the data sets in their research on the political effects of crises.[15]

Continuous measures

There are alternative approaches to measuring financial stress that, while being less used in the literature, not only aim to code extreme stress, but also continuous variation in severity over time. In particular, Romer and Romer use a 16 point scale of the cost of credit intermediation to provide an indication of stress intensity. They code 24 countries using information from the OECD's 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 and addresses potential problems with *ex post* coding.[16]

While their approach is an improvement over previous work, it is limited. First, their data source confines them to a relatively small sample of OECD countries. Second, because their measure is laborious and time consuming to create and update, even if there were a more encompassing corpus, applying the method would be costly. Third, human coders can introduce well-known problems of inter-coder reliability and unreproducibility.[17]

Creating the FinStress Index

We overcome many of these problems by estimating real-time perceptions of financial market stress through machine classification of *Economist Intelligence Unit* reports.[18] Our method uses kernel principle component analysis[19] of monthly country reports from the EIU to create a monthly index for 186 countries from 2003 through 2011.

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[8]Fielding and Rewilak 2015; Herrera, Ordoñez, and Trebesch 2014.

[9]Danielsson, Valenzuela, and Zer 2015.

[10]Keefer 2007; Rosas 2006, 2009.

[11]Reischmann 2016.

[12]Ha and Kang 2015.

[13]Gandrud 2013, 2014; Kleibl 2013.

[14]Broz 2013.

[15]Crespo-Tenorio, Jensen, and Rosas 2014; Chwieroth and Walter 2015; Pepinsky 2012. For an additional review of the literature see Gandrud and Hallerberg 2015, 1-3 and the Online Appendix.

[16]Romer and Romer 2015.

[17]See e.g., Minhas, Ulfelder, and Ward 2015. Please see the Online Appendix and also Kliesen, Owyang, and Vermann 2012 for further critical discussions.

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

[19]Scholkopf, Smola, and Muller 1998; Lodhi et al. 2002; Spirling 2012.

Why the EIU?

The EIU compiles real-time, third-party qualitative assessments of financial market conditions within country-time contexts. Reports are released at regular monthly or, for a small subset of countries, quarterly intervals. These reports contain perceptions of economic conditions. They are an important channel for dissemination to public and private actors. They form a large corpus–more than 20,000 texts–of reports for more than 180 countries over the period 1997-2011. From 2003, they follow a consistent style and format, thus minimizing the extent to which text analysis picks up stylistic features, rather than information on financial market stress. The regularity and frequency of reporting for such a large group of countries in a consistent format distinguishes the EIU from other sources of financial information that we might analyse, chiefly newspaper reports. To take full advantage of format comparability we concentrate on data from 2003.

Summarising financial market stress in the EIU

We want an index that classifies financial conditions on a continuous more-stressed/less-stressed spectrum for as many country-months as possible. Therefore, we need an efficient way to summarize the vast quantity of information in the EIU reports. We first collected and pre-processed the EIU texts–focusing specifically on sections regarding banking and finance. See the Online Appendix. We then used kernel principal component analysis to place the texts onto a financial market stress spectrum.

In political science, texts are frequently summarized using unordered "bags-of-words" approaches that aim to find clusters of topics within texts or clusters of texts around topics.[20] We would like to preserve word order in our texts. Many financial terms such as "credit growth" and "borrowing costs" have different interpretations depending on the adjectives that modify them; consider, 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–e.g. "increasing non-performing loans"–or improving conditions–e.g. "increasing lending". A bags-of-words approach treating each word as having meaning as an individual unit, rather than in ordered associations with other words, would not adequately capture commonly used and radically different meanings.

Kernel principal component analysis–developed by Scholkopf, Smola, and Muller and Lodhi et al.–allows us to address these issues. KPCA can extract structure from our likely high-dimensional EIU corpus while preserving word order.[21]

Note that we also conducted the analysis using bag-of-words PCA. While less computationally intensive to estimate, it resulted in a less valid measure (see the Online Appendix).

Our unit of analysis is a sub-string kernel: a short sequence of letters[22] 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 "credi"

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[20]See Grimmer and Stewart 2013.

[21]Scholkopf, Smola, and Muller 1998; Lodhi et al. 2002. See also Zhang, Wang, and Ma 2010, 6531–6537 and Spirling 2012, who introduced KPCA into political science with a study of Native American-US treaties.

[22]The kernels are similar to n-grams though they do not need to be complete words. 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. See the Online Appendix for a comparison of estimates made using other lengths. The results were very similar regardless of kernel length.

and "redit", but differ on "low c" and "and c", among others. We summarize the similarity of these documents with the frequency distribution of five-length strings that they have in common standardized by document length. We find these pairs for all of the documents in our corpus to create a kernel matrix. We then scale the documents using principal component analysis,[23] using the first component as our indicator (see the Online Appendix), and made two final transformations. First, we rescaled it so that it would be between zero and one.[24] This eases interpretation. Second, we smoothed the results by taking a two period–usually two months–moving average.

Validation and description

The solid lines in Figure 1 show FinStress for a selection of countries. What does this indicator represent? Grimmer and Stewart argue that to validate the results of a text analysis we need "careful thought and close reading . . . extensive and problem-specific validation".[25] We qualitatively examine a selection of the texts classified as being at various FinStress levels. We extensively compare FinStress to other measures of financial market stress. A portion of this exercise is presented here. Please see the Online Appendix for more details.

Qualitative examination

Table 1 shows a progression of texts in the lead up and height of the 2008 United States crisis. The first text is from the observed United States minimum FinStress month–April 2006. The text discusses strong business investment. A year later, the FinStress score increased significantly to 0.41. Likewise, the language changed. The EIU notes a "slump in the housing market" and that liquidity for lower quality mortgages is "drying up". The following year, shortly after the failure of Bear Sterns, the FinStress score increased to 0.5. The text notes that the bail-out of Bear Sterns has "increasingly swung" market participants to think that the worst is over. FinStress is clearly higher than before, but far from its peak, reflecting the cautiously positive assessment in the EIU report. FinStress rose to 0.62 in September 2008 (a report that was released before Lehman Brother's failure). This report notes increasing lending risks as well as threats to the "stability of weak financial institutions". In November 2008 FinStress rose close to the United States maximum with the EIU noting that there is a "credit crunch". FinStress closely tracks EIU reports describing increasingly worrying financial market conditions.

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

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

[25]Grimmer and Stewart 2013, 267.

TABLE 1: Portions of Selected EIU Reports for the United States (2006-2008)

| Month-Year	FinStress	Text Selection
April 2006	0.13	Corporate profitability improved remarkably in 2004-05, and this is allowing firms to fund investment from current profits.
April 2007	0.41	A slump in the housing market is starting to have an impact on the consumer sector . . . with liquidity in the markets for inferior quality mortgages (sub-prime and Alt-A) drying up-through stricter lending standards and rising risk aversion by more mainstream lenders
May 2008	0.5	Financial markets have recovered somewhat in recent weeks, as market participants have increasingly swung to the belief that the worst of the financial crisis is over. Fears about the stability of the US financial system have eased particularly since the Fed supported a dramatic bail-out in mid-March of Bear Stearns, one of Wall Street's oldest and most prominent securities firms.
September 2008	0.62	. . . the slowing economy and rising Unemployment have made lending more risky. With house prices continuing to fall, mortgage defaults and foreclosures are rising. Delinquency rates on automotive, credit-card and student loans have also climbed. The result has been a sharp contraction in credit, imperiling consumer spending as well as the stability of weak financial institutions.
November 2008	0.71	. . . a large share of banks continued to tighten their lending conditions, suggesting that the economy now operates in conditions of a credit crunch
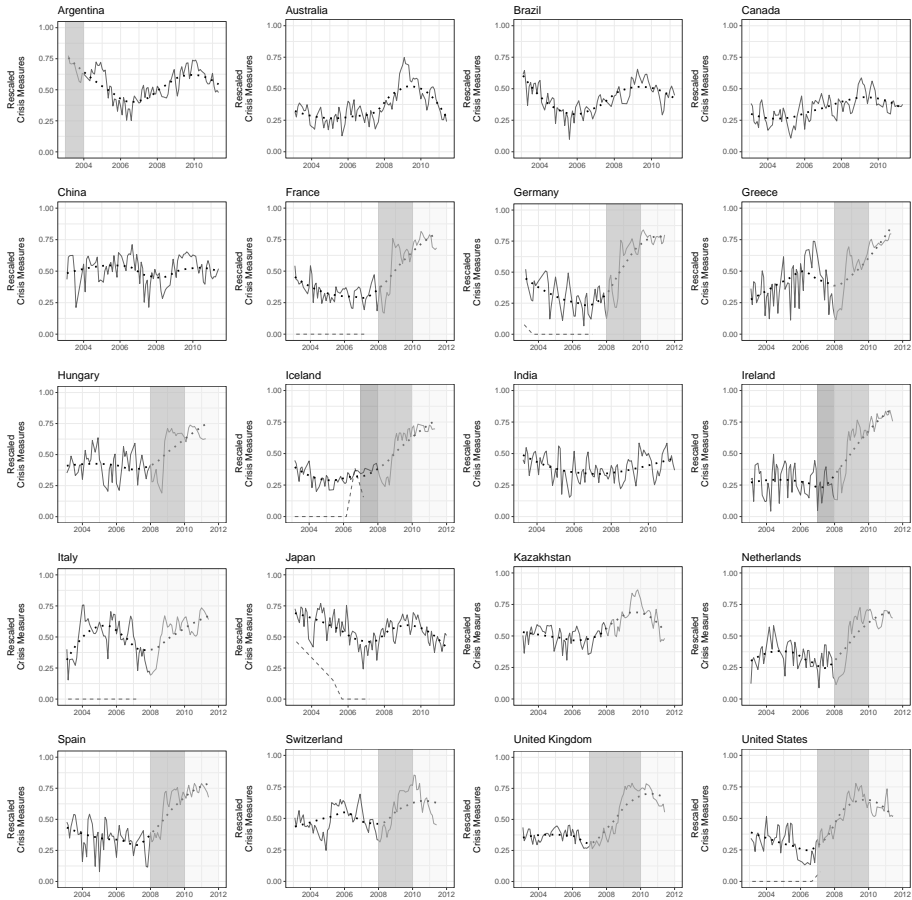
Figure 1: Comparing Perceptions of Financial Market Conditions to Laeven and Valencia 2013, Reinhart and Rogoff 2009, and Romer and Romer 2015

Solid lines show the FinStress Index. Dotted lines represent a loess smoother of these series. Dashed lines show the (rescaled) scores from Romer and Romer 2015.

The lightest shaded areas indicate periods that Laeven and Valencia 2013 classify as systemic banking crises. Crises are automatically terminated at the end of 2011 as the series does not extend beyond this point.

The darkest shaded areas indicate periods that Reinhart and Rogoff 2009 classify as banking crises. Crises are automatically terminated at the end of 2009 due to the series not extending beyond this point.

Areas with medium darkness shading indicate periods where a crisis is recorded for both measures.

Comparison with other indices

We now compare FinStress to the dichotomous measures of banking crisis developed by Reinhart and Rogoff[26] and Laeven and Valencia,[27] as well as Romer and Romer's[28] continuous measure.[29] We expect that our measure is capturing many of the same events, but with more nuance in magnitude and over time.

Figure 1 compares FinStress to three other measures of financial stress. In many cases–conditional on the coverage of each data series[30]–the indices substantively overlap. Comparisons with Romer and Romer 2015 are limited by data availability, but clearly there are cases where FinStress and their index are similar. For example, both indices increase in the US from early 2007. A notable difference is how Romer and Romer classify Japan as being without stress from mid-2005, while FinStress decreases, but to a high level compared to many other economically developed countries at that time. Both indices classify Iceland as being under stress in the late 2000s, the timing is different. Romer and Romer classify Iceland as in stress[31] in 2006-2007. This is earlier than not only a marked increase in the FinStress Index, but also Reinhart and Rogoff and Laeven and Valencia's timing.

High FinStress levels should appear where there is crisis in the dichotomous codes, but the reverse may not be true–the dichotomous indices may miss a building crisis as perceived at the time. Laeven and Valencia and Reinhart and Rogoff should have more Type II errors–there are signs of stress but they miss them. Laeven and Valencia's coding is stricter because countries both have to experience distress and have a particular policy response, so the associated FinStress levels should be higher.

We do find that the mean FinStress level during periods that Laeven and Valencia classify as crises–i.e., financial market stress reached the point where politicians responded using a pre-specified set of policies–is higher than non-crisis periods.[32] Though developing countries tend to have higher FinStress scores, countries defined by Laeven and Valencia as in crisis in both groups have FinStress scores around 0.59 on average. Those not in Laeven and Valencia crises have lower scores.[33] The fact that mean FinStress is higher during periods that Laeven and Valencia classify as crises, but not dramatically, supports the proposition that they miss considerable periods of budding and high stress and perhaps suffer from more Type II errors.

Laeven and Valencia[34] comment that part of the problem with dating financial crises is that each one develops differently:

[26]Reinhart and Rogoff 2009.

[27]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. These are: France, Hungary, Italy, Portugal, Russia, Slovenia, Sweden, and Switzerland.

[28]Romer and Romer 2015.

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

[30]Romer and Romer 2015 do not include the most recent crisis in their sample as they did not collect data past 2007. We rescale their 16-point scale to be between 0 and 1. It should be noted that Romer and Romer 2015 only cover a selection of OECD countries. Reinhart and Rogoff 2009 only cover 70 countries and their data has been updated least recently.

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

[32]0.59 and 0.52, respectively. This is a statistically significant difference using one-sided and two-sided t-tests.

[33]See the Online Appendix for a discussion of the distributions of FinStress scores in developed vs. developing economies.

[34]Laeven and Valencia 2013, 227.

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

FinStress' real-time continuous measurement and monthly periodicity allows us to distinguish these types. We can see in Figure 1 that financial market difficulties in the United States built over a long period, with a few spikes during notable banking difficulties, e.g. Bear Stearns' and Lehman Brothers' collapse. Conversely, countries such as Germany, Hungary, and Iceland have more sudden periods of perceived financial distress. The Greek case presents an interesting trajectory. There is a notable spike in Greek financial stress in 2008–when both Reinhart and Rogoff 2009 and Laeven and Valencia 2013 determine a crisis had started. This is then followed by a stable period, followed by a sudden uptick in 2010, which was when a possible government default severely threatened the banking system.

Kazakhstan is notable for another path: rapid stress onset and just as rapid dissipation. In late 2009 there was a prominent spike in perceptions of stress directly related to a credit crunch resulting from the Global Financial Crisis. According to an IMF assessment, a large and quick policy response–facilitated by the country's sizable National Oil Fund–within a few months returned stability to the country's banking system.[35] Kazakhstan's FinStress score returns almost to its previous trend level at that time. Annual binary measures of crises do not capture these changes.

We can use FinStress 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 in late-2008/2009 is a notable example. It had a clear spike in perceptions of stress shortly after Lehman Brothers' collapse. Fairly quickly thereafter, its FinStress score returned to its previous level. Laeven and Valencia and Reinhart and Rogoff do not distinguish these periods.

FinStress' advantages are also apparent for timing the end of heightened distress. This is a difficult issue for the binary indicators. Crisis onset is well-defined by these measures, but they rarely have a clear or non-*ad hoc* way of determining when a crisis ended. Though we are limited by the time period coverage of the EIU texts, it is clear that some countries, notably Switzerland, the United Kingdom, and the United States, were perceived to have had improved financial market conditions from about 2010. Other countries, particularly Eurozone countries plateaued at a high level through the end of 2011, a period that corresponds with the Eurozone crisis. Laeven and Valencia's measure uses an *ad hoc* definition of crisis termination and so classifies these entire periods as crises with equal intensity.

Application

We now provide examples of how FinStress can be applied in political science research and demonstrate that it performs as well or better than previous binary measures.

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[35]See: http://www.imf.org/external/pubs/ft/survey/so/2010/car081710a.htm. Accessed November 2015
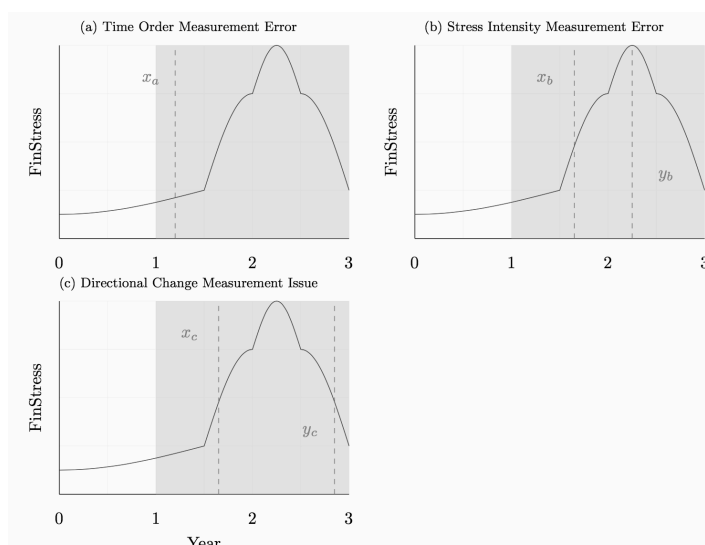
Figure 2: Hypothetical Scenarios of Error in the Measurement of Financial Market Stress at Elections Using an Annual Binary Measure vs. FinStress

Shaded areas indicates years classified as a crisis by a hypothetical binary crisis measure. Dashed vertical lines indicate an election.

Exploring the functional form of the relationship between crisis and electoral volatility

Following the Global Financial Crisis there has been considerable interest in how financial stress may hasten government failure,[36] how crises increase electoral support for extremist parties,[37] and how negative economic events and crises increase electoral volatility, i.e., the degree to which voters switch support for parties from one election to another.[38] Crespo-Tenorio, Jensen, and Rosas and Funke, Schularick, and Trebesch both rely on Laeven and Valencia's binary measure,[39] while Hernández and Kriesi use an even simpler measurement of crisis: whether or not an election occurred after November 2008.[40]

Figure 2 presents hypothetical scenarios to illustrate possible measurement error when estimating the effect of financial market stress on elections. The top-left panel illustrates time-order measurement error. Using annual indicators of crisis may ascribe a level of stress to an election that was not perceived at the time. This type of error could lead to systematic under-estimation of the effect of financial market stress.

The upper-right panel of Figure 2 illustrates incorrectly measuring the intensity of financial market stress for two elections held during a period of heightened stress. Using a binary crisis measure codes the elections as occurring at equivalent stress levels. This error could lead to underestimation of the effect of crisis on election outcomes. Additionally, a binary measure would not allow us to examine if there was a non-linear effect of stress, e.g., perhaps very high stress has an exponentially stronger effect on outcomes than medium levels.

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[36]Crespo-Tenorio, Jensen, and Rosas 2014.

[37]Funke, Schularick, and Trebesch 2015.

[38]Mainwaring, Gervasoni, and Espana-Najera 2016; Hernández and Kriesi 2015.

[39]Crespo-Tenorio, Jensen, and Rosas 2014; Funke, Schularick, and Trebesch 2015.
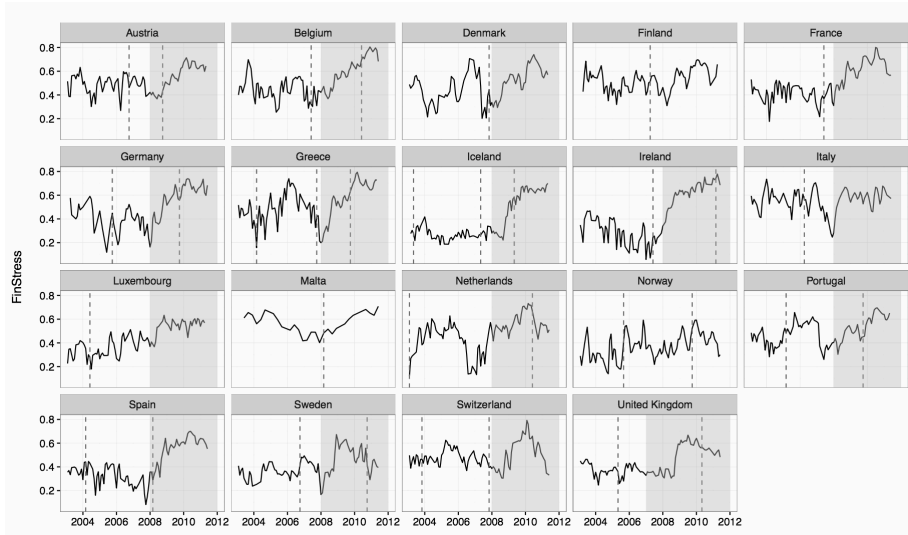
[40]Hernández and Kriesi 2015.

Figure 3: Comparing National Election Timing, FinStress, and Laeven and Valencia's (2013) Banking Crisis Measure in Europe

Dashed vertical lines indicate national government elections.

Lightly shaded areas represent Laeven and Valencia 2013 banking crisis periods.

Finally, the lower-left panel of Figure 2 provides a scenario where both a binary crisis measure and FinStress levels would not capture potentially important features of how voters perceived stress at elections x_c and y_c. Even though the binary and FinStress levels are the same in the former, stress is worsening, while in the latter conditions are improving. Voters might be more hostile to incumbents as conditions worsen and more favorable when conditions improve. The binary measure would not allow us to examine this possibility.

These are not just hypothetical examples. Figure 3 compares national election dates in 19 European countries to FinStress scores and Laeven and Valencia crisis periods. There are elections where notably elevated FinStress levels and Laeven and Valencia 2013 crises overlap. These include Belgium (June 2010), Germany (October 2009), and Iceland (May 2009). There are also notable examples of the binary crisis indicator coding an election as occurring in a crisis well before voters would likely have perceived one in their country. This includes Austria (October 2008), Portugal (October 2009), and Spain (March 2008). It would be inaccurate to estimate the effect of a crisis, which had not yet occurred, in these cases on voters' actions. There are also instances where financial market stress had declined or was notably declining by the time of the election, but the binary crisis measure still coded a full intensity crisis. This includes Sweden (October 2010) and the Netherlands (June 2010).

In light of these measurement issues, and assuming that electoral volatility will be higher under more stressful economic conditions, we anticipate that the binary crisis measure will underestimate the effect of financial market stress on volatility compared to FinStress.

To examine this we use data on electoral volatility in Western European countries from Emanuele.[41] He codes the total electoral volatility of an election by summing vote switching

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[41]Emanuele 2015.

between existing parties, new parties, and failed parties. Because we want to compare the estimated effects of the two financial market stress measures, we separately ran simple normal linear models of volatility including the stress measures on the right-hand side.[42]

Figure 4 shows predicted electoral volatility–which ranges from 2.5 to 29.6 in the sample–under various fitted levels and measures of stress. The first row of plots shows results from simple linear specifications. As expected, while both the binary and continuous measures are estimated to have a significant–at the 10 percent level–positive effect on volatility, the predicted effect of FinStress is somewhat stronger. The bottom-left panel of Figure 4 shows predicted electoral volatility from a model estimated by adding a quadratic term. Above FinStress scores of about 0.6 we estimate a rapidly increasing effect of FinStress on volatility. At the highest levels, volatility is predicted to be much higher than anticipated by the binary measure of crisis and linear FinStress. The average predicted volatility at the highest FinStress levels under the quadratic specification is 20.9, while it is 15.3 in the linear FinStress specification and 14.4 for the binary measure.

The middle-left panel of Figure 4 shows the predicted volatility for the range of observed changes to FinStress from the previous 12-month moving average. Large increases in stress compared to the average level over the previous 12 months is associated–at the 10 percent significance level–with increased electoral volatility. Stated conversely, improving financial market conditions are predicted to lead to less vote switching. The closest analogue to examining the effect of stress changes on volatility for the binary measure is to create a binary crisis-start year variable.[43] In contrast to the estimates with the FinStress change variable, we did not find a statistically significant effect at any level of Laeven and Valencia crisis onset on electoral volatility (Figure 4, middle-right panel).

Comparing model fit

We further compare the usefulness of FinStress to the Laeven and Valencia binary crisis measure by comparing the adjusted R^2 from models with the two indices. A higher adjusted R^2 would indicate that a variable explains more of the variance in the dependent variable.

We use regressions with electoral volatility as the dependent variable, as well as a substantively very different variable: cumulative revisions to EU member state government debt statistics made by the European Union's statistical agency–Eurostat. Gandrud and Hallerberg[44] used this variable to examine the political and economic conditions associated with Eurostat–an independent statistical agency–revising government debt statistics. One of their findings was that governments facing unscheduled elections, during financial crisis were more likely to have their debt statistics revised upwards. The authors argue that this is likely because incumbents under-report debts during stressful times to make themselves more attractive to voters.

We ran identical linear regression models with the dependent variables, changing only whether we included FinStress, the FinStress polynomial discussed earlier, or the binary crisis measure. The results are shown in the Online Appendix. For electoral volatility, the model with polynomial FinStress has an adjusted R^2 about 1.8 times higher than that with the binary measure (0.193 vs. 0.109). For debt revisions the difference is more modest, with the FinStress model having an adjusted R^2 1.08 times that of the binary model (0.405 vs. 0.375). When using debt revisions

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[42]We are solely interested in comparing estimates between the stress measures and given our small sample size, other effects were consigned to the error term. The sample used is that shown in Figure 3.

[43]Following McGrath 2015, we drop observations for years after the start of a crisis. Given the arbitrary five year crisis termination coding used by Laeven and Valencia 2013 and our limited sample, all crises were right-censored, we were not able to examine the effect of coming out of a crisis.
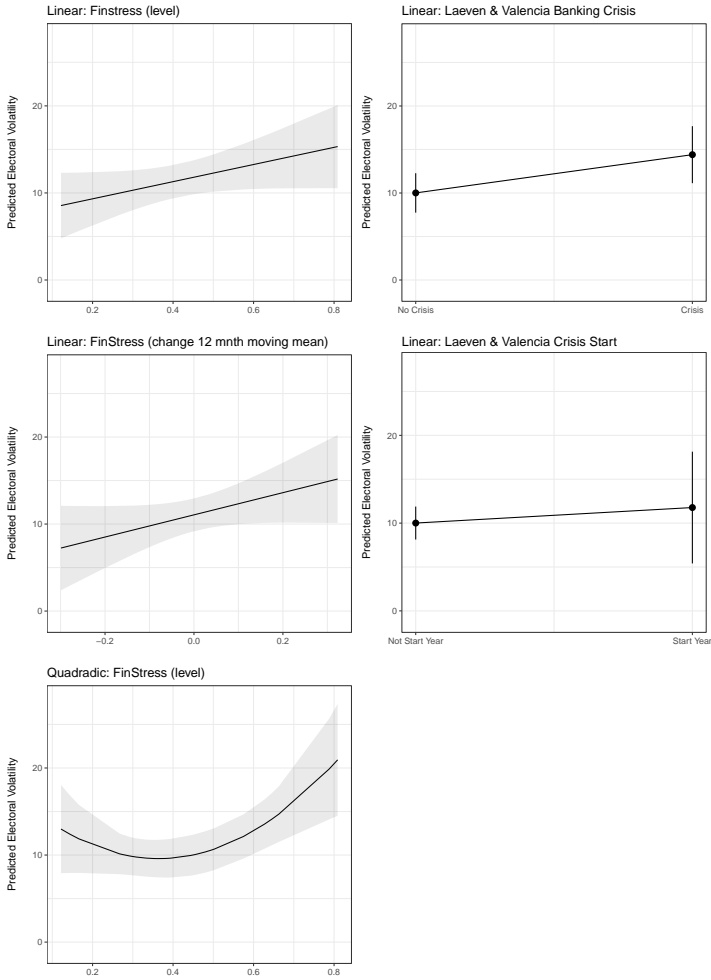
[44]Gandrud and Hallerberg, forthcoming.

Figure 4: Predicted Electoral Volatility for Representative Levels of FinStress and Laeven and Valencia (2013) Banking Crisis

Shaded regions/vertical lines represent 95 percent confidence intervals.

as the dependent variable, monthly FinStress was collapsed into its annual average to put it on the same time scale as the annual dependent variable. It is not surprising that the relative model fit is better with monthly FinStress than when it is collapsed into an annual average, and thus is more similar to the annual binary measure. The former operationalization leverages FinStress' continuous measurement level and high frequency, whereas the latter reduces this information.

CONCLUSION

We introduced a novel continuous measure of real-time perceived financial stress–FinStress–and compared it to prior measures of financial stress and crisis. We showed how this monthly continuous indicator–created with unsupervised text analysis–provides more accurate estimates of the impact stress has on political events like elections than less finely, but more laboriously constructed indicators.

   Our methodological work has implications for the wider research community. We demonstrated how researchers could construct continuous indicators of other political and economic phenomena using machine learning and text analysis of large corpuses of similarly formatted texts. Once a text gathering and analysis "pipeline"[45] has been developed and validated, researchers can efficiently estimate and update new indicators.[46] This approach is especially useful in comparison to time-consuming, expensive, and irreproducible human coding techniques for collections of similarly formatted texts.

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[45]Leek and Peng 2015.

[46]See the Online Appendix where we compare FinStress made with different sub-samples. These are very similar indicating that the method could be used to update an index when new documents become available within a consistently styled corpus.

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