Financial Regulatory Transparency, International Institutions, and Borrowing Costs

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Abstract

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How do markets discipline governments? The most direct way is through sovereign borrowing costs. Investors charge more interest when they anticipate that the risks of default increase. Where markets get their information from and and how they use this information, however, is not well documented. In this paper, we argue that markets consider more than governments' balance sheets–they also consider the risks of the private financial sector to sovereigns. Investors are more confident of their assessments for countries where bank regulators release detailed data on their financial sectors. To test this argument, we use Hierarchical Bayesian Item Response Theory to create a new, global, and comparable Financial Regulatory Transparency (FRT) Index. The Index is a unique measure of a country's willingness to release minimally credible data on their financial system through international organizations. The Index covers the years 1990 through 2011 and includes the 50 high income countries that report financial system data to the World Bank Global Financial Development Database. Using the FRT we find that countries with more financial supervisory transparency through international institutions have more stable sovereign borrowing costs. Financial market

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instability can suddenly strain government budgets and debt sustainability. International financial regulatory transparency allows creditors to better anticipate and therefore price in financial market strain before instability threatens public budget sustainability.

How do markets punish governments? The usual story begins with governments' needing to borrow money. They sell sovereign bonds. Investors buy the bonds directly, then trade them on secondary markets. If investors fear that a sovereign may not honor the bond, the sovereign must offer to pay higher interest rates when it issues the bond.

This then begs the question about how investors know what governments are doing as well as what investors know about the risks that governments face to their fiscal positions. A literature on ”fiscal transparency” focuses on what information governments provide publicly. Indeed, “fiscal transparency” is a popular topic with international organizations, non-government organizations, and academics. Since 2007, the International Monetary Fund (IMF) has actively pushed governments to publish budget information through its Fiscal Transparency Code and through its (voluntary) Fiscal Transparency Evaluations.[1] In terms of measurement of the concept, the International Budget Partnership publishes biannual transparency reports for several countries, and it provides training for civil society groups on how to use information from governments to make those governments more accountable. Higher fiscal transparency, in turn, affects what governments do with their fiscal policies–higher transparency has been found to lead to lower borrowing costs (Glennerster and Shin, 2008) and less creative accounting (Alt, Lassen and Wehner, 2014). Wehner and de Renzio (2013) consider the political determinants of fiscal transparency and conclude that free and fair elections promote more transparent governance.

The focus of this work has been on governments reporting public financial data, that is, on their own accounts. But government bodies also supervise the accounts of private sector actors, and banks in particular. The amount of information such an agency provides to citizens and to investors constitutes an important component of financial supervisory transparency. Following on the broader transparency work, a sub-literature claims that this type of transparency too is desirable–it has been lauded as enhancing market stability (see Arnone, Darbar and Gambini, 2007) and democratic legitimacy (see Gandrud and Hallerberg, 2015). Like for fiscal transparency, international financial institutions have promoted supervisory transparency; the Basel Committee for Banking Supervision, for example, added supervisory transparency to its Core Principles for Effective Banking Supervision in 2006. Following on the East Asian crisis of the late 1990s, the International Monetary Fund included transparency in its Code of Good Practices on Transparency in Monetary and Financial Policies that it issued in 1999.[2] Similar to measures to promote fiscal transparency, the Fund has a Financial Sector Assessment Program where

[1] The Fund revised its Code in 2014 and is in the process of revising its manual that provides additional details; see http://www.imf.org/external/np/fad/trans/. Accessed January 2015.

[2] See http://www.imf.org/external/np/mae/mft/Code/index.htm. Accessed September 2014.

it conducts voluntary reviews of the stability of financial sectors and the development of those sectors, with "transparency" one consideration. While it is up to the country in question to approve publication of the review, most of them are available online, and they usually include a review of the extent to which a given country observes the Fund's standards and codes.[3] Within the European Union, the European Banking Authority has made a number of recent attempts to promote supervisory transparency. Yet on the academic side there have been few examinations of supervisory transparency. One reason for this gap may be because of data problems–we currently lack a robust and cross-nationally comparable way to measure financial regulatory transparency that could be used to test how it affects stability. Such a measure could also be important in future research for understanding why countries become more or less transparent, especially the extent and reasons why international institutions effectively promote transparency.

In this paper we use a Hierarchical Bayesian Item Response Theory (IRT) approach to develop a new Financial Regulatory Transparency (FRT) Index that fills this data gap. The FRT Index measures a country's latent willingness to report minimally credible data about its financial system to international organizations and investors. The approach is influenced by Hollyer, Rosendorff and Vreeland (2014) who created an index of general public data reporting through international institutions.[4] We improve on their method of estimating transparency with Bayesian IRT by using the No-U-Turn Sampler (Hoffman and Gelman, 2014). This gives enhanced computational efficiency.

The FRT Index includes 50 high income countries from 1990 through 2011. It measures these countries' reporting of financial system information to the World Bank's Global Financial Development Database (GFDD). The Index is a unique indicator of countries' willingness to credibly reveal–the data has to pass minimal World Bank and International Monetary Fund quality checks–the structure of their financial system and their regulatory quality. If a country reports data on its financial system through international organizations it is easier for the banking system to be scrutinized by market participants, particularly international investors.

We then use this index to consider whether increased financial regulatory transparency is correlated with changes in sovereign debt costs. The expectation is that markets are also paying attention to the relative stability of the banking sector. They anticipate that financial instability or a crisis will lead to a big increase in the public debt burden. We expect that states with higher FRT scores have lower borrowing costs. This could be because states are most likely to be transparent when the financial system is in good health. We also expect lower volatility of borrowing costs. In our empirical examination of

[3]See http://www.imf.org/external/np/fsap/fssa.aspx. Accessed January 2015.

[4]Though both indices used data published by the World Bank, only one indicator (Domestic credit provided by the financial sector (% GDP) is shared between the two indices. See the Results section for an extended comparison of the two measures.

high income countries 1990-2011, we do not find support for the argument on overall borrowing costs but we do find that countries with higher financial regulatory transparency have lower volatility in the sovereign debt costs.

1 Argument

One consequence of the end of Bretton Woods was the expansion of sovereign debt. The end of capital controls that characterized the earlier period meant that governments could easily borrow from world markets. They did this through the issuance of sovereign bonds. Investors decided whether to purchase such debt and were increasingly comfortable holding bonds from other countries.

Markets also became possible enforcers of government spending behavior. When newly elected President Francois Mitterrand introduced a series of policies, which increased the deficit and in general were seen as bad for capital, investors pulled their capital from the country. Bonds for French debt became much cheaper, pushing up yields and hence the interest rate the government paid on new debt issues. By 1983, the rates were considered so high that the government abandoned several policies and focused on regaining the credibility of markets. It introduced a series of austerity measures.

1.1 Risk informations

This anecdote leads to the following question–when do markets play such as role? The French case suggests some preconditions. First, markets are more effective as enforcers when capital is mobile. In a purely closed economy, it is possible that even domestic investors refuse to buy government bonds and demand higher rates, but world markets are especially liquid. With capital mobility, there is little worry about supply. Second, markets need to know something about a country's fiscal health.

To test market power, one needs to make some assumptions about where that information comes from and what type of information markets care about. The first step would be to look at what the sovereign itself is doing. Very high debt levels could make it more difficult for a government to repay in the future. Deficit levels provide an indicator of the rate of change of debt. Ireland, for example, had a low debt level of below 30 percent of GDP in 2007, but very large deficits, including over 30 percent alone just in 2010, pushed up the debt level considerably. In her study of sovereign debt costs, Mosley (2000) argues that markets pay attention to budget deficits and also to the current interest rate in the belief that borrowing under high interest rates is not sustainable. She finds that other types of indicators governments produce do not affect interest rates that sovereigns pay.[5]

[5] Her dependent variable is the interest rate on longer-term, domestic currency denominated government bonds.

While Mosley (2000) looked at direct measures of debt sustainability, we hypothesize that markets also consider other possible risks to sovereigns' debt positions. These risks may be economic or political. Where do investors get their information about these risks from?

One source of information for markets could be rating agencies, at least since the beginning of the 1990s, when they began to issue ratings for most sovereigns. Such ratings are fairly sticky for the generally developed countries in our data set, however, and often cover several years before they move (if they move much at all) (Cordes, 2014). .

Note to discussants: a future version of this paper will add bond ratings to the analysis

A second source of information, and one that may very well influence sovereign ratings, concerns what the countries themselves report about their financial sectors. The government is usually the only actor that can assist the sector when it gets into a crisis, but the connection is not immediate–financial crises and sovereign debt crises rarely happen concurrently (Laeven and Valencia, 2012). The former may however lead to the latter–Reinhart and Rogoff (2009) find that debt burdens grow on average 82 percent in the first two years after a banking crisis.

This suggests that greater transparency about the financial sector should affect sovereign debt. One can anticipate that it would affect the level of interest rates–governments may try to take pro-active measures to clean up their banking sectors if they know that markets have good information. At the same time, under such circumstances there are fewer surprises for markets and volatility of rates (all else equal) should be lower.

1.2 Why transparency through international institutions matters

International institutions such as the World Bank, International Monetary Fund, and the Bank of International Settlements frequently gather data from supervisors about their financial systems and publish this data at regular–usually yearly–intervals. What role does reporting supervisory data to international institutions play in international investors decision-making? Would not a national supervisor revealing information on their own have the effect of influencing investor decision-making? Individual supervisor transparency may certainly be important, but transparency through international institutions additionally improves information accessibility and credibility.

For supervisory data to be useful to investors it needs to be accessible, comparable, and credible. Releasing data to international organizations such as the IMF and World Bank helps achieve these goals. By aggregating and publishing national supervisory data, international institutions make it much more accessible for investors.[6] International institutions request data that is comparable across countries. They

[6] For example, all of the underlying data used in the FRT Index was downloaded from the World Bank using effectively two lines of R (R Core Team, 2014) code. In contrast, Gandrud and Hallerberg (2015) found that it is often very difficult to gather data directly from national supervisors and use this data to make meaningful comparisons. This is due not only to a lack of electronic availability, but also inconsistent file formats, definitions, and periodicity.

also conduct minimal quality checks on the data. These checks are done by international institution staff who are independent of national supervisors, governments, and banks.[7] They have little or no incentive to have the data present an unduly positive picture of a country's banking sector. By submitting data for review by international institutions, national supervisors are committing to more reliable supervision. International institutions also apply consistent definitions across data quantities, further improving their usefulness for investors decision-making.

How can one measure international data transparency from the financial sector? How does this transparency affect sovereign borrowing costs?

2 Creating the FRT Index

We created a new indicator of supervisory data transparency to international institutions that we call the Financial Regulatory Transparency–FRT–Index. In this section we discuss previous measures of supervisory transparency, the construction of the FRT Index using Bayesian IRT, and how the measure compares to less computationally intensive methods.

2.1 Previous measures of financial supervisory transparency

Previous assessments of supervisory transparency have tended to be based on self-reported surveys of supervisors' rules and practices. They have not examined reporting to international institutions. Financial supervisory transparency indices have largely been constructed by summing responses to survey question. For example, Liedorp et al. (2013) sent a 15 question survey to 42 banking supervisors, 57 percent of which replied. The survey had questions on a variety of components related to multiple aspects of supervisory transparency including what they termed economic, procedural, political, policy, and operational transparency. They then created composite scores by summing responses to the survey questions for each of the five areas as well as creating a total sum score. Arnone, Darbar and Gambini (2007) used a four point scale devised from classified IMF staff assessments of country compliance with IMF codes of good practice. Masciandaro, Quintyn and Taylor (2008) conducted a survey of supervisory accountability and included some items related to transparency. Seelig and Novoa (2009) also conducted a survey of supervisory practices, including transparency, but as Liedorp et al. (2013, 316) note the questions and country details are not publicly available.

Beyond the fact that a number of these transparency indices are (ironically) not themselves transparent and do not measure reporting to international institutions, they have other shortcomings. First, survey methods are laborious, requiring numerous contacts with supervisors and secondary verification,

[7]From an email exchange with IMF staff.

largely via institutions' websites. Second, they rely on temporally ephemeral information, e.g. institutional websites and staff with institutional knowledge. These two issues are of substantive importance because they prevent both the easy updating of the indices at regular intervals and the extension of the indices back in time. These indices are usually snapshots that cannot readily be turned into up-to-date time-series for time-series-cross-sectional analysis.

Third, these surveys, at least those not conducted by the IMF, have high non-response rates. Non-response information is discarded in the construction of the indices. Fourth, their construction involves summing responses. This assumes that each item is equally important for measuring transparency. Fifth, the indices do not include explicit estimation of the uncertainty that they are estimated with. Sixth, and finally, these approaches either do not incorporate prior information into their estimates or do not do so transparently.

2.2 Included indicators

To create an index that overcomes these issues, we treat financial regulatory data transparency as an unobserved latent variable that summarizes countries' likelihood of reporting yearly data on items included in the World Bank's Global Financial Development Database. Čihák et al. (2012) created the first version of the database by collating information that had been collected over many years by a number of international institutions and corporations.[8]

We gathered information on whether or not governments reported data on a subset of indicators that are included in the World Bank's GFDD. We build on 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 1990-2011. 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 indicators from World Bank sponsored surveys, such as the Global Financial Inclusion Survey and the Enterprise Survey. In addition we excluded data 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.

Sixth, we aim to focus on countries that have banking systems at comparable levels of development.

[8] Access to the most updated version of the data set is available through http://data.worldbank.org/data-catalog/global-financial-development. Accessed December 2014. Please see the Appendix for a discussion of how we addressed data that was missing in this version database compared to another version of the same data published by the Federal Reserve Bank of St. Louis.

As such we include only countries and jurisdictions that the World Bank classifies as "high income".[9] Lower income countries' financial systems are likely not sophisticated enough to have a number of the quantities reported by the GFDD in the FRT. There are 10 mostly non-national-level jurisdictions[10] that are classified as high income, but which are not recorded as reporting any items in the GFDD. We excluded these jurisdictions from the data set.[11]

Using these criteria our model has 50 countries, 14 items, and 22 years (1990-2011). Table 1 shows the list of included items and their descriptions.

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

Series Code	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: 1980-2011
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

Series Code is the GFDD variable identifier.

IFS = International Financial Statistics, IMF

2.3 The model

Building on Stan Development Team (2014*b*, 49-50) and Hollyer, Rosendorff and Vreeland (2014), we let $y_{k,c,t} \in \{0,\ 1\}$ indicate a variable that is 1 when a country c reports GFDD item k in year t. It is 0 otherwise. We then estimate the model:

$$\Pr(y_{k,c,t} = 1|\alpha_{c,t}) = \text{logit}^{-1}(\exp(\gamma_k) * (\alpha_{c,t} - \beta_k + \delta)) \tag{1}$$

where:

- $\alpha_{c,t}$ is the estimated propensity for country c at year t to report. This can be thought of as the **transparency** (FRT Index) score for country c at year t,
- γ_k is the **discrimination** parameter for item k,

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

[10] Andora, Bermuda, Cayman Islands, Curacao, Faeroe Islands, French Polynesia, Isle of Man, Liechtenstein, Monaco, New Caledonia

[11] Note that in earlier versions they were included. Their inclusion largely only changes the range of FRT scores estimated rather than the relative placement of each country for each year.

- β_k is the **difficulty** parameter for item k,
- δ is the **mean transparency**

The discrimination parameter (γ_k) indicates how well reporting item k predicts reporting other items.[12] The difficulty parameter (β_k) indicates on average the degree to which countries report indicator k in the GFDD over the entire time span. Higher parameter estimates indicate that the item is more 'difficult' to report, i.e. reported less often.[13]

Taking the fraction of items a country reports in a given year as an indicator of transparency would be equivalent to assuming that β_k and γ_k 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 too sensitive to report. The Bayesian IRT approach allows us to relax the equivalence assumption. We directly estimate the degree to which countries find it 'difficult' to report items and how reporting (or not) one item is related to non-reporting of other items. γ_k is exponentiated to identify the sign in the model as positive. This avoids the unlikely possibility that items are more likely to be reported by less transparent countries than more transparent countries.

The transparency values in 1990 are drawn from a normal prior ($\alpha_{c,1990} \sim N(0,\ 1)$). We then recentered these values by subtracting the mean transparency score and dividing by the standard deviation at each iteration. These measures fixed the scale and location of the Index. We found that we did not need to explicitly fix the Index's direction. Countries we expected based on previous qualitative research (Gandrud and Hallerberg, 2015) to have high data transparency consistently were estimated to have positive FRT values and vice versa.

For each transparency parameter estimate after 1990 we used a system of random-walk priors such that $\alpha_{c,t} \sim N(\alpha_{c,t-1},\ \sigma_{\alpha c}) \forall t > 1$, where σ_c acts as a country-specific smoothing parameter. Each σ_c is estimated with a weakly informative half-Cauchy prior $\sigma_{\alpha c} \sim Cauchy(0,\ 0.05)$. This is in contrast to Hollyer, Rosendorff and Vreeland (2014) who use a Gamma prior distribution. Half-Cauchy priors have been shown to be more appropriate with hierarchical data (see Gelman, 2007; Polson and Scott, 2012). Finally, we used similar, though slightly less restrictive priors–$Cauchy(0,\ 0.25)$–[14] when estimating the discrimination and difficulty parameters. The mean transparency δ was given a half-Cauchy–$Cauchy(0,\ 0.05)$–prior.

Previous projects using Bayesian IRT for estimating transparency have used a Markov Chain Monte Carlo algorithm with Just Another Gibbs Sampler (JAGS) for model estimation. In contrast, we used

[12] It can equivalently be thought of an item specific slope for the logistic regression.

[13] Mean transparency δ can be treated as the location parameter for the transparency scores (Stan Development Team, 2014*b*, 48).

[14] We used a more restrictive prior for the transparency parameter in order to rein in the bounds of the Index.

the No-U-Turn Sampler (NUTS), an extension of the Hamiltonian Monte Carlo algorithm. NUTS is more efficient than other methods with models estimated from highly correlated data, as our, and IRT models in general are (Hoffman and Gelman, 2014). We implemented the model with Stan (Stan Development Team, 2014*a*).[15] An additional small, though non-trivial benefit of using Stan is that its more thoroughly vectorised code is considerably more compact and easy to interpret than its JAGS equivalent.[16] We ran the model for 4 chains of 10,000 iterations (5,000 of which were burn-in) and used the Gelman-Rubin Diagnostic (Gelman and Rubin, 1992) to assess convergence with the 1.1 threshold.

3 Description, validity, and value added

3.1 The FRT Index

Figure 1 provides snapshots of the Financial Regulatory Transparency Index in 1990 (the first year) 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 FRT Index passes a face validity test. Jurisdictions that are known for their banking secrecy, often in order to attract capital, tend to have lower transparency scores. These countries include San Marino and Luxembourg.[17] At the high end of the scale we also see countries that have been known for their transparency. Gandrud and Hallerberg (2015) noted a high level of financial regulatory data transparency in the United States relative to 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. Gandrud and Hallerberg (2015) also found that the United Kingdom had lower financial data transparency–interestingly in contrast to their generally high fiscal transparency (see Wehner and de Renzio, 2013). Correspondingly, the UK consistently had a median FRT score below 0.

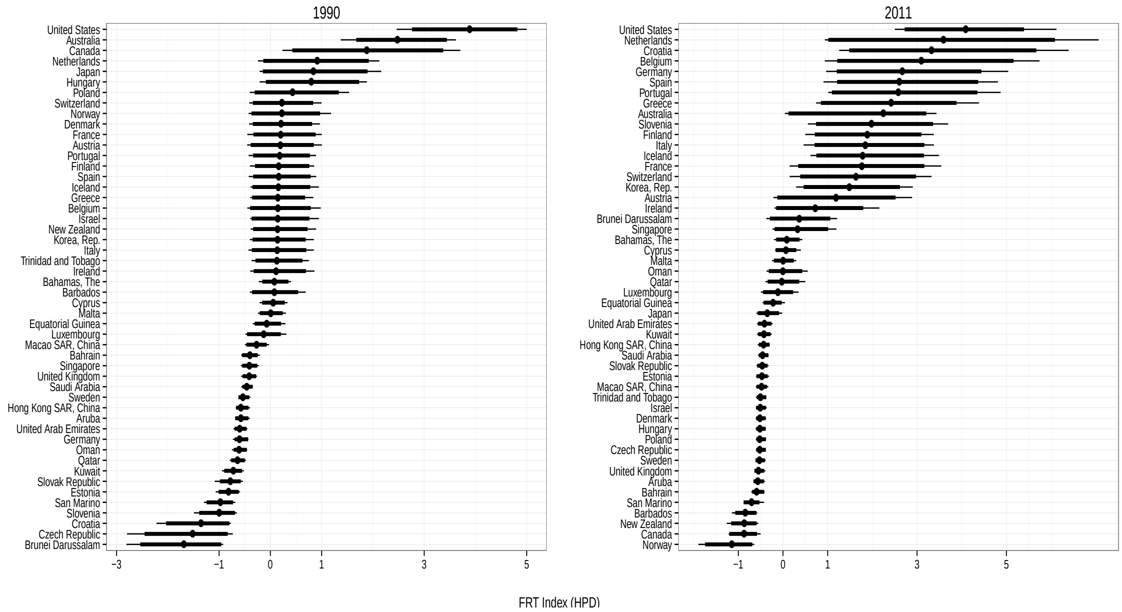
Though some countries–such as the United States on the high end and a number of the offshore locations on the lower end–have fairly stable FRT scores, many countries' scores do change considerably over time. Please see the Appendix for plots of FRT scores over time for all countries in the sample. FRT score changes reflect substantively meaningful policy changes. Hungary is a prime example. Figure 2 shows the trajectory of Hungary's FRT Index scores. In 1990 Hungary had a somewhat high FRT score, with a median around 1. This score changes over time, first increasing in the late-1990s and then making a clear shift to low transparency 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

[15] The Stan model can be found at in the Appendix

[16] The Stan version of the model is approximately 67 lines of code where as equivalent JAGS model is over 150.

[17] In an earlier version of the Index we included 10 jurisdictions that never reported any of the items on the GFDD. These jurisdictions all had the lowest scores. The jurisdictions, including Bermuda and the Cayman Islands, are noted for having very secretive banking systems.

Figure 1: Financial Regulatory Transparency Index in Selected Years



Thin lines represent 95% highest probability density intervals. Thick lines represent 90% intervals. Points represent the median of the posterior distribution.

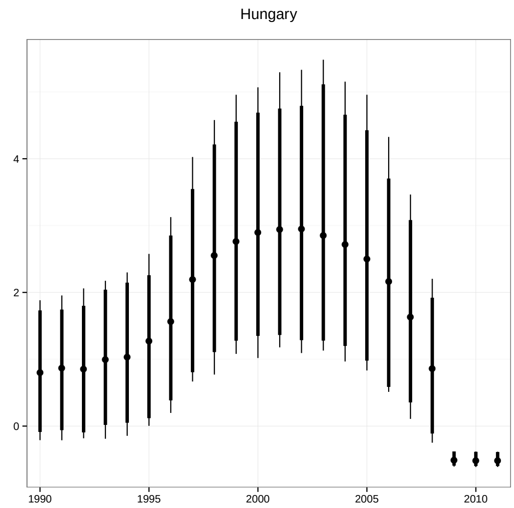
entered government. This government introduced a number of major economic and financial policy changes that sometimes directly contradicted Hungary's international economic commitments, including reducing the independence of the central bank.

Other countries increased their transparency during periods when they opened their financial markets. For example, Qatar and the United Arab Emirates improved their transparency from the mid- to late-aughts as they attempted to become international financial centers. A number of former Soviet bloc countries including Estonia, the Czech Republic, Hungary and the Slovak Republic increased their transparency in the early- to mid-1990s as they transitioned towards market economies.

In other cases, under-reporting is associated with financial distress. For example, France's FRT score noticeably drops during its mid- to late-1990s financial difficulties. Many countries including Poland, Japan, Canada, and Norway reported fewer items and have lower scores beginning around the start of the Global Financial Crisis.

Additional research is needed to fully understand why countries become more or less transparent. At this point we simply wish to demonstrate the validity of the FRT Index as a substantively meaningful indicator of latent transparency by demonstrating how changes in FRT Index scores are associated with actual policy changes and events. Score changes also highlight the importance of developing a dynamic indicator that can incorporate policy shifts over relatively short time intervals. Using a single year indicator and treating it as representative of longer time spans is likely to create biased inferences.

Figure 2: Financial Regulatory Transparency Index for Hungary



Thin lines represent 95% highest probability density intervals. Thick lines represent 90% intervals. Points represent the median of the posterior distribution.

3.2 Value added: comparison to a naive frequency method

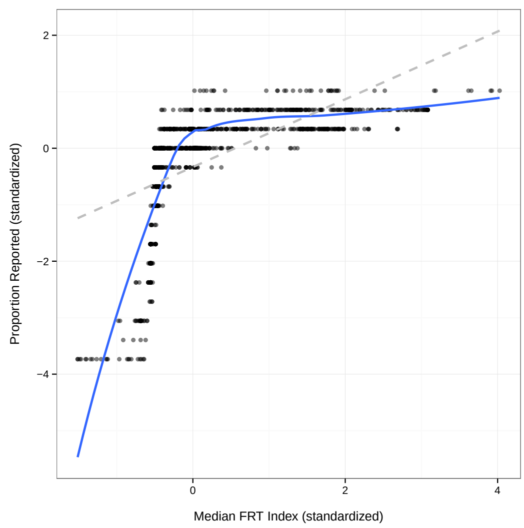
A less computationally intensive method for developing an annual financial regulatory transparency index would be to examine item reporting frequencies with sum-scores–i.e. summing the number of items reported per country-year–or some normalizing transformation of this, such as the proportion of items a country reported in a year.[18] These approaches, as with the aggregate scores from the Liedorp et al. (2013) transparency survey, implicitly assume that reporting any one item is equivalent to reporting any other. This may not be the case. Reporting one item may be 'more difficult' than reporting another as it may be more politically sensitive or be on a quantity that is hard for regulators to observe without being intrusive. Using Bayesian IRT allows us to adjust for the fact that some items may be easier to report 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 3 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.[19] Rather than having a linear relationship, we can see that the FRT Index is less sensitive to indicator reporting than the frequency measure for countries that report fewer items. The FRT does not over-estimate the effect of reporting only the easy

[18] See figures 12, 13, and 12 in the Appendix for the proportions of items reported for each country in our sample.

[19] Both are standardized by subtracting their mean and dividing by their standard deviation. The plot also excludes Canada. It was the only country to report all of the items from 1990 through 2006 and so has a very high FRT Index score. It's exclusion from the plot makes the plot easier to read.

Figure 3: Comparing Frequency Reported vs. FRT Index



Both the Proportion Reported transparency indicator and the FRT Index scores are standardized by subtracting their medians and dividing by their standard deviations. To ease interpretation, the plot excludes scores for Canada.

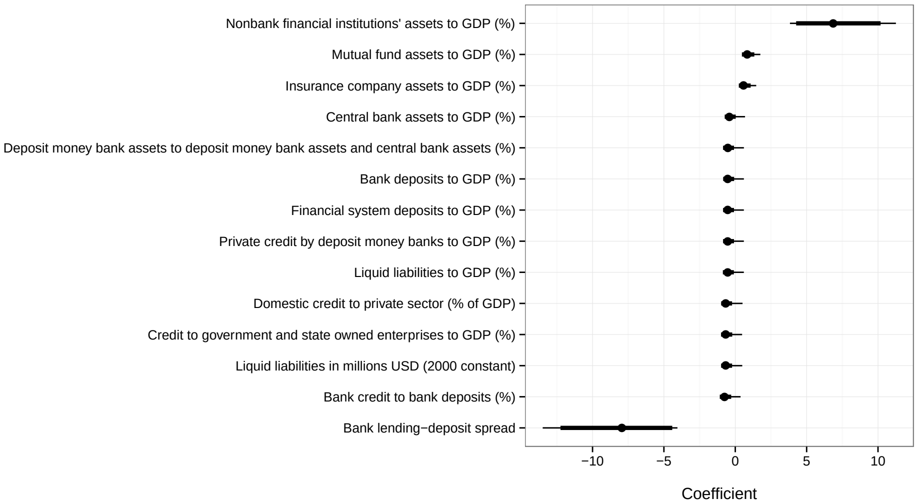
items the way that the frequency measure does. It is more sensitive when countries report many items. There is a wide range of FRT scores for countries that report more items as it can distinguish between the harder and easier items to report.

3.3 Value added: Indicator difficulty and discrimination

In addition to comparing the FRT Index to proportions of items reported, we can 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 4 and 5 show the estimated difficulty and discrimination parameters for all of the included items, respectively. We can see that reporting one item is not equivalent to reporting another item.

Remember that the difficulty parameters shown in Figure 4 indicate on average how often an item is reported. Higher difficulty parameter estimates indicate that an item is more difficult to report, i.e. is less likely to be reported. The items least often reported are Nonbank financial institution's assets to GDP (%), Mutual fund assets to GDP (%), and Insurance company assets to GDP (%). Reporting on all of these quantities requires that the country has these markets, that they are regulated, and that they are willing to report data on these markets to international organizations. Deposit banking is much more common and often more heavily regulated than mutual fund and insurance markets. Mutual fund assets to GDP is in fact only reported about 19 percent of the time in the sample. At the other end,

Figure 4: Estimated Item Difficulty Parameters



Thin lines represent 95% highest probability density intervals. Thick lines represent 90% intervals. Points represent the median of the posterior distribution.

many countries report bank lending-deposit spreads as this is 'easier' to report.

Because these two sets of items are so infrequently/frequently reported it is not surprising that they are less discriminating, i.e. their non-reporting/reporting isn't particularly indicative of reporting other items. We can see that they all have low discrimination scores in Figure 5. Reporting Bank deposits to GDP (%), on the other hand, is much more indicative of how likely a country is to report other items. This is a fairly basic indicator of a country's financial system, that nonetheless requires more intrusive supervision than the bank lending-deposit spread. When countries don't report the size of their bank deposits, they tend to report very few other items, i.e. they are being very opaque with international organizations. When countries begin reporting the volume of their bank deposits–for example the Czech Republic in 1994, Oman in 2002, Qatar in 2003, and the United Arab Emirates in 2008–the country often undergoes a major shift towards more reporting overall.

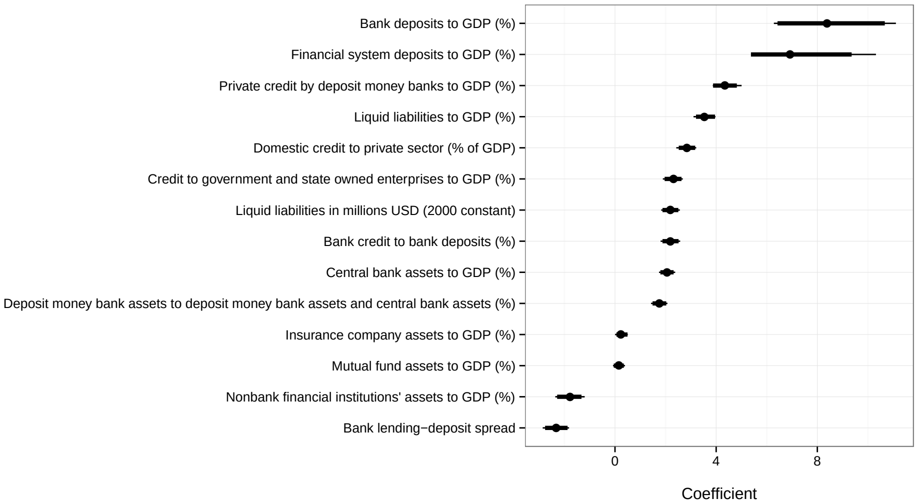
Please see the Appendix for comparisons of the FRT Index with Liedorp et al.'s (2013) frequency-survey measure of supervisory transparency.

4 Analysis

In this section, we conduct an initial empirical test of the FRT Index. Drawing on a data set of 29 high-income countries from 1991 to 2011,[20] we explore the relationship between financial regulatory transparency and long-term government borrowing costs.

[20] $N = 514$. Please see Table 4 in the Appendix for the list of countries included. Data availability determined inclusion.

Figure 5: Estimated Item Discrimination Parameters



Thin lines represent 95% highest probability density intervals. Thick lines represent 90% intervals. Points represent the median of the posterior distribution.

4.1 Dependent variables

We run model specifications using three dependent variables, each of which captures a different dimension of sovereign borrowing costs. Our first variable is the long-term (10-year) government bond yield for country c in year t, expressed in percentage points. Data are taken from the OECD's OECD.Stat database[21] and the Federal Reserve Bank of St. Louis' FRED portal.[22] The second dependent variable is the annualized average spread (in percentage points) over US long-term government bonds for each country-year in the data set.[23] Finally, the third dependent variable in our analysis is the volatility of long-term government bonds. As our measure of volatility, we calculate the coefficient of variation (COV) of average monthly bond yields in year t for each country c in our data set. Data for the latter two dependent variables are taken from the same OECD and Federal Reserve sources as the long-term bond yields.[24]

4.2 Independent variables

Our core explanatory variable, as discussed previously, is the FRT Index measuring financial regulatory transparency. In addition, we include a set of additional variables as controls for key country-specific and international-level factors influencing sovereign borrowing costs. At the country level, our first control is

[21] Available at: http://stats.oecd.org/. Accessed January 2015.
[22] Available at: http://research.stlouisfed.org/fred2/. Accessed January 2015.
[23] The US is excluded from the model specifications using this bond spread as the dependent variable.
[24] The coefficient of variation (COV) here is defined as $\frac{\text{standard deviation of monthly bond yields}}{\text{mean monthly bond yields}} * 100$.

the pre-existing level of central government debt as a percentage of GDP. For this variable, we draw on the IMF's Historical Public Debt Database, which provides data on gross government debt/GDP from 1880 to the present (Abbas et al., 2010).[25] Second, we include the inflation rate, calculated as the annual percentage change in the consumer price index. Data for this variables is taken from the IMF's World Economic Outlook (WEO) database.[26]

We also include three measures of international factors that influence sovereign borrowing costs across time and space. First, we include the yield on short-term (three month) US Treasury bills–the benchmark short-term sovereign lending rate in the global economy. Second, we include the average GDP growth rate of OECD countries as a measure of the overall state of major industrialized economies. Finally, we include the annualized average CBOE VIX Index. Frequently referred to as the "fear index", the VIX index is a measure of implied volatility, or the uncertainty and risk that investors see in the future short-term movements of the US stock market (specifically, the S & P 500). We include it here as a broad measure of investors' short-term concerns about instability and uncertainty in global financial markets. Data on US short-term interest rates and the VIX index are drawn from the FRED database of the Federal Reserve Bank of St. Louis. The OECD growth data are calculated from country-specific growth data in the IMF's WEO.

In further robustness checks we include a dummy variable for Eurozone membership equaling one in years that a country was a Eurozone member and 0 otherwise. We also include each country's GDP growth rate from the World Bank's Development Indicators[27] and structural budget balance as a percent of GDP from the WEO.

4.3 Models and Results

We employ a single-equation error correction model (ECM) for our analysis. The ECM specification is appropriate in cases where there are both long-term equilibrium relationships between X and Y and short-run fluctuations as a result of period-to-period changes in the explanatory variables (Best, 2008).[28] ECMs are useful for estimating both relationships and are applicable to both integrated and stationary time series. [29] The basic specification is:

$$\Delta Y_t = \alpha + \beta_0 \Delta X_t - \beta_1 (Y_{t-1} - \beta_2 X_{t-1}) + \beta \epsilon_t, \tag{2}$$

[25]For more inhttps://www.imf.org/external/pubs/cat/longres.cfm?sk=24332.0. Our results are substantively similar if we substitute similar metrics from the IMF's World Economic Outlook and the World Bank's World Development Indicators.

[26]Available at http://www.imf.org/external/pubs/ft/weo/2014/02/weodata/index.aspx. Accessed January 2014.

[27]Available at: http://data.worldbank.org/indicator/NY.GDP.MKTP.KD.ZG. Accessed January 2014.

[28]See also https://files.nyu.edu/mrg217/public/timeseries.pdf.

[29]Dickey-Fuller tests indicate that non-stationarity is not a problem in our dataset for any of the dependent variables. Results available on request.

which can be reformulated and estimated as

$$\Delta Y_t = \alpha + \beta_0 \Delta X_t - \beta_1 Y_{t-1} + \beta_2 X_{t-1} + \beta \epsilon_t. \tag{3}$$

In this specification, changes in Y are a function of contemporaneous changes in X, as well as the one period lagged values of both X and Y. If the ECM is appropriate, then $-1 < \beta_1 < 0$ and statistically significant.

Our main results are shown in Table 2. The first and second columns of Table 2 show results from models that use the first two dependent variables: changes in long-term sovereign bond yields and changes in long-term bond spreads over US Treasuries. We can see that FRT is not significantly associated with these quantities. On the other hand, the coefficient on the lagged dependent variables are significant, negative, and in the range indicating that the ECM specification is appropriate. In addition, several of the country-specific control variables are significant and signed as expected in these models. Increases in both government debt and inflation increase long-term interest rates and spreads over US Treasuries, while an increase in country-specific GDP growth reduces both yields and spreads. Similarly, international-level factors also influence both long-term interest rates and spreads: an increase in the VIX index–investors' expectations of greater stock market volatility–reduces both yields and spreads, indicating that investors engage in a "flight to quality" in times of greater expected market uncertainty. US short-term interest rates also matter: higher 3-month T-bill rates and increases in these rates increase long-term bond yields, while an increase in the 3-month T-bill rate reduces a country's long-term bond spread over US bonds.

In contrast to the long-term interest rate and bond spread models, we see in the final three columns of Table 2 that the FRT Index has a significant effect on the volatility of long-term government bonds. Column 3 shows the main specification, while Column 4 excludes Canada–the largest outlier in our sample on the FRT Index–and Column 5 introduces additional controls for a country's structural budget balance (as a percentage of GDP) and for membership in the eurozone. Across all three specifications, we find consistent results. The level of FRT, which captures the effect of the level of supervisory transparency on the equilibrium level of volatility of long-term interest rates, is negative and significant in each of these models. This effect is also substantively large. A one unit increase in FRT, from the sample mean of 2.1 to 3.1, reduces the annual coefficient of variation on long-term sovereign bond yields by 0.19, a 35 percent reduction from the sample mean annual change in COV of 0.54.[30]

[30]The mean annual level of COV is 7.45 in our sample. First differences calculated using CLARIFY (Tomz, Wittenberg and King, 2003), holding all other variables constant at their sample means.

Table 2: Sovereign Bond Prices and the Financial Regulatory Transparency Index (FRT)

	Δ Long-term (10-year) interest rate (%)	Δ LT rate spread (US 10-year bond, %)	Δ Coefficient of variation, LT bond (annual, based on monthly data)	Δ Coefficient of variation, LT bond (annual, based on monthly data), **Excluding Canada**	Δ Coefficient of variation, LT bond (annual, based on monthly data)
LT rate$_{t-1}$	-0.22***				
	(0.04)				
LT rate spread$_{t-1}$		-0.29***			
		(0.06)			
LT rate COV$_{t-1}$			-0.76***	-0.75***	-0.78***
			(0.05)	(0.05)	(0.05)
FRT$_{t-1}$	0.01	0.00	**-0.19****	**-0.57****	**-0.14****
	(0.01)	(0.01)	**(0.08)**	**(0.25)**	**(0.06)**
Δ FRT	0.03	-0.01	0.06	-0.49	0.14
	(0.02)	(0.02)	(0.14)	(0.58)	(0.21)
Public debt/GDP (%)$_{t-1}$	0.01	0.01*	0.03	0.03	0.00
	(0.00)	(0.00)	(0.02)	(0.02)	(0.03)
Δ Public debt/GDP	0.03***	0.04***	0.14***	0.15***	0.10
	(0.01)	(0.01)	(0.05)	(0.04)	(0.07)
Inflation (%) $_{t-1}$	-0.02	-0.04	-0.07	-0.12	-0.07
	(0.07)	(0.07)	(0.14)	(0.13)	(0.14)
Δ Inflation (%)	0.09**	0.10**	-0.16	-0.19	-0.14
	(0.04)	(0.04)	(0.13)	(0.14)	(0.13)
US 3-month interest rate (%)$_{t-1}$	0.16***	-0.01	-0.85***	-0.94***	-1.01***
	(0.04)	(0.03)	(0.17)	(0.20)	(0.23)
Δ US 3-month interest rate (%)	0.26***	-0.09**	-0.56***	-0.68***	-0.62***
	(0.03)	(0.03)	(0.17)	(0.18)	(0.21)
OECD average GDP growth$_{t-1}$	-0.01	0.04	0.52***	0.59***	0.65***
	(0.06)	(0.06)	(0.14)	(0.17)	(0.20)
Δ OECD average GDP growth	-0.01	-0.06*	0.64***	0.65***	0.67***
	(0.03)	(0.04)	(0.12)	(0.12)	(0.16)
VIX index$_{t-1}$	-0.01	-0.01	0.02	0.02	0.09**
	(0.01)	(0.01)	(0.03)	(0.03)	(0.03)
Δ VIX index	-0.02*	-0.03**	0.16***	0.14***	0.25***
	(0.01)	(0.01)	(0.03)	(0.03)	(0.05)
Domestic GDP growth (%)$_{t-1}$	-0.14***	-0.14***			0.11
	(0.03)	(0.03)			(0.12)
Δ Domestic GDP growth (%)	0.00	0.00			0.00
	(0.00)	(0.00)			(0.01)
Structural budget balance/GDP (%)$_{t-1}$					-0.31**
					(0.15)
Δ Structural budget balance/GDP					0.14
					(0.17)
Eurozone Member					-0.62
					(0.68)
Constant	0.65	0.22	5.55***	6.56***	5.02**
	(0.63)	(0.59)	(1.75)	(1.60)	(2.10)
Countries	29	28	29	28	29
Observations	513	492	514	493	450
Adjusted R-squared	0.39	0.44	0.38	0.39	0.40

All regressions include country fixed effects.

Hollyer et al.'s Transparency Index and Bond Prices As a robustness check we reran the models with Hollyer, Rosendorff, and Vreeland's (2014) transparency index–HRV. The FRT and the HRV are substantively different. The FRT measures international financial system transparency specifically, while the HRV looks at more general government reporting to the World Bank's Development Indicators. Only one variable in the FRT is from the Development Indicators: Domestic credit to the private sector (% GDP). However, it could be that general government transparency measured in the HRV is a reasonable proxy for financial sector transparency.

The FRT and HRV indices are weakly positively correlated.[31] Overall, countries that are more transparent with their general government data are also more transparent with their financial system data. However, as we can see in Figure 8 in the Appendix there is considerable variance in the relationship between the two measures.

Given that the two transparency measure are positively correlated, we re-examined the key models with the HRV Index in place of the FRT. Table 3 shows the results of this investigation. We can see that unlike the Financial Regulatory Transparency Index, the HRV is not statistically significantly associated with bond price volatility or any other derivation of bond prices. These results suggest that it is specifically financial supervisory transparency, rather than general government transparency that dampens bond price volatility.

Fiscal transparency A clear extension of our work would be to examine the effects of fiscal transparency on bond prices. As mentioned earlier, there is a sizable literature on the causes and effects of fiscal transparency. Glennerster and Shin (2008) in particular found that between 1999 and 2002 financing became cheaper for countries that released their IMF Section IV reports and met other international data dissemination standards. These data releases included information about fiscal policies. Hameed (2005) contends that more transparent countries have higher sovereign debt ratings and higher primary balances. The empirical evidence, however, is only bi-variate.

A major obstacle for testing the effect of fiscal transparency on borrowing costs and especially comparing this to financial regulatory transparency's effect is a lack of good data. Previous work into the direct effect of fiscal transparency on other outcomes has used either the Open Budget Survey's Open Budget Index (OBI)[32] (e.g. Wehner and de Renzio, 2013), a data set originally created by Alt and Lassen Alt and Lassen (2006*b*,*a*) and updated by Lassen (2010), or some combination of the two (e.g. Alt, Lassen and Wehner, 2014). All of these approaches are very limiting. The OBI Index is currently only available in four waves between 2006 and 2012. The vast majority of the countries are low income and coverage of

[31] The correlation coefficient is 0.14 and is significant at all standard levels.
[32] The OBI can be downloaded from: http://survey.internationalbudget.org/#download. Accessed January 2015.

Table 3: Re-examining Sovereign Bond Prices using the Hollyer, Rosendorff, and Vreeland (2014) Transparency Index (HRV)

	Δ Long-term (10-year) interest rate (%)	Δ LT rate spread (US 10-year bond, %)	Δ Coefficient of variation, LT bond (annual, based on monthly data)
LT rate$_{t-1}$	-0.27***		
	(0.02)		
LT rate spread$_{t-1}$		-0.37***	
		(0.03)	
LT rate COV$_{t-1}$			-0.82***
			(0.05)
HRV$_{t-1}$	0.03	0.00	-0.31
	(0.03)	(0.02)	(0.21)
Δ HRV	-0.00	0.01	0.47
	(0.07)	(0.06)	(0.34)
Public debt/GDP (%)$_{t-1}$	0.01**	0.01**	0.02
	(0.00)	(0.00)	(0.02)
Δ Public debt/GDP	0.02**	0.03***	0.18***
	(0.01)	(0.01)	(0.05)
Inflation (%) $_{t-1}$	0.10***	0.08*	-0.30*
	(0.03)	(0.04)	(0.17)
Δ Inflation (%)	0.14***	0.17***	-0.22
	(0.05)	(0.05)	(0.14)
US 3-month interest rate (%)$_{t-1}$	0.24***	0.04	-0.20
	(0.03)	(0.03)	(0.14)
Δ US 3-month interest rate (%)	0.27***	-0.09**	-0.24
	(0.04)	(0.04)	(0.19)
OECD average GDP growth$_{t-1}$	-0.15***	-0.10**	-0.05
	(0.04)	(0.05)	(0.24)
Δ OECD average GDP growth	-0.03	-0.10***	0.52***
	(0.03)	(0.03)	(0.15)
VIX index$_{t-1}$	-0.01*	-0.02**	-0.00
	(0.01)	(0.01)	(0.03)
Δ VIX index	-0.02***	-0.03***	0.11***
	(0.01)	(0.01)	(0.03)
Domestic GDP growth (%)$_{t-1}$	-0.11***	-0.11***	
	(0.02)	(0.02)	
Δ Domestic GDP growth (%)	0.00	0.00	
	(0.00)	(0.00)	
Constant	0.44	0.13	7.14***
	(0.35)	(0.35)	(2.02)
Countries	24	23	24
Observations	421	401	422
Adjusted R-squared	0.46	0.53	0.47

All regressions include country fixed effects.

high income countries is scant. As such its coverage is not closely comparable to our sample.[33] Due to the OBI's limited coverage, previous research has been constrained to looking at very short time spans. Wehner and de Renzio (2013), for example, only include data from 2008 in their parametric models. Alt and Lassen's measure and their method of aggregating it with the OBI creates a time-invariant indicator. In Alt and Lassen (2006*b*) and Alt, Lassen and Wehner (2014), for example, they are only able to include indicators of fiscal transparency in fixed effects regressions with cross-country time-series data by interacting them with other political variables that are time-variant. Due to a lack of adequate data, we are unable to run comparable regression models with fiscal transparency on the right-hand side.[34]

It is interesting to note, however, that in the small subset of data where data is available for both financial supervisory and fiscal transparency–as measured by the OBI–there is no statistically significant correlation between the two. Consistently strong performers on the OBI, as almost all developed countries are, have mixed financial supervisory scores. For example, the United States and the United Kingdom are consistently top ranked countries on the OBI, while on the FRT the United States scores consistently high and the United Kingdom is a lower scorer.

Conversely, the HRV and OBI are strongly positively correlated with one another.[35] This indicates that the processes causing fiscal and general public sector transparency may be similar, but that financial regulatory transparency is distinct.

Conclusion

In this paper we have introduced a new Financial Regulatory Transparency Index. This work builds on the approach pioneered by Hollyer, Rosendorff and Vreeland (2014), to create an indicator that measures an important and unique aspect of government transparency. The FRT measures a country's latent ability and desire to release minimally credible financial supervisory data 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 approach of estimating transparency–primarily employing the No-U-Turn Sampler and using half-Cauchy rather than Gamma priors.

We used the unique FRT Index to examine an issue that has so far not been studied in the academic literature: the relationship between financial supervisory transparency and sovereign borrowing costs. The recent North Atlantic and Eurozone crises have dramatically highlighted the immense and sudden

[33] For example, the OBI wave, the largest so far, does not include Australia, Austria, Belgium, Canada, Denmark, Iceland, Israel, Japan, Luxembourg, or the Netherlands among their high income countries.

[34] There are only 52 observations from 14 countries where the OBI overlaps with the FRT and their complete observations on the other covariates, even when making strong assumptions about OBI scores in non-wave years.

[35] In our sample, the correlation coefficient is 0.6 and statistically significant at all conventional levels.

costs that governments often incur when addressing financial stability problems (see Laeven and Valencia, 2012). Sovereign debt sustainability and domestic financial system stability are intimately linked both directly in terms of assistance to the financial sector and indirectly in terms of creating wider economic shocks that lead to falling tax revenues and prompt fiscal stimulus packages (Reinhart and Rogoff, 2009, 164). Therefore market actors are wise to consider the risks of financial system instability to sovereign debt sustainability. In this paper we find evidence that sovereign creditors do incorporate financial regulatory information provided through international organizations into their prices, specifically the volatility of these prices. Borrowing costs are less volatile when investors are better able to anticipate instability because they have access to financial regulatory information.

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Appendix

Discrepancies between World Bank and FRED versions

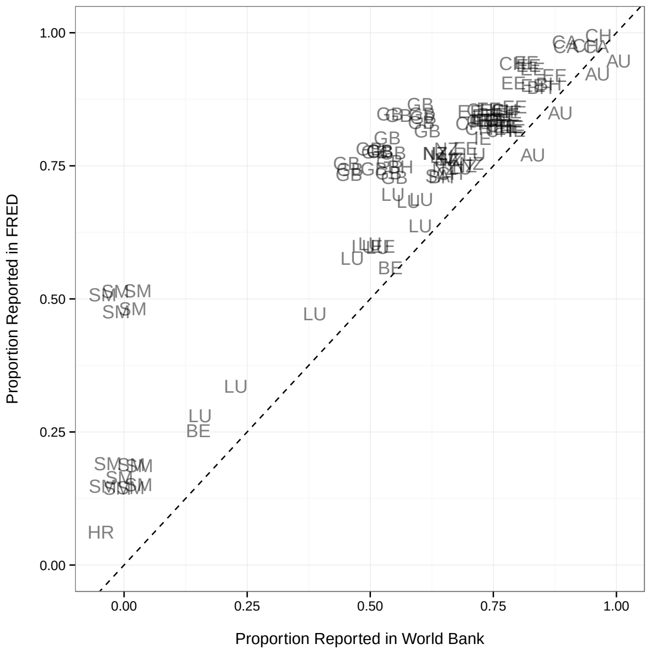
We aimed to ensure that missing-ness in the GFDD data set was due to decisions made by national governments, rather than data handling issues at the international institutions that publish the data. In the course of these investigations we found that the version of the GFDD published by the World Bank in 2014 was incomplete.

The Federal Reserve Bank of St. Louis maintains the Federal Reserve Economic Data (FRED) database.[36] This database includes a mirror of much of the GFDD data set. FRED uses the same variable ID numbers as the GFDD and credits the GFDD as its source. However, item reporting coverage differs between the two data sets. This is illustrated in Figure 6 which shows the proportion of items reported in the two versions of the data set where they do not match.[37] If the FRED and World Bank data sets matched exactly in terms of the items reported per country-year then the points would be on the 45 degree line.

[36] Available at: `http://research.stlouisfed.org/fred2/`. Accessed December 2014.

[37] The FRED database does not include two variables from the GFDD that we looked at. These are Domestic credit to private sector (%) and Liquid liabilities in millions of USD. We only compare items for which any data is available in the two versions.

Figure 6: Comparison of GFDD Data Reported in the World Bank and FRED's Versions



Labels are ISO two-letter country codes.
The labels are jittered to make the plot more legible.
The dashed line indicates where the two versions of the data would match.
Note: only country-years where the FRED and World Bank versions of the GFDD differ are plotted.

In general, FRED has more data, though the World Bank has more data for Australia ("AU"). The biggest difference between the two data sets is for San Marino ("SM"). From 2005 to 2009 San Marino is recorded as having reported half of the items in the FRED version of the GFDD. In the World Bank version, San Marino only reports two items between 1993 and 1998. It then reports none of the items the rest of the time. Under-reporting in the World Bank version notably also occurs for the United Kingdom ("GB"), New Zealand ("NZ"), Estonia ("EE"), Switzerland ("CH"), and Luxembourg ("LU"), among others. Overall 118 country-years differ between the two data sets. FRED included more information in 114 of these.

As the FRED data claims to be a copy of the World Bank's GFDD, we assume that discrepancies between the two data sets are caused by data handling problems at either institution, rather than a decision made by a national government to report or withhold data. As such we treat an item as reported for a country-year if it is published in *either* the FRED or World Bank versions of the GFDD.

Value added: comparison to Liedorp et al. (2013) frequency survey

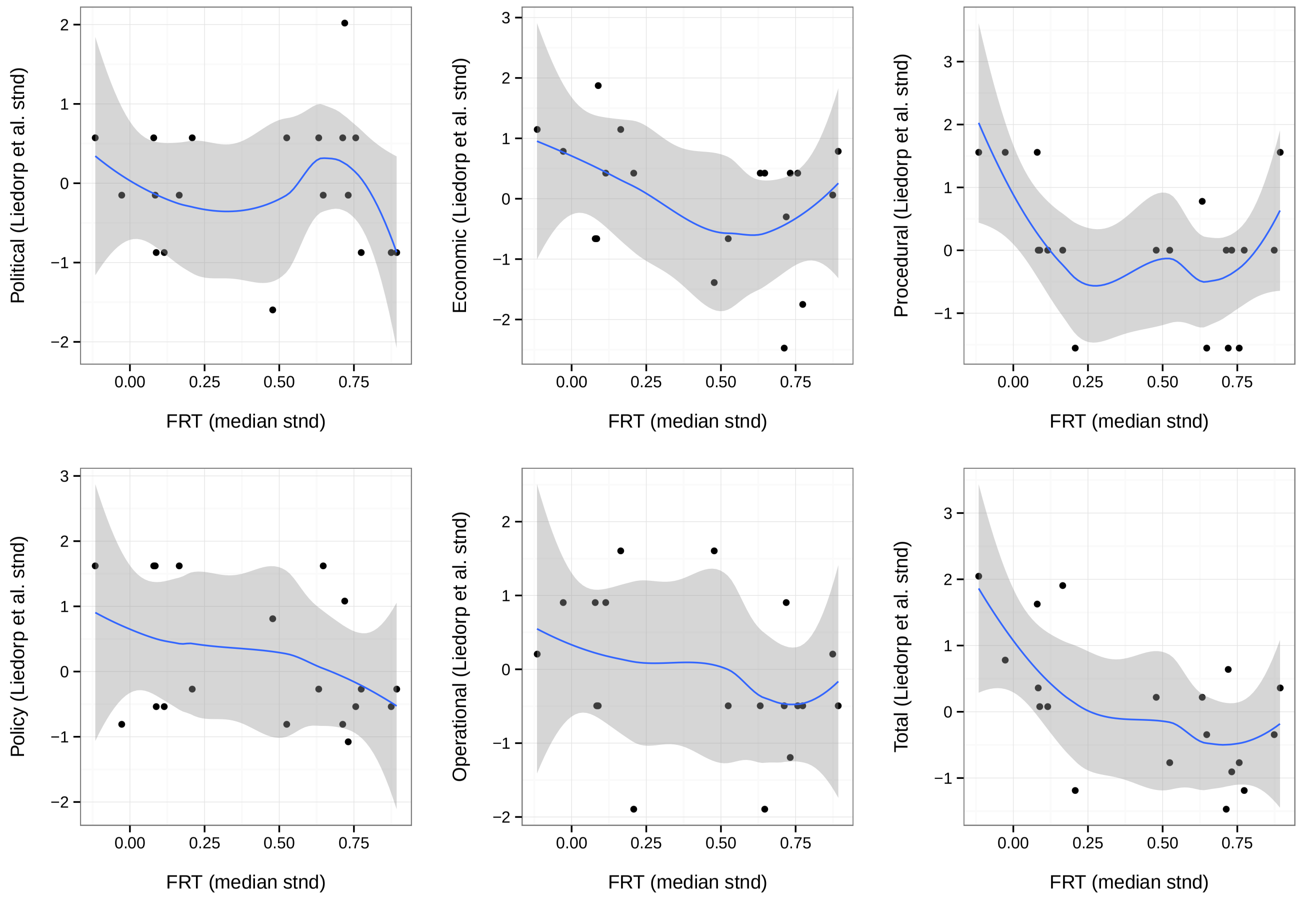
Before directly comparing the FRT Index to Liedorp et al.'s frequency-survey measure, it's important to consider the substantive and practical differences between the two indices. The indices by design are estimates of different aspects of transparency. A considerable portion of Liedorp et al.'s index is devoted to capturing formal and procedural components of supervision, including if the supervisor has a stated "supervisory strategy", does it have clear objectives, and are there formal arrangements for independence from politicians. The survey it is based on has a number of questions about what they term "economic" transparency that are broadly similar to what the FRT captures, namely making off-site inspection reports publicly available. Though again, this is not exactly the same as the FRT Index, which captures how transparent supervisors are with financial supervisory data to a specific audience: international institutions and investors.

Nonetheless, it is interesting to see how closely, if at all the two measures are related. Figure 7 compares the FRT Index to the components of the Liedorp et al. (2013) index as well as the total score for country-years where both indices have information available. We mean-standardized the measures as above. The top-right panel shows the relationship between Liedorp et al.'s economic transparency measure–the closest to our international data transparency index. There is very little, if any relationship between the two measures. There is also a negative relationship between Liedorp et al.'s total score (bottom-right panel).

Interestingly, some countries with very high Liedorp et al. scores–namely Norway (the highest scorer) and the United Kingdom–have low data transparency scores in 2010. Norway's data transparency as measured by the FRT was indeed very high during most of the early 2000s. It actually reported all 14 items between 2000 and 2006. However, in 2007 through 2009 it reported only about a third of the items. In 2010–the year of Liedorp et al.'s survey–Norway only reported two items.[38] The United Kingdom consistently only reported about 75 percent of the items.

[38] Mutual fund assets to GDP (%) and Insurance company assets to GDP (%)

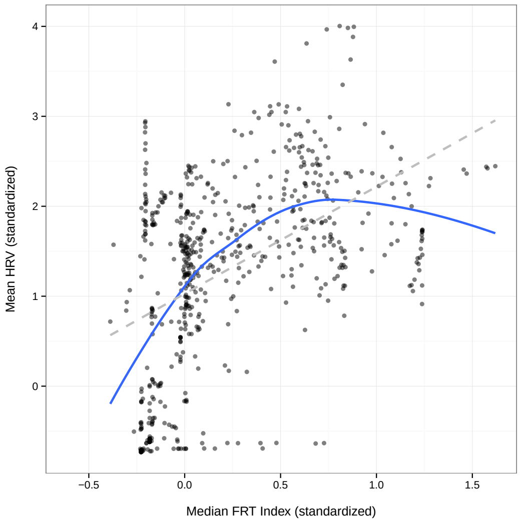
Figure 7: Comparison of the FRT Index to Liedorp et al. (2013)



Note: both measures were standardized by subtracting their medians and dividing by standard deviations.

Visual comparison of the FRT and Hollyer, Rosendorff and Vreeland's (2014) Transparency Index

Figure 8: Comparison of the FRT Index to the HRV Transparency Index



Both the HRV and FRT scores are standardized by subtracting their medians and dividing by their standard deviations. To ease interpretation, the plot excludes scores for Canada.

Regression model country sample

Table 4: Country Sample Used in the Models Shown in Tables 2, 3, and 5

Australia	Korea, Republic of
Austria	Luxembourg
Belgium	Netherlands
Canada	New Zealand
Denmark	Norway
Finland	Poland
France	Portugal
Germany	Slovakia
Greece	Slovenia
Hungary	Spain
Iceland	Sweden
Ireland	Switzerland
Israel	United Kingdom
Italy	United States
Japan	

Robustness check: log transformation of the FRT

As mentioned earlier, the FRT has a number of outlier country-years. These are primarily for Canada from the mid-1990s through the mid-2000s. To examine if this distribution affected the results we created a log-transformed version of the FRT[39] and re-ran the models for our core findings. Table 5 shows the results with the log-transformed FRT variable. We can see that the results are substantively the same as without the log-transformation, i.e. higher financial supervisory transparency is associated with lower bond price volatility. This is true even when Canada is excluded from the sample.

[39] We added 2.5 to the scale so that all values were above zero and then found the natural log.

Table 5: Sovereign Bond Prices and the Financial Transparency Index (FRT): Logged

	Δ Coefficient of variation, LT bond (annual, based on monthly data)	Δ Coefficient of variation, LT bond (annual, based on monthly data), **Excluding Canada**
LT rate COV$_{t-1}$	-0.77***	-0.77***
	(0.05)	(0.05)
FRT (log)$_{t-1}$	**-2.00*** **	**-2.30** **
	(0.59)	**(0.85)**
Δ FRT (log)	0.36	-0.22
	(0.63)	(1.16)
Public debt/GDP (%)$_{t-1}$	0.03	0.03
	(0.02)	(0.02)
Δ Public debt/GDP	0.15***	0.15***
	(0.04)	(0.04)
Inflation (%) $_{t-1}$	-0.12	-0.13
	(0.13)	(0.13)
Δ Inflation (%)	-0.18	-0.18
	(0.13)	(0.13)
US 3-month interest rate (%)$_{t-1}$	-0.93***	-0.94***
	(0.17)	(0.19)
Δ US 3-month interest rate (%)	-0.59***	-0.66***
	(0.18)	(0.18)
OECD average GDP growth$_{t-1}$	0.51***	0.53***
	(0.14)	(0.16)
Δ OECD average GDP growth	0.61***	0.62***
	(0.12)	(0.12)
VIX index$_{t-1}$	0.01	0.01
	(0.03)	(0.03)
Δ VIX index	0.16***	0.15***
	(0.03)	(0.03)
Constant	8.21***	9.27***
	(1.84)	(1.92)
Countries	29	28
Observations	508	492
Adjusted R-squared	0.39	0.39

All regressions include country fixed effects.

The FRT's Stan estimation model

```
data {
    int<lower=1> C;                  // number of countries
    int<lower=1> T;                  // number of years
    int<lower=1> K;                  // number of items
    int<lower=1> N;                  // number of observations
    int<lower=1> cc[N];              // country for observation n
    int<lower=1> tt[N];              // time for observation n
    int<lower=1,upper=K> kk[N];      // item for observation n
    int<lower=0,upper=1> y[N];       // response for observation n
}
```

```
parameters {
    real delta;                // mean transparency
    vector[C] alpha1;          // initial alpha for t = 1 before recentering
    matrix[C,T] alpha;         // transparency for c,t - mean
    vector[K] beta;            // difficulty of item k
    vector[K] log_gamma;       // discrimination of k

    //// all scale parameters have an implicit half Cauchy prior ////
    real<lower=0> sigma_alpha[C];     // scale of abilities, per country
    real<lower=0> sigma_beta;         // scale of difficulties
    real<lower=0> sigma_gamma;        // scale of log discrimination
}

transformed parameters {
    //// re-centers transparency for t = 1 ////
    vector[C] recentered_alpha1;
    real mean_alpha1;
    real<lower=0> sd_alpha1;

    mean_alpha1 <- mean(alpha1);
    sd_alpha1 <- sd(alpha1);
    for (c in 1:C)
        recentered_alpha1[c] <- ( alpha1[c] - mean_alpha1 ) / sd_alpha1;
}

model {
    alpha1 ~ normal(0,1);   // informed constraints on the ability
                            // numerical issues with larger sd
    for (c in 1:C) {
        alpha[c,1] ~ normal(recentered_alpha1[c],0.001);
            // addresses current Stan limitation
        for (t in 2:T)
            alpha[c,t] ~ normal(alpha[c,t-1], sigma_alpha[c]);
```

```
    }

    beta ~ normal(0,sigma_beta);
    log_gamma ~ normal(0,sigma_gamma);
    delta ~ cauchy(0,0.05);

    sigma_alpha ~ cauchy(0,0.05);
    sigma_beta ~ cauchy(0,0.25);
    sigma_gamma ~ cauchy(0,0.25);

        for (n in 1:N)
            y[n] ~ bernoulli_logit(
            exp(log_gamma[kk[n]])
            * (alpha[cc[n],tt[n]] - beta[kk[n]] + delta) );
}
```

Figure 9: Individual Countries' FRT Scores Over Time (1)

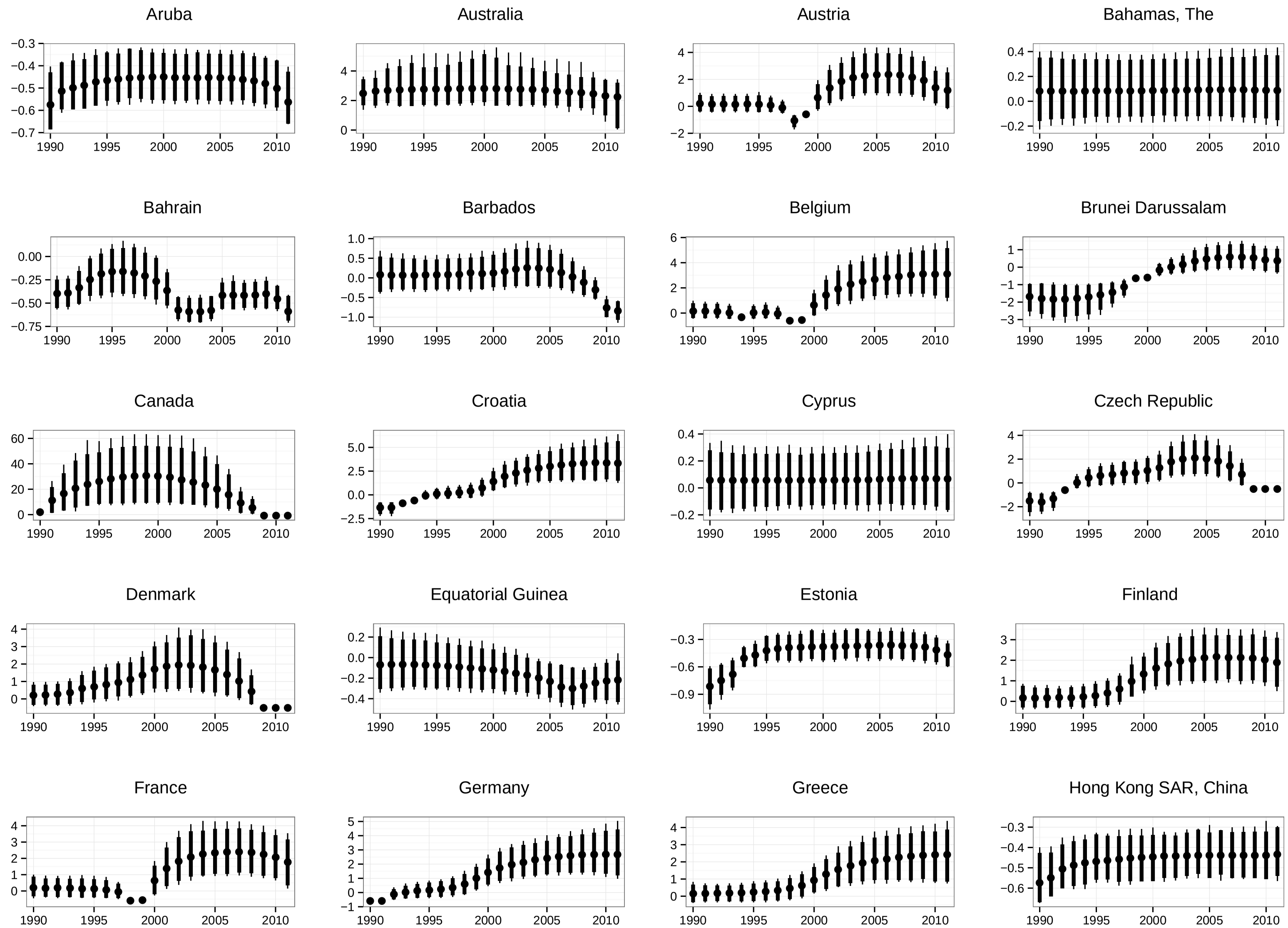


Figure 10: Individual Countries' FRT Scores Over Time (2)

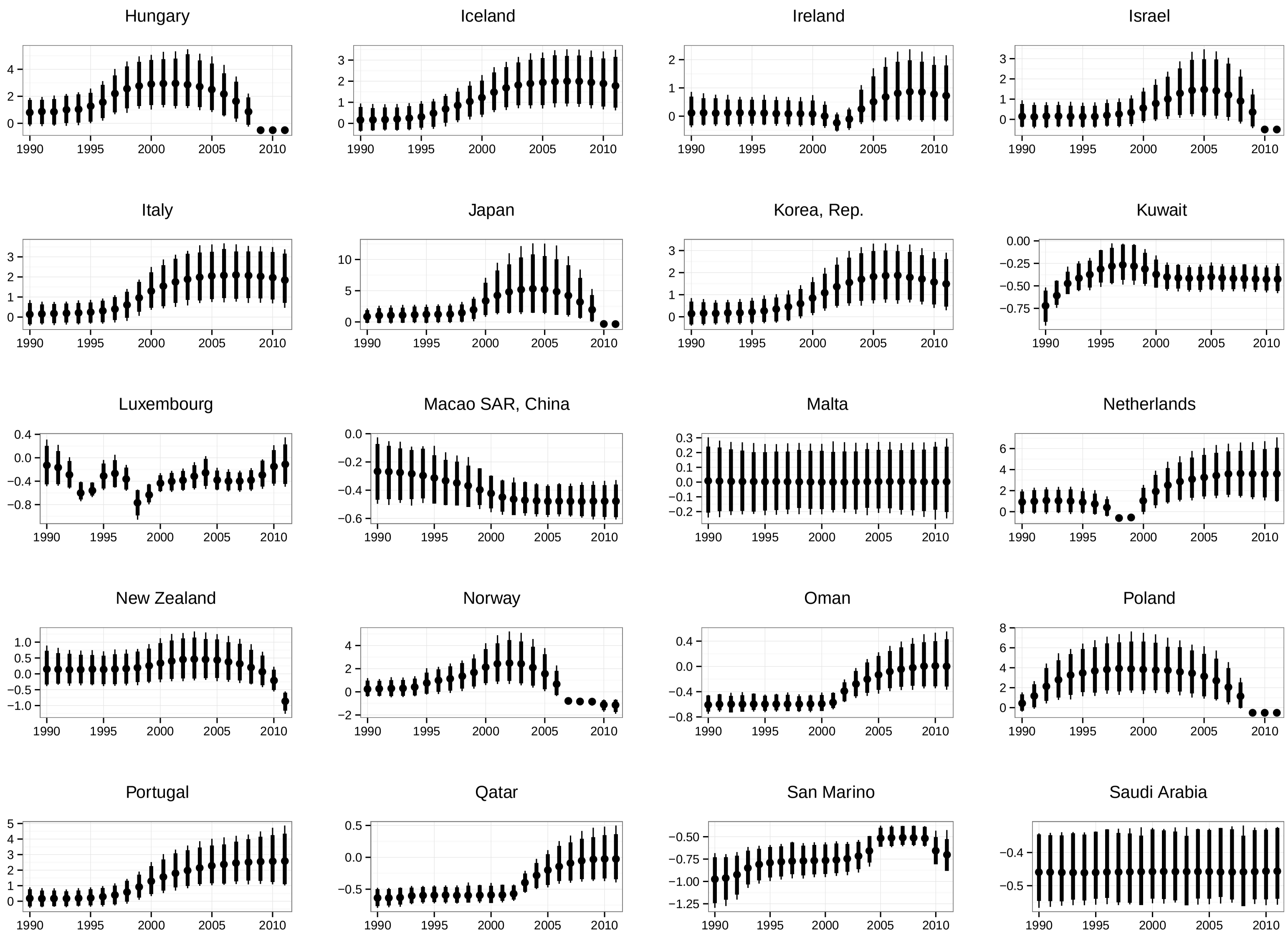


Figure 11: Individual Countries' FRT Scores Over Time (3)

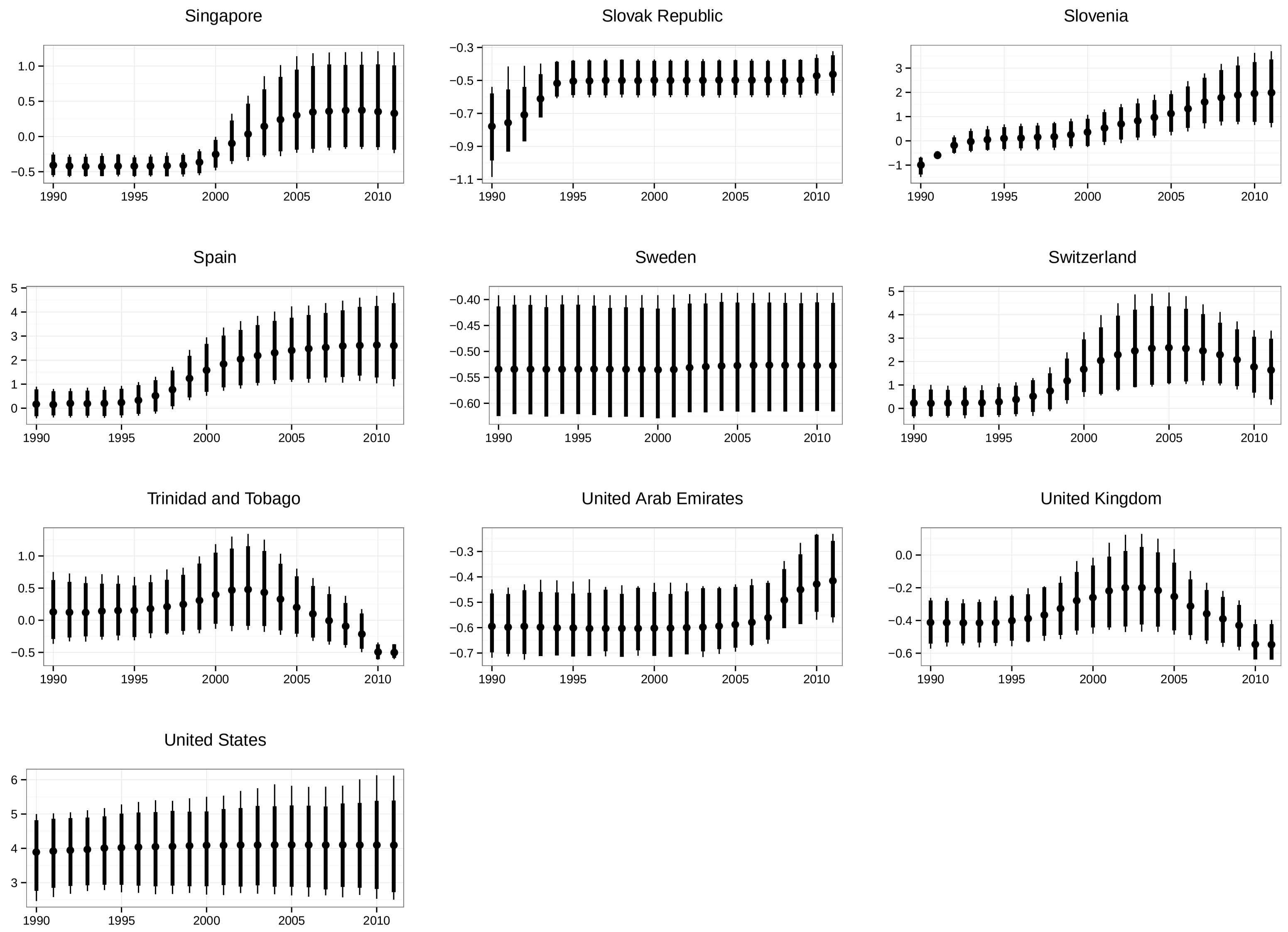


Figure 12: Individual Countries' Proportions of Items Reported Over Time (1)

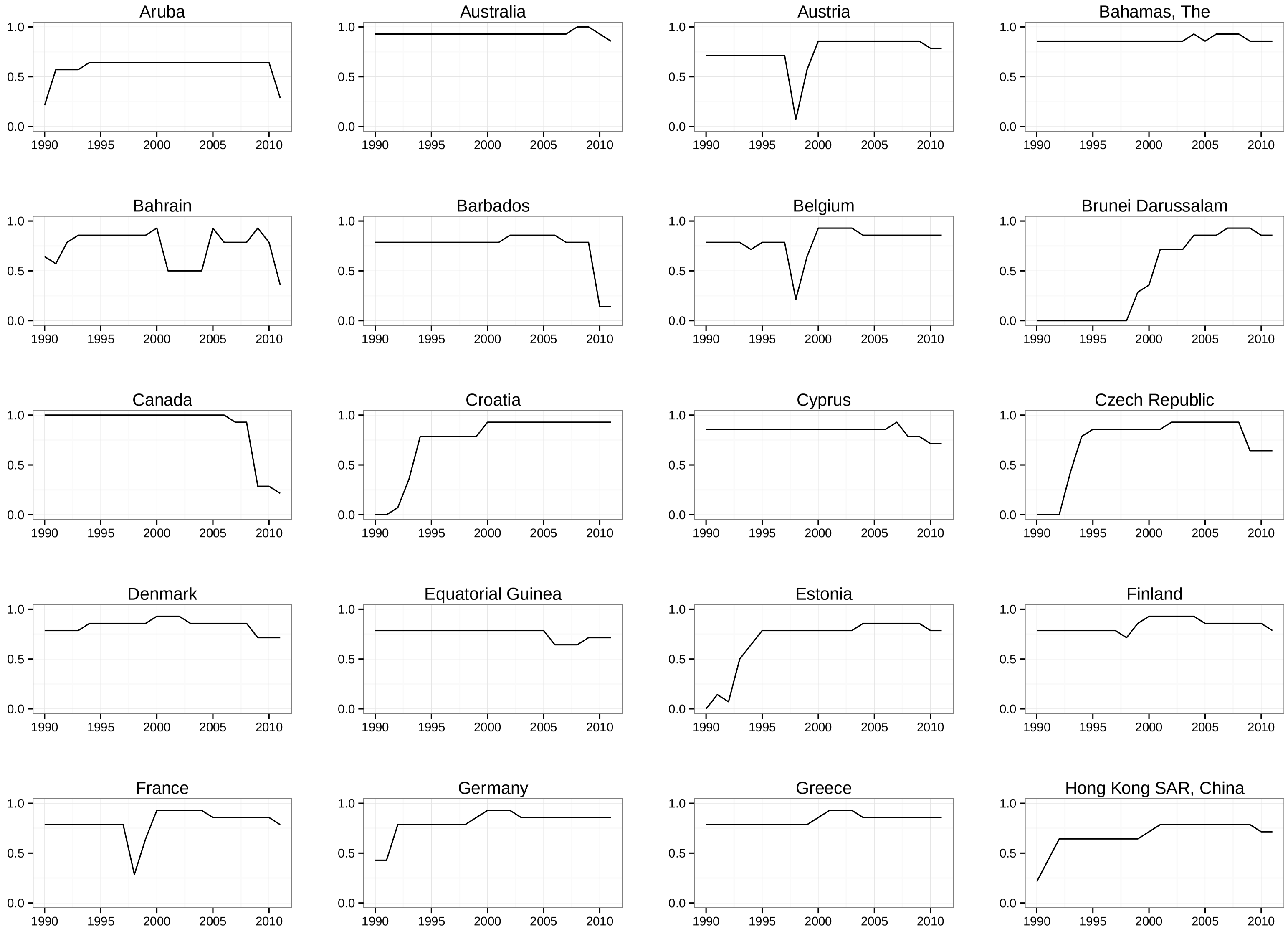


Figure 13: Individual Countries' Proportions of Items Reported Over Time (2)

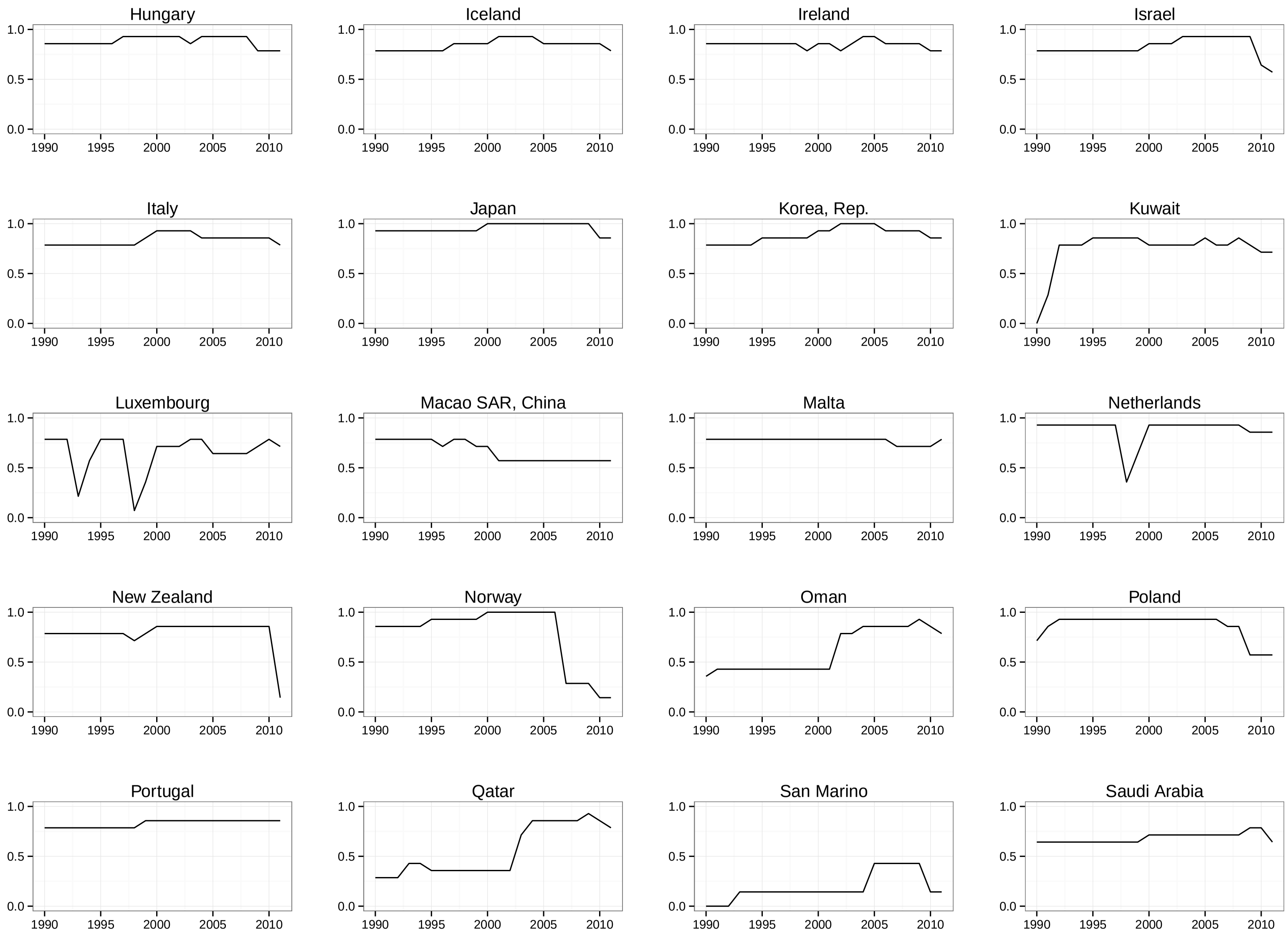


Figure 14: Individual Countries' Proportions of Items Reported Over Time (3)