Signalling to International Capital Markets: Financial regulatory transparency, capital flows, and banking system stability

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Abstract

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Why do countries release data on their financial systems to international organizations such as the IMF and World Bank? What are the consequences of releasing this data for their financial systems' stability? To answer these questions we start by using Bayesian Item Response Theory to create a new, global, and comparable Financial Regulatory Transparency (FRT) Index. The Index covers the years 1998 through 2011. It includes the 60 high income countries and jurisdictions that report financial system data to the World Bank Global Financial Development Database. The FRT Index is a distinct indicator of government willingness to gather and make available to international institutions and investors minimally credible information about their financial systems. Using the Index we find that the effect of transparency on banking system stability is contingent on a country's economic institutional quality. Countries with high quality institutions gain more stability with greater transparency. Countries with lower quality institutions that increase transparency, often as part of an effort to attract international investment, conversely have less stable financial institutions. This may be because their regulators are unable to respond effectively to increased capital inflows.

In previous research a number of us have found that even within the relatively homogeneous European Union where there are supranational authorities tasked with gathering and reporting aggregate financial data from member states that there is considerable variation in what is actually reported (see Gandrud

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All material for replicating the FRT Index and the analysis in this paper can be found at: `https://github.com/FGCH/FRTIndex`.

and Hallerberg, forthcoming). We currently lack a comparable cross-national way of measuring country's level of financial regulatory transparency. Furthermore, though supervisory transparency is often lauded as enhancing market stability (see Liedorp et al., 2013), there have been few empirical tests of this assertion especially within the the wider political and international investor environment. In this paper we build on a Bayesian Item Response Theory (IRT) approach recently employed by Hollyer, Rosendorff and Vreeland (2014) to develop a new Financial Regulatory Transparency (FRT) Index. We use the Index to examine how supervisory transparency to international investors interacts with bureaucratic capacity and capital flows to promote or harm financial stability. Furthermore, we improve on the general method of estimating transparency with Bayesian IRT by using the No-U-Turn Sampler Hoffman and Gelman (2014). This produces similar results to previous methods, but with considerable improvements to computation efficiency.

The Index includes 60 high income countries from 1990 through 2011. It measures these countries' reporting of financial system items to the World Bank's Global Financial Development Database (GFDD). The Index is a unique indicator of countries' willingness to credibly–the data has to pass minimal World Bank and International Monetary Fund quality checks–reveal the structure of their financial system and their regulatory quality, so that they can be scrutinized by market participants, particularly international investors.

In this paper we first discuss why government transparency has been argued for and found to be important for good governance and also how previous researchers have attempted to measure it. We then discuss the construction of the FRT Index. In the following section we describe a selection of the Index's notable features and demonstrate its 'value added' over less computationally intensive methods. Finally, we use the Index to examine the relationships between measures of financial regulatory quality and financial system stability.

1 Motivation: the importance of transparency

Lit. review of (a) why transparency is important and (b) how it has been measured before.

2 Creating the FRT Index

We treat financial regulatory transparency as an unobserved latent variable that effectively summarizes countries likelihood of reporting yearly data to indices included in the World Bank's Global Financial Development Database first created by Čihák et al. (2012).[1] In this section we describe how we selected

[1] Access to the most updated version of the data set is available through http://data.worldbank.org/data-catalog/global-financial-development. Accessed February 2014.

the items and country-years to include in the Index as well as the estimation model that creates it.

2.1 Included indicators

To measure financial supervisory transparency we first gather data on whether or not governments reported data on a subset of indicators that are included in the World Bank's GFDD. We follow Hollyer et al.'s (2014) criteria for inclusion of items and country-years. First, we only include indicators that are reported by at least one country for each year in the period 1998-2011. This gave us the greatest coverage of indicators that are comparable across countries. Second, we exclude all indicators that were explicitly gathered for only a subset of countries. As such we avoid including data where the primary source is the Bank for International Settlements. Third, we do not include any indicator that is from a non-governmental source. This included both indicators from World Bank sponsored surveys, such as the Global Financial Inclusion Survey and the Enterprise Survey. Other non-government sources that we exclude are data primarily derived from Swiss Re's Sigma Reports, Standard & Poor's, Bankscope, and Bloomberg. Fourth, we do not include variables that are linear combinations of other variables. Fifth, we do not include variables that are simply references to the same quantity in different units or whose reporting is perfectly linearly correlated.[2]

Additionally for the FRT Index, sixth, we aim to focus on countries that have relatively highly developed banking systems. As such we include only countries and jurisdictions that the World Bank classifies as 'high income'.[3] Countries with lower levels of income likely do not have financial systems sophisticated enough to have a number of the quantities reported in the items.

Using these criteria our model has 60 countries, 14 items, and 22 years (1990-2011). Table 1 shows the list of indicator items and descriptions.

2.2 The model

As in Hollyer, Rosendorff and Vreeland (2014) we let $y_{j,c,t} \in \{0,\ 1\}$ indicate a variable that is 1 when a country c reports a GFDD variable j in year t. It is 0 otherwise. We then estimate the model:

$$\Pr(y_{j,c,t} = 1 | transparency_{c,t}) = \text{logit}(\delta_j + \beta_j transparency_{c,t}) \tag{1}$$

The following parameters are estimated in the model:

- δ_j is the difficulty parameter of item j,

[2] Items GFFD.DI.01, GFFD.DI.02, and GFFD.D1.12 reporting was perfectly correlated. These all relate in some way to private credit. As such we only included GFFD.DI.01 (Private credit by deposit money banks to GDP (%).

[3] We include both OECD and non-OECD high income countries.

Table 1: Indicators included in the FRT Index from the World Bank's Global Financial Development Database

SeriesCode	Indicator.Name	Source	Periodicity
GFDD.DI.01	Private credit by deposit money banks to GDP (%)	IFS	Annual: 1961-2011
GFDD.DI.03	Nonbank financial institutions' assets to GDP (%)	IFS	Annual: 1961-2011
GFDD.DI.04	Deposit money bank assets to deposit money bank assets and central bank assets (%)	IFS	Annual: 1960-2011
GFDD.DI.05	Liquid liabilities to GDP (%)	IFS	Annual: 1961-2011
GFDD.DI.06	Central bank assets to GDP (%)	IFS	Annual: 1961-2011
GFDD.DI.07	Mutual fund assets to GDP (%)	World Bank	Annual: 1980-2011
GFDD.DI.08	Financial system deposits to GDP (%)	IFS	Annual: 1961-2011
GFDD.DI.11	Insurance company assets to GDP (%)	World Bank	Annual: 1980-2011
GFDD.DI.14	Domestic credit to private sector (% of GDP)	World Bank	Annual:
GFDD.EI.02	Bank lending-deposit spread	IFS	Annual: 1980-2011
GFDD.EI.08	Credit to government and state owned enterprises to GDP (%)	IFS	Annual: 1980-2011
GFDD.OI.02	Bank deposits to GDP (%)	IFS	Annual: 1961-2011
GFDD.OI.07	Liquid liabilities in millions USD (2000 constant)	IFS	Annual: 1960-2011
GFDD.SI.04	Bank credit to bank deposits (%)	IFS	Annual: 1960-2011

SeriesCode is the GFDD variable identifier.

IFS = International Financial Statistics, IMF

- β_j the discrimination parameter for item j,
- $transparency_{c,t}$ is the estimated propensity of a given country-year c, t to disclose financial regulatory data

δ_j indicates on average the degree to which countries report indicator j in the GFDD over the entire time span. β_j indicates how well reporting item j predicts reporting other items.

As Hollyer, Rosendorff and Vreeland (2014) note, simply taking the fraction of items a country reports in a given year as an indicator of transparency would be equivalent to assuming that δ_j and β_j are constant across all variables. However, some items are 'harder' to report than others as they reveal information that regulators may find difficult to gather without being more intrusive or, if they do gather it, they may consider it more sensitive for whatever reason. The IRT approach allows us to relax the equivalence assumption. Instead we directly estimate the degree to which countries find it 'difficult' to report items and how reporting an item (or not) is related to non-reporting of other items.

In order to fix the scale and location of the the FRT Index we followed Hollyer, Rosendorff and Vreeland (2014) by subtracting it by the mean and dividing by the standard deviation of the first year of the data set (1990) at each iteration.

The Index values in 1998 are draw from a diffuse normal prior ($Transparency_{c,1998} \sim N(0,\ 100)$) before re-centering. For each transparency value after 1998 we used a system of random-walk priors such that $transparency_{c,t} \sim N(transparency_{c,t-1},\ \tau_c) \forall t > 1$, where τ_c acts as a country-specific smoothing parameter. Each τ_c is estimated with the prior $\tau_c \sim Cauchy(0,\ 0.25)$. This is in contrast to Hollyer, Rosendorff and Vreeland (2014) who use a Gamma prior distribution. However, half Cauchy priors have been shown to be more appropriate with hierarchical data (see Gelman, 2007; Polson and Scott, 2012). Finally, we used similar priors when estimating the discrimination and difficulty parameters:

In contrast to Hollyer, Rosendorff and Vreeland (2014) who use Markov Chain Monte Carlo algorithm using Just Another Gibbs Sampler (JAGS) to estimate their model, we used the No-U-Turn Sampler (NUTS), an extension of the Hamiltonian Monte Carlo algorithm. NUTS is particularly efficient compared to other methods with models estimated from highly correlated data, as IRT models are (Hoffman and Gelman, 2014). We implemented the model with STAN (Stan Development Team, 2014).[4]. NUTS is ideal for This allowed us to reach convergence dramatically faster than when using JAGS. Running comparable models in STAN and JAGS, with additional vectorisation, resulted in convergence (as measured by the Gelman-Rubin diagnostic) with 1,000 rather than 10,000 simulations for each of 4 chains. Furthermore the more thoroughly vectorised STAN code is considerably more compact and easy to interpret.

3 Description and Validity

3.1 The FRT Index

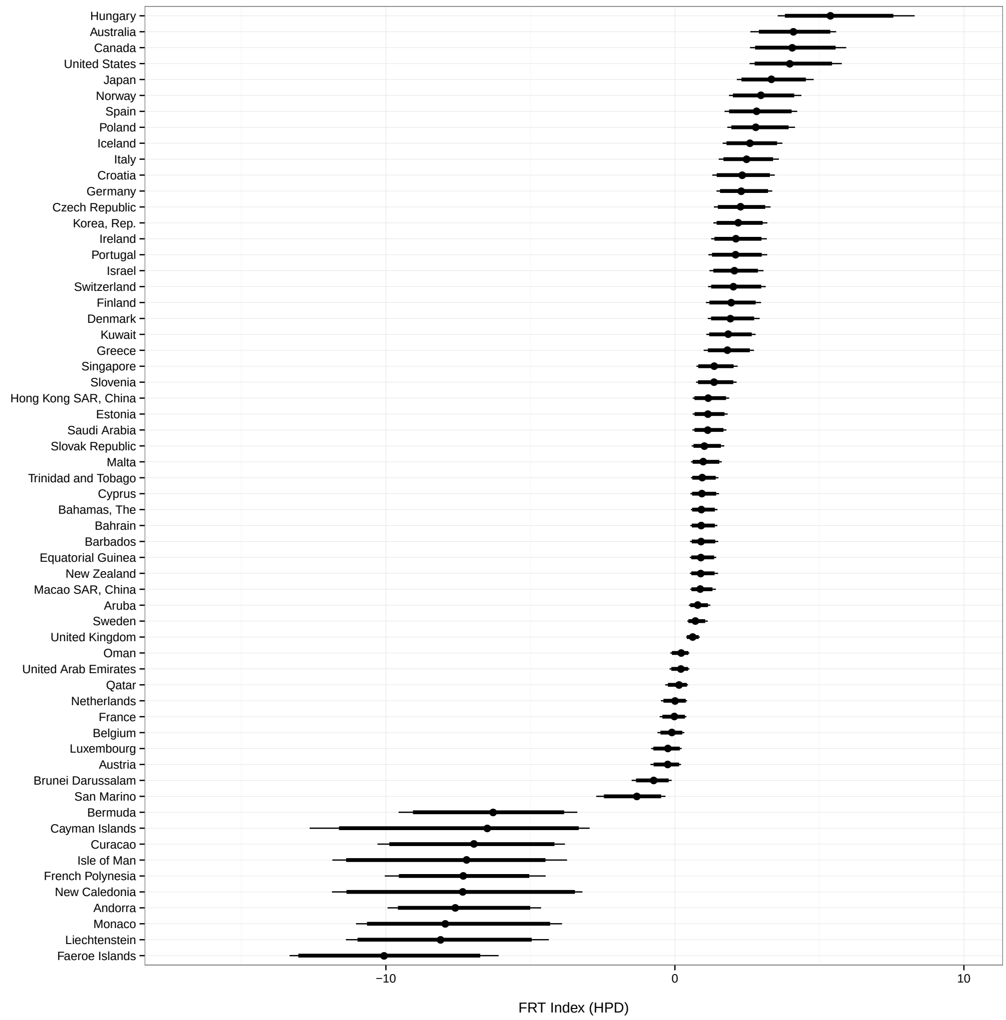
Figures 1, 2, and 3 provide snapshots of the Financial Regulatory Transparency Index in the years 1998 (the Index's first year), 2007, and 2011 (the Index's current end year). Higher scores on the FRT Index indicate higher financial regulatory transparency.

We should first notice that the index passes a face validity test. There is a noticeable cluster of countries with very low FRT scores. These countries include the Bermuda, Cayman Islands, the Isle of Man, and Monaco. All of these jurisdictions are known for their banking secrecy, often as explicit policy decisions to attract capital from those seeking to avoid paying taxes in their home jurisdictions. At the high end of the scale we also see countries that have been known for their transparency. Gandrud and Hallerberg (forthcoming) noted a high level of financial regulatory transparency in the United States' financial regulatory reporting practices relative to practices among many European Union countries. As we would expect from this work, the United States is regularly placed among the countries with the highest FRT scores.

Changes in countries' FRT scores over time also reflect substantively meaningful policy changes. Hungary is a prime example. Figure 4 shows Hungary's FRT Index across all of the years in the sample. In 1998 it is estimated to have one of the highest FRT scores, with a median well above 5. However, this declines over time with a clear break to very low transparency levels starting in 2009. The 2009 figures would have been reported to international institutions in 2010, the year that Viktor Orbán's Christian Democratic People's Party entered government. This government introduced a number of major economic

[4]The original STAN model can be found at: https://github.com/FGCH/FRTIndex/blob/stanTest/source/FRT_Stan_v_02_1990.R

Figure 1: Financial Regulatory Transparency Index in 1998



Thin lines represent the 95% highest posterior density interval. Thick lines represent the 90%. Points represent the median.

and financial policy changes that sometimes directly contradicted Hungary's international commitments, including reducing the independence of the central bank.

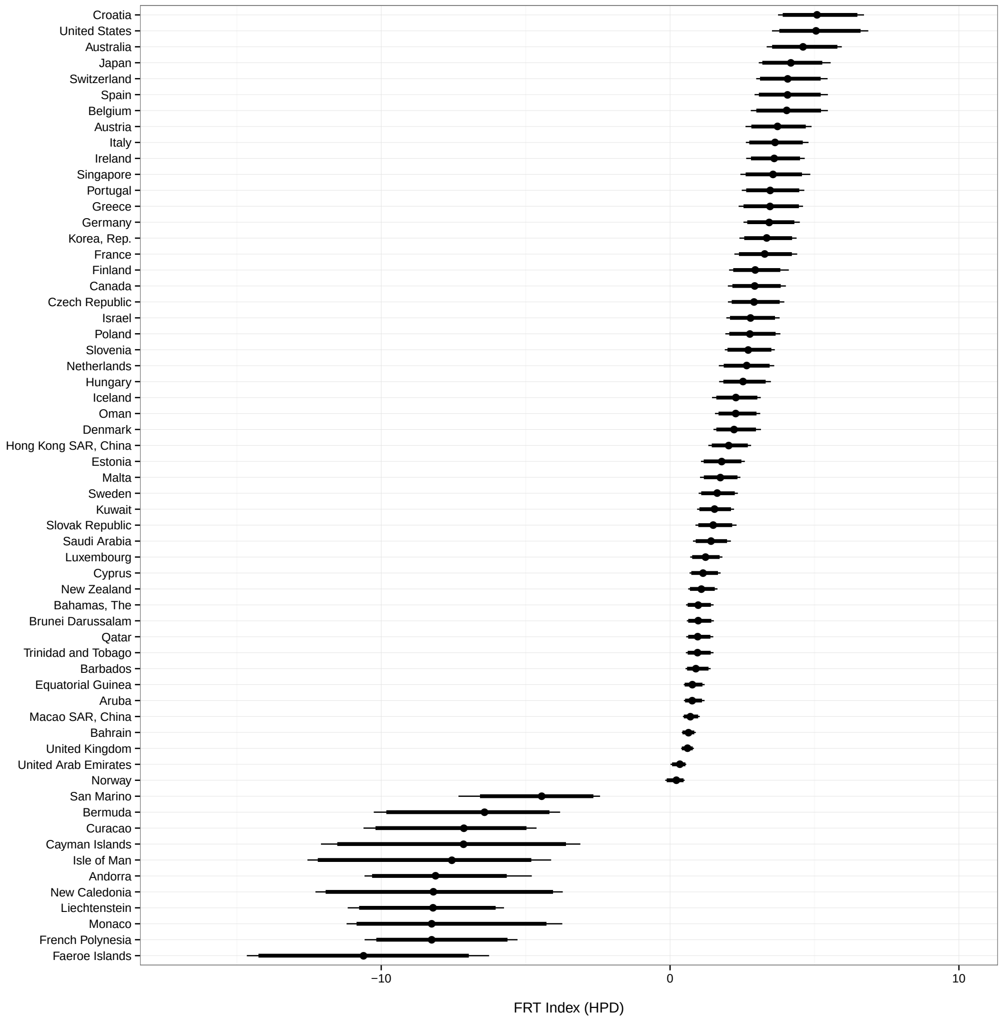
It's important to also note that the FRT Index provides distinct information from more general transparency indices, such as Hollyer et al.'s HRV Index and Freedom House.

COMPARE COUNTRY PLACEMENT TO HRV INDEX AND LIEDORP_ETAL, ESPECIALLY SWEDEN.

3.2 Value added: comparison to frequency methods

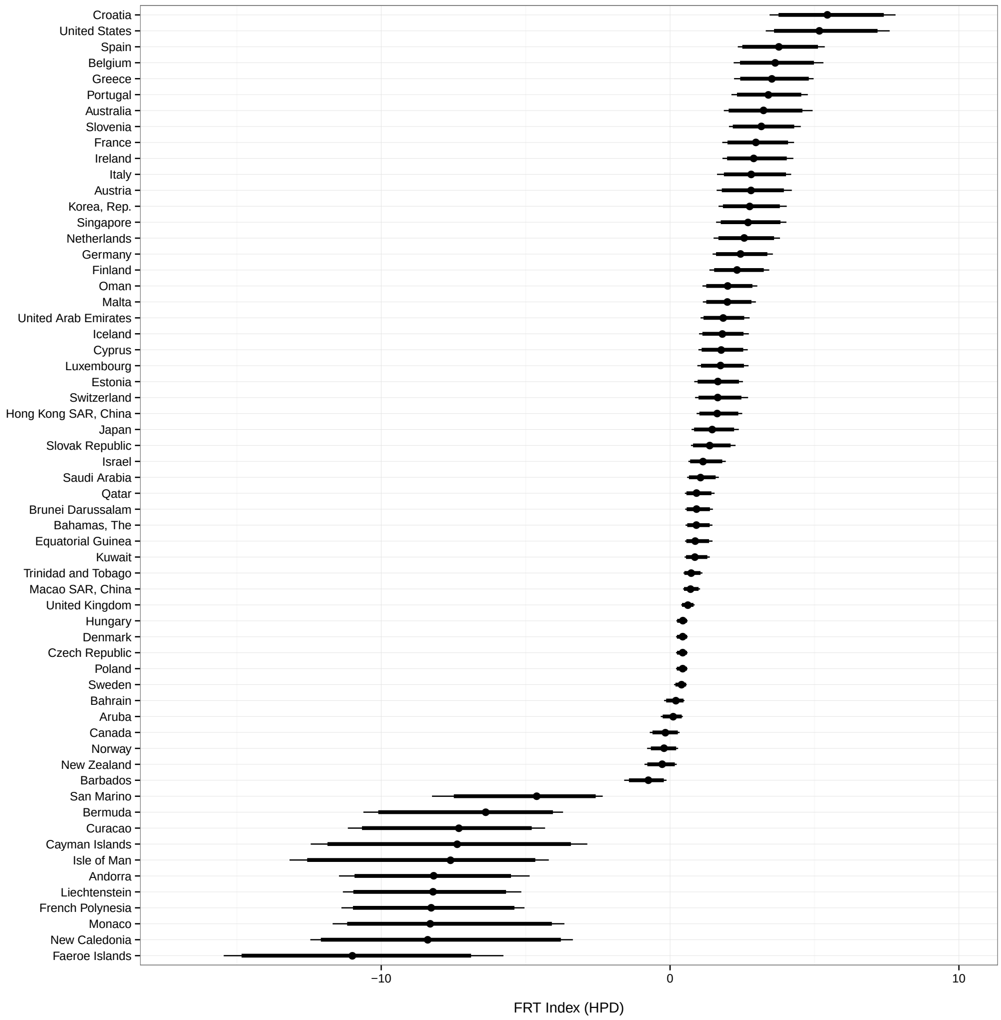
A less computationally intensive method for developing a financial regulatory transparency index include would be to examine item reporting frequencies with sum-scores (summing the number of items reported

Figure 2: Financial Regulatory Transparency Index in 2007



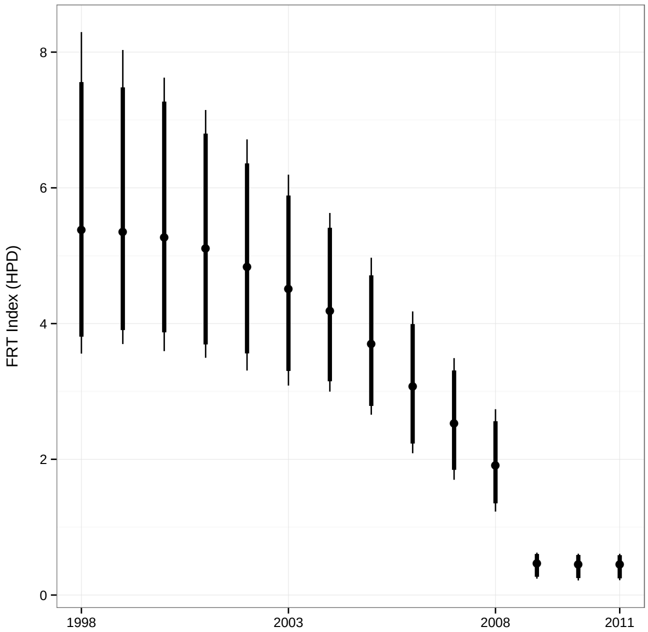
Thin lines represent the 95% highest posterior density interval. Thick lines represent the 90%. Points represent the median.

Figure 3: Financial Regulatory Transparency Index in 2011



Thin lines represent the 95% highest posterior density interval. Thick lines represent the 90%. Points represent the median.

Figure 4: Financial Regulatory Transparency Index for Hungary



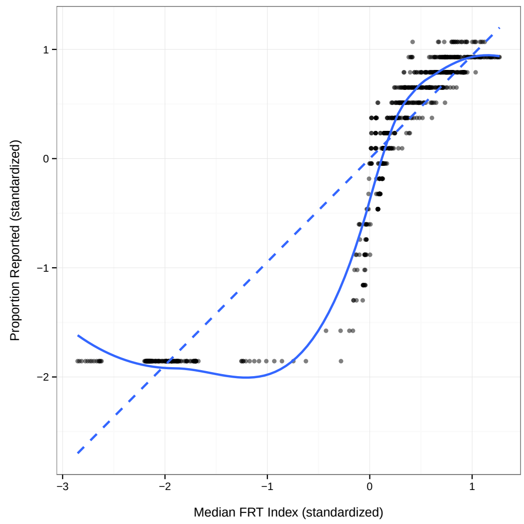
Thin lines represent the 95% highest posterior density interval. Thick lines represent the 90%. Points represent the median.

per country-year) or some normalizing transformation of this like finding the proportion of items a country reported in a year. These approaches implicitly assume that reporting any one item is equivalent to reporting any other item. This may not be the case. Reporting one item may be 'more difficult' than reporting another. Using IRT allows us to adjust for the fact that some items may be more readily reported than others.

A basic test for examining if a frequency method would be just as appropriate and, because it is dramatically less computationally intensive, preferable to Bayesian IRT for constructing a transparency measure is to see if there is a linear association between the Bayesian IRT scores and frequency scores. Figure 5 compares the proportion of items used (a frequency measure) in the FRT Index a country reported in a given year to that country-year's FRT score.[5] Rather than having a linear relationship, we can see that the FRT Index is much more sensitive to indicator reporting than the frequency measure. This is especially true of countries that report relatively few items. They do substantially worse in the FRT Index than if we measured transparency with proportion of items reported.

[5]Both are standardized by subtracting their mean and dividing by their standard deviation.

Figure 5: Comparing Frequency Reported vs. FRT Index



Both the Proportion Reported transparency indicator and the FRT Index scores were standardized by subtracting their means and dividing by their standard deviations.

3.3 Indicator difficulty and discrimination

In addition to comparing the FRT Index to proportions of items reported, we can also examine the difficulty and discrimination parameters to determine whether or not the FRT has value added. If reporting one item is actually equivalent to reporting any other item then we would expect the estimated difficulty and discrimination parameters to be the same across all items. Figures 6 and 7 show the estimated difficulty and discrimination parameter estimates for all of the included items, respectively.

4 Preliminary Analysis

To demonstrate the potential usefulness of the FRT Index we examine a number of associations between the Index and the occurrence and potential occurrence of financial crisis.

A standard measure of a banking system's health is the jurisdiction level 'Z-Score'. This measure attempts to capture the probability of individual bank insolvency, but is sometimes aggregated to the jurisdiction level. The World Bank's GFDD includes a Z-score calculated by using Bankscope, Bureau van Dijk unconsolidated bank-level data. Aggregated to the jurisdiction level it compares commercial banks' buffers (capitalization and returns) to the volatility of those returns. A higher Z-score indicates that there is a higher probability of insolvency.

In models by itself, the FRT Index is not significantly associated with the probability of a country's aggregated Z-Score. However, when we interact it with a measure of economic institutional quality, there

Figure 6: Estimated Item Difficulty Parameters

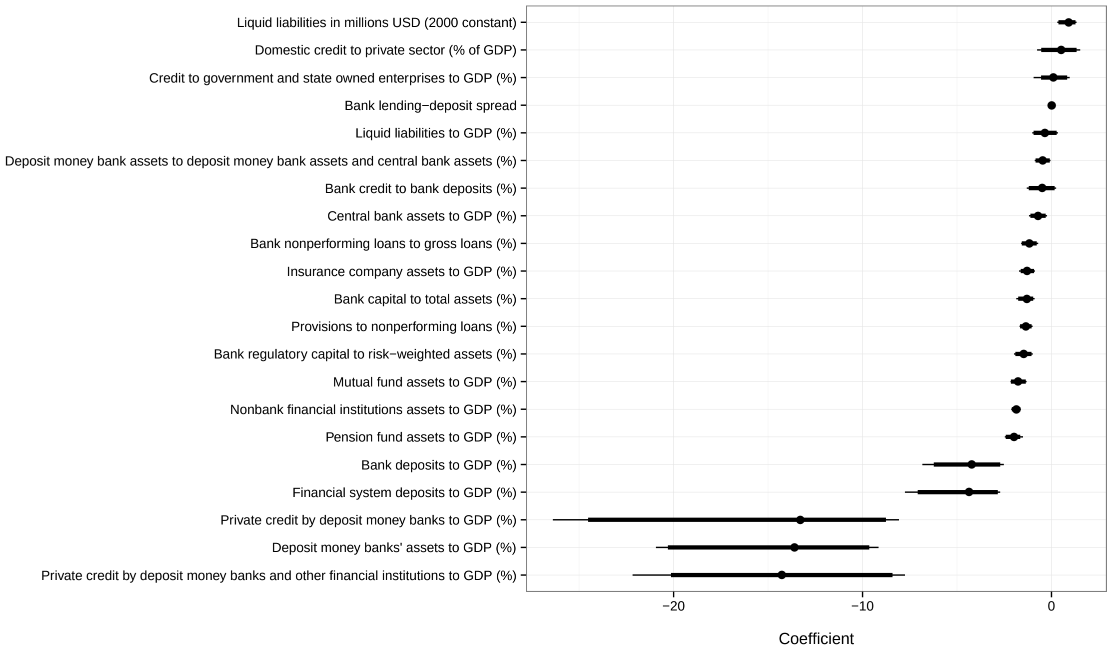


Figure 7: Estimated Item Discrimination Parameters

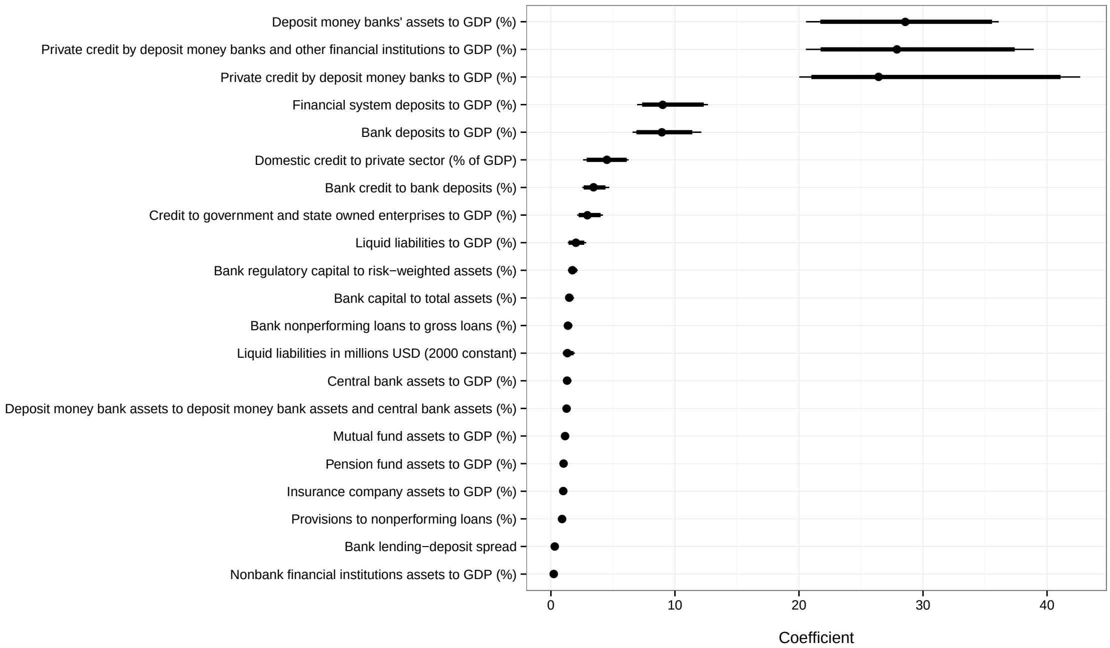
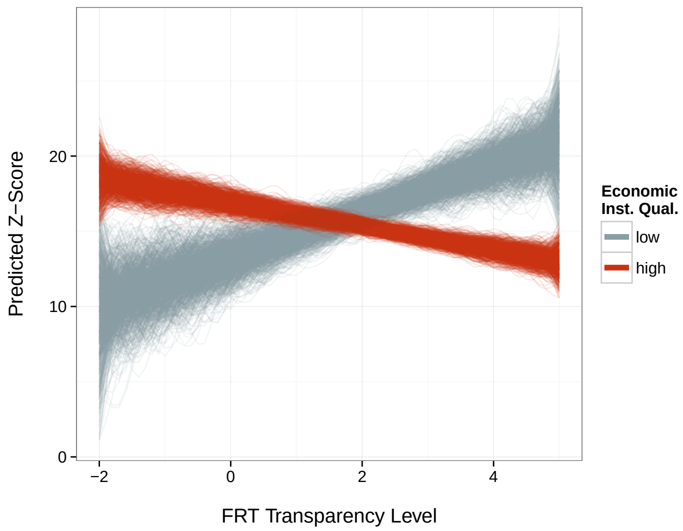


Figure 8: Predicted Z-Score for Various levels of FRT Transparency and Economic Capacity



From 1,000 simulations from the multivariate normal distribution with means and variances estimated using a normal linear regression. See King, Tomz and Wittenberg (2000); Gandrud (forthcoming)

is an interesting association. The indicator of economic institutional quality that we use is from KUNČIČ (2014). This variable was created with a factor analysis of a number of economic institutional indicators including those from the Index of Economic Freedom, the World Bank's Governance Indicators, and the Fraser Institutes' EFW Index. The variable is available from 1990 through 2010.

Figure 8 shows predicted Z-Scores from a simple linear regression model where the FRT Index and Economic Institutional Quality were lagged by one year. We can see that the positive effect of transparency on financial system stability is contingent on economic instituational quality. Countries with higher quality institutions are predicted to have more stability with higher transparency. However, the results are

Conclusion

In this paper we have introduced a new Financial Regulatory Transparency Index. This work builds directly on the approach pioneered by Hollyer, Rosendorff and Vreeland (2014) to measuring countries' attempts to release minimally credible information to international institutions and investors. In so doing we have not only applied the method to measuring financial supervisory transparency, but also made a number of important improvements to the fundamental model–primarily using the No-U-Turn Sampler, using half Cauchy rather than Gamma priors, and vectorising the model–that dramatically improve the accuracy and computational efficiency of the modelling process.

We have also begun to explore how this type of transparency actually affects financial system stability. We will continue to develop this work and furthermore use it to help estabilish the causal process by examining how changes in international supervisory transparency levels affect capital inflows.

References

Čihák, Martin, Asli Demirgüç, Erik Feyen and Ross Levine. 2012. "Benchmarking Financial Systems Around the World." *World Bank Policy Research Working Paper* (6175). Available at: http://www-wds.worldbank.org/external/default/WDSContentServer/IW3P/IB/2012/08/31/000158349_20120831220007/Rendered/PDF/wps6175.pdf. Accessed February 2014.

Gandrud, Christopher. forthcoming. "simPH: An R Package for Illustrating Estimates from Cox Proportional Hazard Models Including for Interactive and Nonlinear Effects." *Journal of Statistical Software* .

Gandrud, Christopher and Mark Hallerberg. forthcoming. "Does Banking Union Worsen the EU's Democratic Deficit? The need for greater supervisory data transparency." *Journal of Common Market Studies* .

Gelman, Andrew. 2007. "Prior distributions for variance parameters inhierarchical models." *Bayesian Analysis* 1(3):515–533.

Hoffman, Matthew D. and Andrew Gelman. 2014. "The No-U-Turn Sampler: Adaptively Setting Path Lengths in Hamiltonian Monte Carlo." *Journal of Machine Learning Research* 15(Apr):1593–1623.

Hollyer, James R., B. Peter Rosendorff and James Raymond Vreeland. 2014. "Measuring Transparency." *Political Analysis* . doi: 10.1093/pan/mpu001.

King, Gary, Michael Tomz and Jason Wittenberg. 2000. "Making the Most of Statistical Analyses: Improving Interpretation and Presentation." *American Journal of Political Science* 44(2):347–361.

KUNČIČ, ALJAŽ. 2014. "Institutional quality dataset." *Journal of Institutional Economics* 10(1):135–161.

Liedorp, Franka, Robert Mosch, Carin van der Cruijsen and Jakob de Haan. 2013. "Transparency of Banking Supervisors." *IMF Economic Review* 61(2):310–335.

Polson, Nicholas G and James G Scott. 2012. "On the Half-Cauchy Prior for a Global Scale Parameter." *Bayesian Analysis* 7(4):887–902.

Stan Development Team. 2014. *Stan Modeling Language Users Guide and Reference Manual, Version 2.4.*
URL: *http://mc-stan.org/*