Supplementary Materials for: Financial Data Transparency, International Institutions, and Sovereign Borrowing Costs

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Force $REVEAL$ at high debt levels

One potentially interesting subset of the game is a special case where interest rates are at their highest level–e.g. very high over two stages–and explicit debt is not decreasing. In these cases, governments may be required to make reforms in order to be able to borrow at all. Investors, especially those that lend to governments at the interest rate ceiling like the International Monetary Fund, would likely want the government to choose a $REVEAL$ policy in order to gauge risks over the longer-term. As such we could add an assumption that governments are forced to $REVEAL$ when offered very high rates and their debt (X) is not decreasing. Otherwise investors would not offer to buy the government's debt at all. We can see in Table A-1 that this assumption is equivalent to assuming that governments receive $c = 1$ from switching to a $REVEAL$ in these situations.

Examining the game over two stages when $c = 1$ exposes a counter-intuitive hypothesis about interest rate costs when governments increase transparency. Figure A-1 shows that under a specific scenario countries with increasing debt and increasing transparency can have higher interest rates. In all other cases of increasing debt, the interest rates are the same regardless of the change (or not) in transparency

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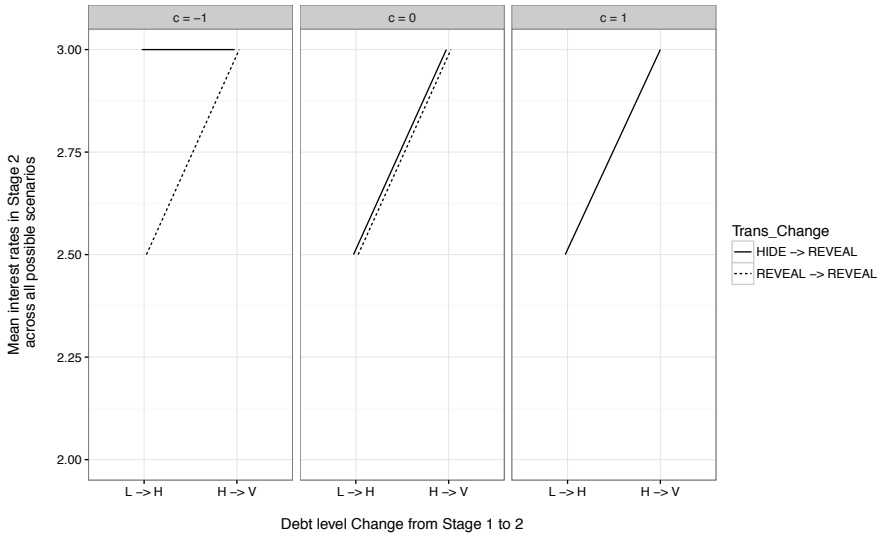
Figure A-1: Average Interest Rate Charged in Stage 2 Over all Possible Outcomes Given Transparency Changes and Increasing Explicit Debt (X) Levels



Note: overlapping lines were dodged to enable visibility.

choice. The reason for this has to do with the situations under which governments with increasing debt would become more transparent. These are countries that have a cost to changing their level of transparency and would prefer to continue hiding but are forced to open as their financial market conditions and debt worsen and thus their interest rates worsen.

If this effect does exist, we anticipate that it will be small on average as it is caused by a specific scenario. In addition to this outcome applying to a specific debt scenario, governments may be able to rely on creditors who do not force transparency and other policies, such as by increasing domestic demand for its debt and having the central bank hold debt. So we do not expect forced openings even in all situations with very high and increasing debt, especially in economically developed countries with more tools to rein in very high interest rates. Future work could examine these types of scenarios in detail.

Note on Table A-1

P^G indicates the preferred transparency level for the government in the second stage of the game. Likewise, the utilities U and whether or not transparency would be Forced refer to the second stage of the game in scenarios discussed in the previous section.

What an investor learns from the government changing their level of transparency

If the government has $c = -1$, then they never benefit from switching their transparency level from the status quo ante. So observing that a government with $c = -1$ continues to $HIDE$ or $REVEAL$ is not informative about Γ. They will stay with the status quo transparency level regardless, except if they are forced to $REVEAL$.

When $c = 0$ then governments always prefer REVEAL, as we saw earlier, except when the status quo ante is $HIDE$ and they are indifferent between $HIDE/REVEAL$. In these cases status quo bias inclines them to continue hiding (unless they are forced to $REVEAL$). Such indifference occurs when debt is very high regardless of Γ or when X is low or high and Γ is high. As such, when $c = 0$ observing that the government chose $HIDE$ is equivalent to observing Γ_H.

When there is an intrinsic benefit to changing the level of transparency ($c = 1$), the status quo ante is $REVEAL$ and $X_H \wedge \Gamma_H$ or $X_V \wedge (\Gamma_L \vee \Gamma_H)$, then the government would initially prefer to switch their transparency level to $HIDE$. Doing so for X_H indicates to the investor that Γ is high, as if Γ_L they would have been indifferent between $REVEAL$ and $HIDE$ and so would have chosen $REVEAL$. In all of these situations, the investor would force $REVEAL$. When X is low and the status quo ante is $REVEAL$ if Γ_L then the government will be indifferent so will choose $REVEAL$. While if Γ_H they will choose $HIDE$, so the choice of $HIDE$ is equivalent in terms of the information it provides to the investor to revealing Γ_H.

Table A-1: Extensive Form Government Payoffs for All Valid Scenarios in 2 Stage Transparency Games

ID	X_1	X_2	Γ_1	Γ_2	$Transp._1$	$Transp._2$	r_1	r_2	$U^G_{c=0}$	$U^G_{c=-1}$	$U^G_{c=1}$	$P^G_{c=0}$	$P^G_{c=-1}$	$P^G_{c=1}$	Forced?
1	L	L	L	L	HIDE	HIDE	2.0	2.0	-1.0	-1.0	-1.0		P		
1	L	L	L	L	HIDE	REVEAL	2.0	1.0	0.0	-1.0	1.0	P		P	
2	L	L	L	L	REVEAL	HIDE	1.0	2.0	-1.0	-2.0	0.0				
2	L	L	L	L	REVEAL	REVEAL	1.0	1.0	0.0	0.0	0.0	P	P	P	
3	H	L	L	L	HIDE	HIDE	3.0	2.0	-1.0	-1.0	-1.0		P		
3	H	L	L	L	HIDE	REVEAL	3.0	1.0	0.0	-1.0	1.0	P		P	
4	H	L	L	L	REVEAL	HIDE	2.0	2.0	-1.0	-2.0	0.0				
4	H	L	L	L	REVEAL	REVEAL	2.0	1.0	0.0	0.0	0.0	P	P	P	
5	H	H	L	L	HIDE	HIDE	3.0	3.0	-2.0	-2.0	-2.0		P		
5	H	H	L	L	HIDE	REVEAL	3.0	2.0	-1.0	-2.0	0.0	P		P	
6	H	H	L	L	REVEAL	HIDE	2.0	3.0	-2.0	-3.0	-1.0				
6	H	H	L	L	REVEAL	REVEAL	2.0	2.0	-1.0	-1.0	-1.0	P	P	P	
7	V	H	L	L	HIDE	HIDE	3.0	3.0	-2.0	-2.0	-2.0		P		
7	V	H	L	L	HIDE	REVEAL	3.0	2.0	-1.0	-2.0	0.0	P		P	
8	V	H	L	L	REVEAL	HIDE	3.0	3.0	-2.0	-3.0	-1.0				
8	V	H	L	L	REVEAL	REVEAL	3.0	2.0	-1.0	-1.0	-1.0	P	P	P	
9	V	V	L	L	HIDE	HIDE	3.0	3.0	-2.0	-2.0	-2.0	P	P		
9	V	V	L	L	HIDE	REVEAL	3.0	3.0	-2.0	-3.0	-1.0			P	F
10	V	V	L	L	REVEAL	HIDE	3.0	3.0	-2.0	-3.0	-1.0			P	
10	V	V	L	L	REVEAL	REVEAL	3.0	3.0	-2.0	-2.0	-2.0	P	P		
11	L	L	H	H	HIDE	HIDE	2.0	2.0	-1.0	-1.0	-1.0	P	P		
11	L	L	H	H	HIDE	REVEAL	2.0	2.0	-1.0	-2.0	0.0			P	
12	L	L	H	H	REVEAL	HIDE	2.0	2.0	-1.0	-2.0	0.0			P	
12	L	L	H	H	REVEAL	REVEAL	2.0	2.0	-1.0	-1.0	-1.0	P	P		
13	L	H	H	H	HIDE	HIDE	2.0	3.0	-2.0	-2.0	-2.0	P	P		
13	L	H	H	H	HIDE	REVEAL	2.0	3.0	-2.0	-3.0	-1.0			P	F
14	L	H	H	H	REVEAL	HIDE	2.0	3.0	-2.0	-3.0	-1.0			P	
14	L	H	H	H	REVEAL	REVEAL	2.0	3.0	-2.0	-2.0	-2.0	P	P		
15	H	L	H	H	HIDE	HIDE	3.0	2.0	-1.0	-1.0	-1.0	P	P		
15	H	L	H	H	HIDE	REVEAL	3.0	2.0	-1.0	-2.0	0.0			P	
16	H	L	H	H	REVEAL	HIDE	3.0	2.0	-1.0	-2.0	0.0			P	
16	H	L	H	H	REVEAL	REVEAL	3.0	2.0	-1.0	-1.0	-1.0	P	P		
17	H	H	H	H	HIDE	HIDE	3.0	3.0	-2.0	-2.0	-2.0	P	P		
17	H	H	H	H	HIDE	REVEAL	3.0	3.0	-2.0	-3.0	-1.0			P	F
18	H	H	H	H	REVEAL	HIDE	3.0	3.0	-2.0	-3.0	-1.0			P	
18	H	H	H	H	REVEAL	REVEAL	3.0	3.0	-2.0	-2.0	-2.0	P	P		
19	H	V	H	H	HIDE	HIDE	3.0	3.0	-2.5	-2.5	-2.5	P	P		
19	H	V	H	H	HIDE	REVEAL	3.0	3.0	-2.5	-3.5	-1.5			P	F
20	H	V	H	H	REVEAL	HIDE	3.0	3.0	-2.5	-3.5	-1.5			P	
20	H	V	H	H	REVEAL	REVEAL	3.0	3.0	-2.5	-2.5	-2.5	P	P		
21	V	H	H	H	HIDE	HIDE	3.0	3.0	-2.0	-2.0	-2.0	P	P		

21	V	H	H	H	HIDE	REVEAL	3.0	3.0	-2.0	-3.0	-1.0			P	
22	V	H	H	H	REVEAL	HIDE	3.0	3.0	-2.0	-3.0	-1.0			P	
22	V	H	H	H	REVEAL	REVEAL	3.0	3.0	-2.0	-2.0	-2.0	P	P		
23	V	V	H	H	HIDE	HIDE	3.0	3.0	-2.5	-2.5	-2.5	P	P		
23	V	V	H	H	HIDE	REVEAL	3.0	3.0	-2.5	-3.5	-1.5			P	F
24	V	V	H	H	REVEAL	HIDE	3.0	3.0	-2.5	-3.5	-1.5			P	
24	V	V	H	H	REVEAL	REVEAL	3.0	3.0	-2.5	-2.5	-2.5	P	P		
25	L	L	L	H	HIDE	HIDE	2.0	2.0	-1.0	-1.0	-1.0	P	P		
25	L	L	L	H	HIDE	REVEAL	2.0	2.0	-1.0	-2.0	0.0			P	
26	L	L	L	H	REVEAL	HIDE	1.0	2.0	-1.0	-2.0	0.0			P	
26	L	L	L	H	REVEAL	REVEAL	1.0	2.0	-1.0	-1.0	-1.0	P	P		
27	H	L	L	H	HIDE	HIDE	3.0	2.0	-1.0	-1.0	-1.0	P	P		
27	H	L	L	H	HIDE	REVEAL	3.0	2.0	-1.0	-2.0	0.0			P	
28	H	L	L	H	REVEAL	HIDE	2.0	2.0	-1.0	-2.0	0.0			P	
28	H	L	L	H	REVEAL	REVEAL	2.0	2.0	-1.0	-1.0	-1.0	P	P		
29	H	H	L	H	HIDE	HIDE	3.0	3.0	-2.0	-2.0	-2.0	P	P		
29	H	H	L	H	HIDE	REVEAL	3.0	3.0	-2.0	-3.0	-1.0			P	F
30	H	H	L	H	REVEAL	HIDE	2.0	3.0	-2.0	-3.0	-1.0			P	
30	H	H	L	H	REVEAL	REVEAL	2.0	3.0	-2.0	-2.0	-2.0	P	P		
31	V	H	L	H	HIDE	HIDE	3.0	3.0	-2.0	-2.0	-2.0	P	P		
31	V	H	L	H	HIDE	REVEAL	3.0	3.0	-2.0	-3.0	-1.0			P	
32	V	H	L	H	REVEAL	HIDE	3.0	3.0	-2.0	-3.0	-1.0			P	
32	V	H	L	H	REVEAL	REVEAL	3.0	3.0	-2.0	-2.0	-2.0	P	P		
33	V	V	L	H	HIDE	HIDE	3.0	3.0	-2.5	-2.5	-2.5	P	P		
33	V	V	L	H	HIDE	REVEAL	3.0	3.0	-2.5	-3.5	-1.5			P	F
34	V	V	L	H	REVEAL	HIDE	3.0	3.0	-2.5	-3.5	-1.5			P	
34	V	V	L	H	REVEAL	REVEAL	3.0	3.0	-2.5	-2.5	-2.5	P	P		
35	L	L	H	L	HIDE	HIDE	2.0	2.0	-1.0	-1.0	-1.0		P		
35	L	L	H	L	HIDE	REVEAL	2.0	1.0	0.0	-1.0	1.0	P		P	
36	L	L	H	L	REVEAL	HIDE	2.0	2.0	-1.0	-2.0	0.0				
36	L	L	H	L	REVEAL	REVEAL	2.0	1.0	0.0	0.0	0.0	P	P	P	
37	L	H	H	L	HIDE	HIDE	2.0	3.0	-2.0	-2.0	-2.0		P		
37	L	H	H	L	HIDE	REVEAL	2.0	2.0	-1.0	-2.0	0.0	P		P	
38	L	H	H	L	REVEAL	HIDE	2.0	3.0	-2.0	-3.0	-1.0				
38	L	H	H	L	REVEAL	REVEAL	2.0	2.0	-1.0	-1.0	-1.0	P	P	P	
39	H	L	H	L	HIDE	HIDE	3.0	2.0	-1.0	-1.0	-1.0		P		
39	H	L	H	L	HIDE	REVEAL	3.0	1.0	0.0	-1.0	1.0	P		P	
40	H	L	H	L	REVEAL	HIDE	3.0	2.0	-1.0	-2.0	0.0				
40	H	L	H	L	REVEAL	REVEAL	3.0	1.0	0.0	0.0	0.0	P	P	P	
41	H	H	H	L	HIDE	HIDE	3.0	3.0	-2.0	-2.0	-2.0		P		
41	H	H	H	L	HIDE	REVEAL	3.0	2.0	-1.0	-2.0	0.0	P		P	
42	H	H	H	L	REVEAL	HIDE	3.0	3.0	-2.0	-3.0	-1.0				
42	H	H	H	L	REVEAL	REVEAL	3.0	2.0	-1.0	-1.0	-1.0	P	P	P	
43	H	V	H	L	HIDE	HIDE	3.0	3.0	-2.0	-2.0	-2.0	P	P		
43	H	V	H	L	HIDE	REVEAL	3.0	3.0	-2.0	-3.0	-1.0			P	F

44	H	V	H	L	REVEAL	HIDE	3.0	3.0	-2.0	-3.0	-1.0			P		
44	H	V	H	L	REVEAL	REVEAL	3.0	3.0	-2.0	-2.0	-2.0	P	P			
45	V	H	H	L	HIDE	HIDE	3.0	3.0	-2.0	-2.0	-2.0		P			
45	V	H	H	L	HIDE	REVEAL	3.0	2.0	-1.0	-2.0	0.0	P		P		
46	V	H	H	L	REVEAL	HIDE	3.0	3.0	-2.0	-3.0	-1.0					
46	V	H	H	L	REVEAL	REVEAL	3.0	2.0	-1.0	-1.0	-1.0	P	P	P		
47	V	V	H	L	HIDE	HIDE	3.0	3.0	-2.0	-2.0	-2.0	P	P			
47	V	V	H	L	HIDE	REVEAL	3.0	3.0	-2.0	-3.0	-1.0			P	F	
48	V	V	H	L	REVEAL	HIDE	3.0	3.0	-2.0	-3.0	-1.0			P		
48	V	V	H	L	REVEAL	REVEAL	3.0	3.0	-2.0	-2.0	-2.0	P	P			

R source code for costless transparency decisions in one stage

The following code was used to model the payoffs displayed in Figure **??**.

```
# Create scenarios -----------------
payoff <- data.frame(
    x = rep(1:3, 2), # 1 = L, 2 = H, 3 = V
    gamma = c(rep(0, 3), rep(1, 3)) # 0 = L, 1 = H
)

# REVEAL
payoff$trans <- 0

# HIDE
payoff2 <- payoff
payoff2$trans <- 1

payoff <- rbind(payoff, payoff2)

# Find real debt level D
payoff$D_actual <- payoff$x + payoff$gamma
payoff$D_actual[payoff$D_actual > 3] <- 3

# Find investors belief about D under an assumption that they don't want to be
# 'caught out'
payoff$D_I_belief <- NA
for (i in 1:nrow(payoff)) {
    if (payoff[i, 'trans'] == 0) payoff[i, 'D_I_belief'] <- payoff[i, 'D_actual']
    else payoff[i, 'D_I_belief'] <- payoff[i, 'x'] + 1
}

payoff$D_I_belief[payoff$D_I_belief > 3] <- 3

# Interest rate based on Investor's beliefs
payoff$r <- payoff$D_I_belief
```

```
# Government's utility
payoff$u_g <- 1 - payoff$r
payoff$u_i <- payoff$r - payoff$D_actual
```

Transparency game with costly transparency changes over two stages

The following R source code was used to find the results in Table A-1.

```
# Create scenarios ------------------
# Constant \Gamma at a low level
scen1 <- data.frame(
    x1 = rep('L', 12),
    x2 = c(rep('L', 4), rep('H', 4), rep('V', 4)),
    gamma1 = rep('L', 12),
    gamma2 = rep('L', 12),
    trans1 = rep(c('HIDE', 'HIDE', 'REVEAL', 'REVEAL'), 3),
    trans2 = rep(c('HIDE', 'REVEAL', 'HIDE', 'REVEAL'), 3)
)
scen1$r1 <- NA
scen1$r2 <- NA

scen1_h <- scen1
scen1_h$x1 <- 'H'

scen1_v <- scen1
scen1_v$x1 <- 'V'

scen1 <- rbind(scen1, scen1_h, scen1_v)

# Constant \Gamma at a high level
scen2 <- scen1
scen2$gamma1 <- 'H'
scen2$gamma2 <- 'H'
```

```
# Increasing \Gamma -----
scen3 <- scen1
scen3$gamma2 <- 'H'

# Decreasing \Gamma -----
scen4 <- scen1
scen4$gamma1 <- 'H'

scen <- rbind(scen1, scen2, scen3, scen4)

# Keep only valid scenarios, where change in debt is caused by change in
## \Gamma or \Gamma high -----
for (i in 1:4) scen[, i] <- as.character(scen[, i])

# Keep only valid scenarios, where change in debt is one step
# Debt can only go up when \Gamma is high
scen <- scen %>% filter(x1 == x2 |
                    (x1 == 'L' & x2 == 'H' & gamma1 == 'H' & gamma2 == 'H') |
                    (x1 == 'L' & x2 == 'H' & gamma1 == 'H' & gamma2 == 'L') |
                    (x1 == 'H' & x2 == 'V' & gamma1 == 'H' & gamma2 == 'H') |
                    (x1 == 'H' & x2 == 'V' & gamma1 == 'H' & gamma2 == 'L') |
                    (x1 == 'V' & x2 == 'H') |
                    (x1 == 'H' & x2 == 'L')
)

# Find interest rate choice ------------------------------------------------
for (i in 1:nrow(scen)) {
    for (u in 1:2) {
        # Low explicit debt
        if (scen[i, paste0('x', u)] == 'L' &
            scen[i, paste0('gamma', u)] == 'L' &
            scen[i, paste0('trans', u)] == 'HIDE') {
            scen[i, paste0('r', u)] <- 2
        }
```

```
if (scen[i, paste0('x', u)] == 'L' &
    scen[i, paste0('gamma', u)] == 'L' &
    scen[i, paste0('trans', u)] == 'REVEAL') {
    scen[i, paste0('r', u)] <- 1
}

if (scen[i, paste0('x', u)] == 'L' &
    scen[i, paste0('gamma', u)] == 'H' &
    scen[i, paste0('trans', u)] == 'HIDE') {
    scen[i, paste0('r', u)] <- 2
}
if (scen[i, paste0('x', u)] == 'L' &
    scen[i, paste0('gamma', u)] == 'H' &
    scen[i, paste0('trans', u)] == 'REVEAL') {
    scen[i, paste0('r', u)] <- 2
}
# High explicit debt
if (scen[i, paste0('x', u)] == 'H' &
    scen[i, paste0('gamma', u)] == 'L' &
    scen[i, paste0('trans', u)] == 'HIDE') {
    scen[i, paste0('r', u)] <- 3
}
if (scen[i, paste0('x', u)] == 'H' &
    scen[i, paste0('gamma', u)] == 'L' &
    scen[i, paste0('trans', u)] == 'REVEAL') {
    scen[i, paste0('r', u)] <- 2
}

if (scen[i, paste0('x', u)] == 'H' &
    scen[i, paste0('gamma', u)] == 'H' &
    scen[i, paste0('trans', u)] == 'HIDE') {
    scen[i, paste0('r', u)] <- 3
}
if (scen[i, paste0('x', u)] == 'H' &
```

```
            scen[i, paste0('gamma', u)] == 'H' &
            scen[i, paste0('trans', u)] == 'REVEAL') {
            scen[i, paste0('r', u)] <- 3
        }
        # Very high explicit debt
        if (scen[i, paste0('x', u)] == 'V') {
            scen[i, paste0('r', u)] <- 3
        }
    }
}

# Find changes from stages 1 to 2 ---------
scen$delta_r = scen$r2 - scen$r1

# Gov. Utilities: Costless transparency change scenario (Stage 1) --------------
scen$u1 = 1 - scen$r1

# Gov. interest rate ceiling cost of 0.5 for x = V and gamma = H (Stage 1) -----
for (i in 1:nrow(scen)) {
    if (scen[i, 'x1'] == 'V' & scen[i, 'gamma1'] == 'H') {
        scen[i, 'u1'] <- scen[i, 'u1'] - 0.5
    }
}

# Gov. Utilities: Constant change cost = -1 (Stage 1)  ------
scen$u1_costly <- scen$u1
for (i in 1:nrow(scen)) scen[i, 'u1_costly'] <- scen[i, 'u1'] + -1

# Gov. Utilities: Constant change benefit = +1 (Stage 1) ---
for (i in 1:nrow(scen)) scen[i, 'u1_benefit'] <- scen[i, 'u1'] + 1

# Gov. Utilities: Costless scenario (Stage 2) ----------------------------------
scen$u2 = 1 - scen$r2
```

```
# Gov. interest rate ceiling cost of 0.5 for x = V and gamma = H (Stage 2) -----
for (i in 1:nrow(scen)) {
    if (scen[i, 'x2'] == 'V' & scen[i, 'gamma2'] == 'H') {
        scen[i, 'u2'] <- scen[i, 'u2'] - 0.5
    }
}

# Gov. Utilities: Constant change cost = -1 (Stage 2)  -------------------------
scen$u2_costly <- scen$u2
for (i in 1:nrow(scen)) {
    if (scen[i, 'trans1'] != scen[i, 'trans2']) {
        scen[i, 'u2_costly'] <- scen[i, 'u2'] + -1
    }
}

# Gov. Utilities: Constant change benefit = +1 (Stage 2) -----------------------
scen$u2_benefit <- scen$u2
for (i in 1:nrow(scen)) {
    if (scen[i, 'trans1'] != scen[i, 'trans2']) {
        scen[i, 'u2_benefit'] <- scen[i, 'u2'] + 1
    }
}

# Find preferred strategies -----------------------
scen$scenario_id_2 <- with(scen, paste(x1, x2, gamma1, gamma2, trans1,
                                       sep = '_'))

preferred <- function(x, t1, t2) {
    x <- x == max(x)
    # Minimal switching cost, i.e. status quo bias under conditions of indifference
    if (!missing(t2) & length(x[x == TRUE]) > 1) {
        x[t1 != t2] <- FALSE
    }
    x <- as.character(x)
```

```
    x[x == 'TRUE'] <- 'P'
    x[x == 'FALSE'] <- ''
    return(x)
}

# Stage 2 preferred transparency
scen <- scen %>% group_by(scenario_id_2) %>%
    mutate(preferred2_costless = preferred(u2, trans1, trans2),
           preferred2_costly = preferred(u2_costly, trans1, trans2),
           preferred2_benefit = preferred(u2_benefit, trans1, trans2)
           )

# Forced REVEAL under very high interest rates ------------
scen$forced <- ''
scen$forced[scen$trans1 == 'HIDE' & scen$trans2 == 'REVEAL' &
                scen$r2 == 3 & !(scen$x1 == 'V' & scen$x2 == 'H') &
                !(scen$x1 == 'H' & scen$x2 == 'L')
            ] <- 'F'
```

FDT inclusion criteria

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 a minimal level of development where they would actually have quantities on the included indicators. As such we include countries and

jurisdictions that the World Bank classifies as "high income".[1] There are 10 mostly non-national-level jurisdictions[2] 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.[3] We also include developing countries that are in JP Morgan's Emerging Market Bond Index (EMBI),[4] as well as China and India.[5]

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 2015 was incomplete.

The Federal Reserve Bank of St. Louis maintains the Federal Reserve Economic Data (FRED) database.[6] 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 A-2 which shows the proportion of items reported in the two versions of the data set where they do not match.[7] 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.

In general, FRED has more data, though the World Bank has more data for a few countries such as 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 about 30 percent of items in the FRED version of the GFDD. In the World Bank version, San Marino reported almost none. 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.

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

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

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

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

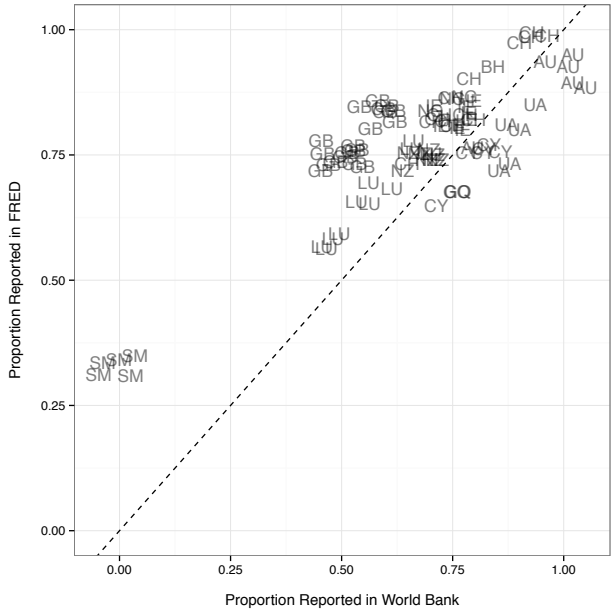
[4] See: https://www.jpmorgan.com/pages/jpmorgan/investbk/solutions/research/indices/product. Accessed May 2015. The countries included in the EMBI as of this writing are: Argentina, Brazil, Colombia, Ecuador, Egypt, Mexico, Morocco, Nigeria, Panama, Peru, Philippines, Poland, Russian Federation, South Africa, Turkey, Ukraine, and Venezuela.

[5] Note that we originally estimated the index with only high income countries. Estimated scores largely matched those when the index was run with the full sample.

[6] Available at: http://research.stlouisfed.org/fred2/. Accessed February 2016.

[7] 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 A-2: 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.

reported for a country-year if it is published in *either* the FRED or World Bank versions of the GFDD.

Further details on FDT estimation model priors and convergence criteria

For each transparency parameter estimated 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 et al. (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–$Cauchy(0,\ 0.25)$–[8]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 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

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

in general are (Hoffman and Gelman, 2014). We implemented the model with Stan (Stan Development Team, 2015).[9] 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 the JAGS equivalent.[10] We ran the model for 4 chains of 120,000 iterations (half of which were burn-in) and used the Gelman-Rubin Diagnostic (Gelman and Rubin, 1992) to assess convergence with the 1.1 threshold (Gelman et al., 2014, 287).

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.[11] 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 A-3 compares the proportion of items used (a frequency measure) in the FDT Index a country reported in a given year to that country-year's FDT score.[12] Rather than having a linear relationship, we can see that the FDT Index is less sensitive to indicator reporting than the frequency measure for countries that report fewer items. The FDT does not over-estimate the effect of reporting only the easy items the way that the frequency measure does. It is more sensitive when countries report many items. There is a wide range of FDT scores for countries that report more items as it can distinguish between the harder and easier items to report.

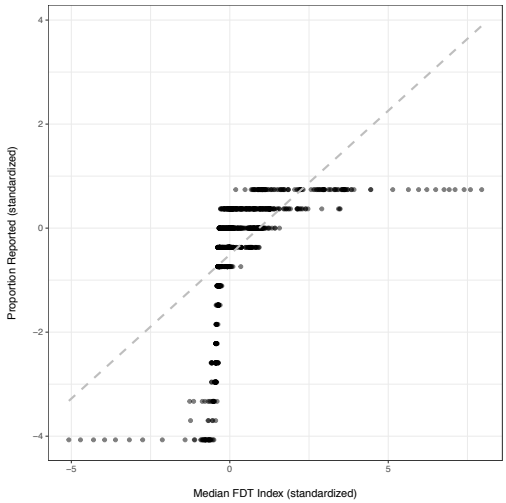
[9] The Stan model can be found at in the Appendix

[10] The Stan version of the model is approximately 67 lines of code whereas equivalent JAGS model is over 150.

[11] See figures A-12, A-13, A-14, and A-15 in the Appendix for the proportions of items reported for each country in our sample.

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

Figure A-3: Comparing Frequency Reported vs. FDT Index



Both the Proportion Reported transparency indicator and the FDT Index scores are standardized by subtracting their medians and dividing by their standard deviations.

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

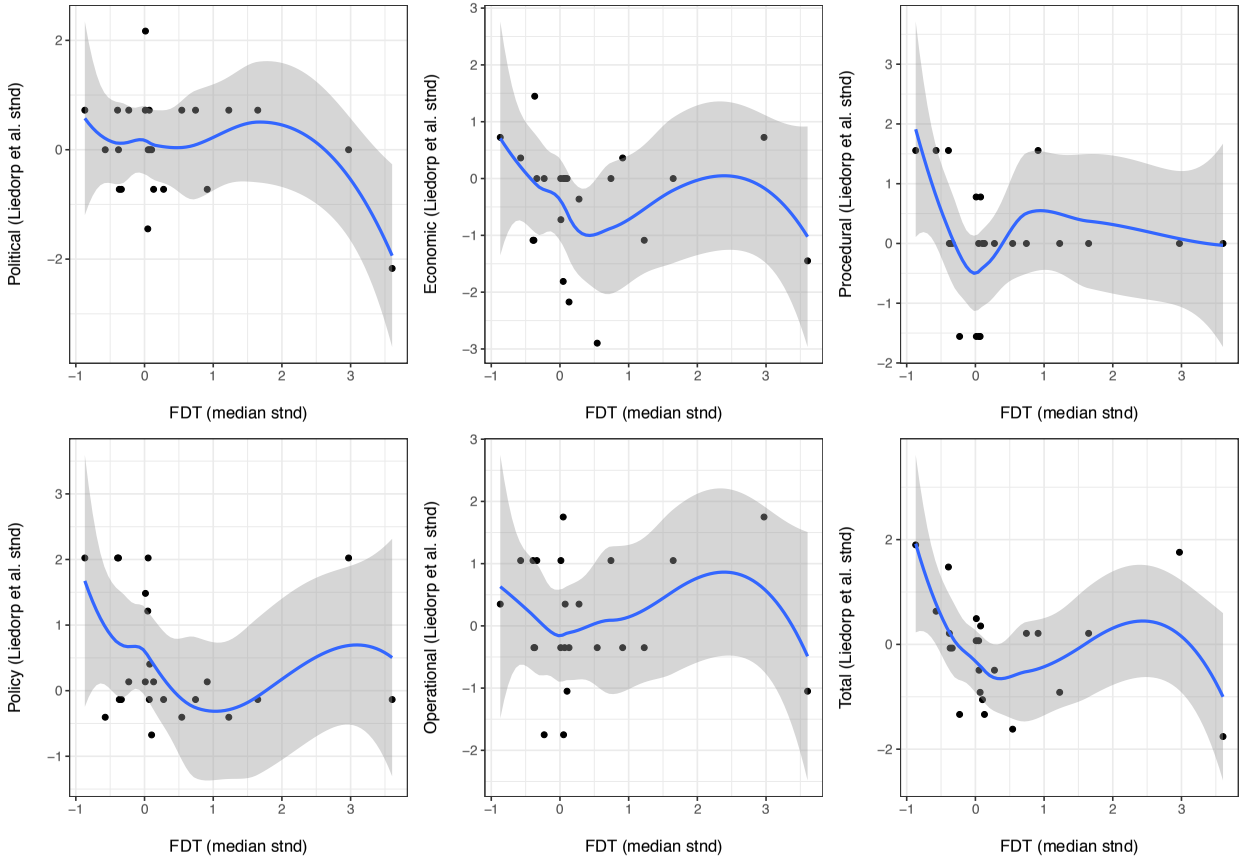
Before directly comparing the FDT Index to Liedorp et al.'s frequency-survey measure, it is important to consider the substantive and practical differences between the two indices. The indices, by design, are estimates of different aspects of transparency. A considerable portion of Liedorp et al.'s index 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 FDT captures, namely making off-site inspection reports publicly available. Though again, this is not exactly the same as the FDT 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 A-4 compares the FDT 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 FDT 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.[13] The United Kingdom consistently only reported about 75 percent of the items.

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

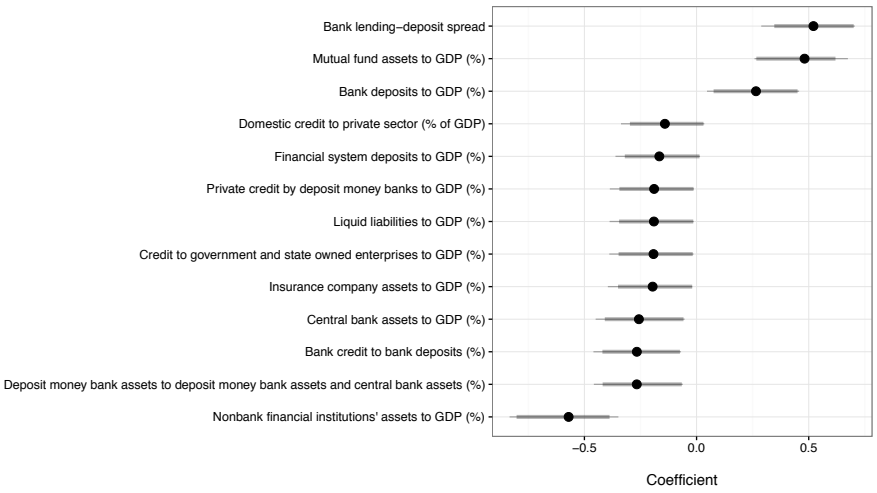
Figure A-4: Comparison of the FDT Index to Liedorp et al. (2013)



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

Item difficulty parameter estimates

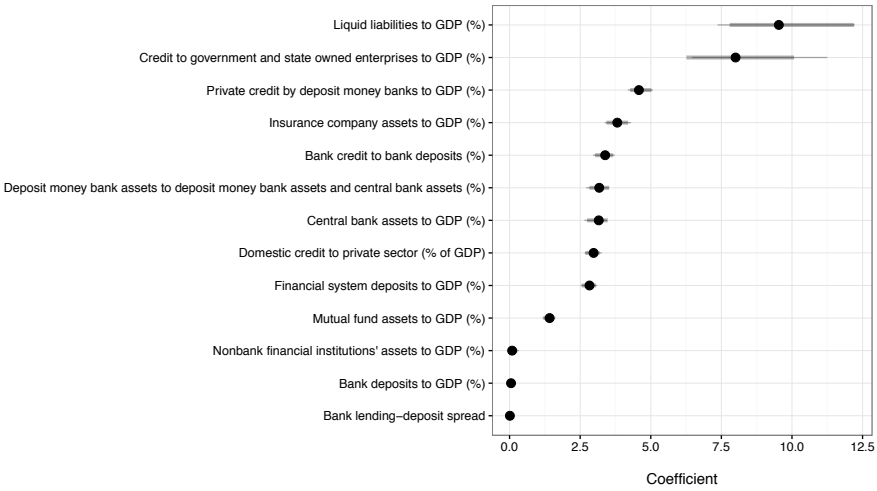
Figure A-5: Estimated Item Difficulty Parameters



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

Item discrimination parameter estimates

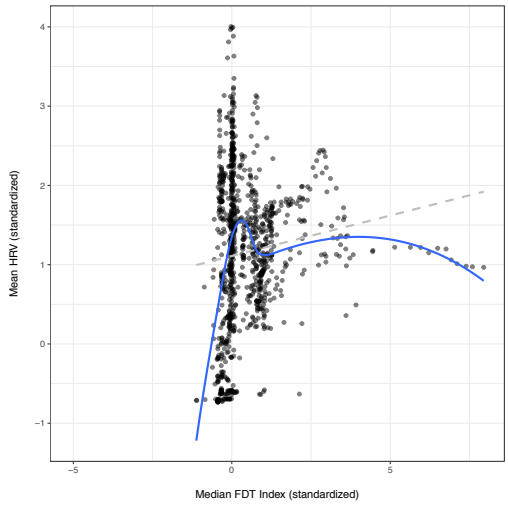
Figure A-6: Estimated Item Discrimination Parameters



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

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

Figure A-7: Comparison of the FDT Index to the HRV Transparency Index



Both the HRV and FDT scores are standardized by subtracting their medians and dividing by their standard deviations.

The FDT'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<lower=0>[K] 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 {
    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);

    for (c in 1:C) {
        alpha[c,1] ~ normal(recentered_alpha1[c],0.001); // overcome Stan issue
        for (t in 2:T)
            alpha[c,t] ~ normal(alpha[c,t-1], sigma_alpha[c]);
    }

    beta ~ normal(0,sigma_beta);
    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(gamma[kk[n]])
            * (alpha[cc[n],tt[n]] - beta[kk[n]] + delta) );
}
```

Figure A-8: Individual Countries' FDT Scores Over Time (1)

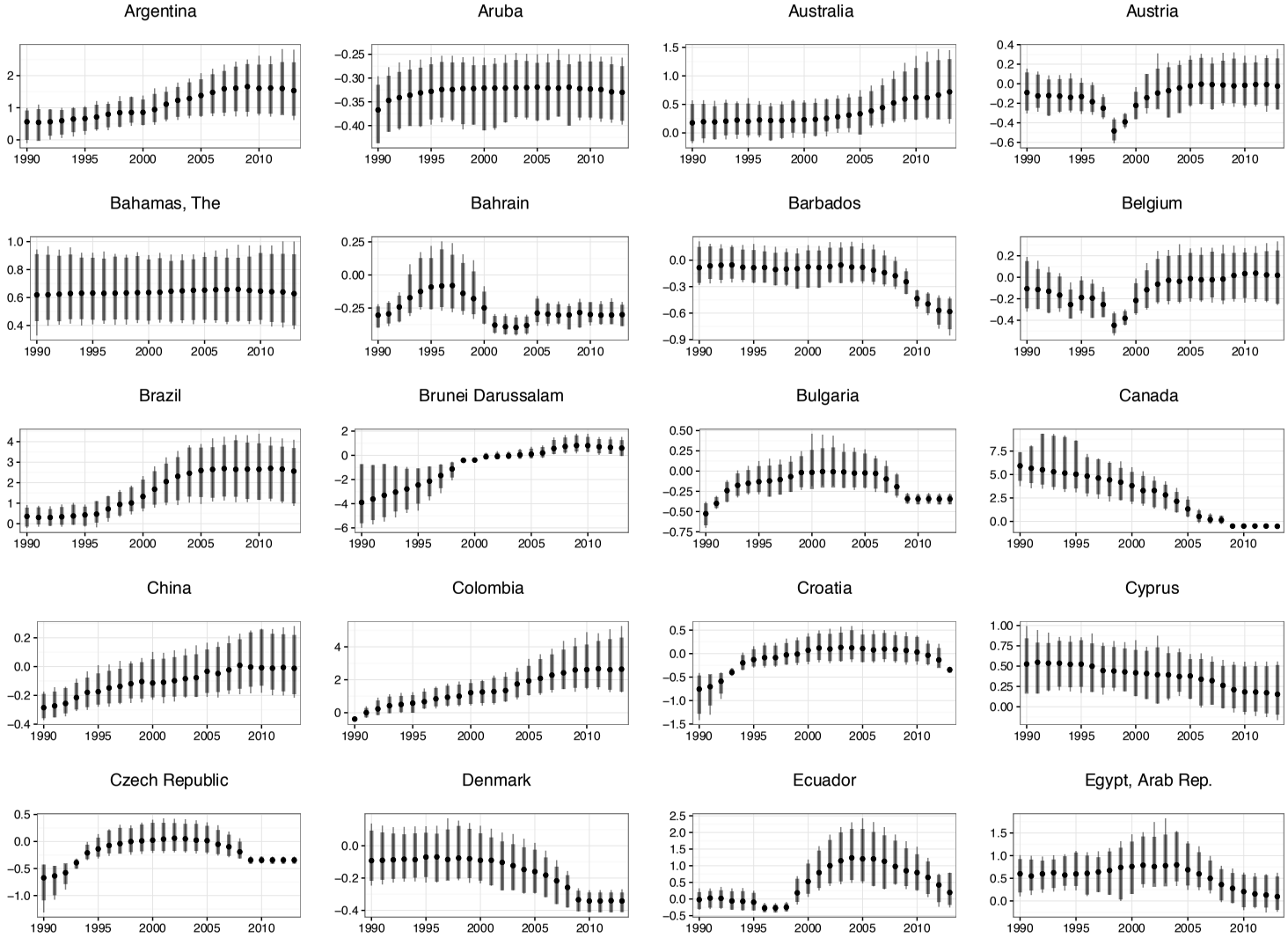


Figure A-9: Individual Countries' FDT Scores Over Time (2)

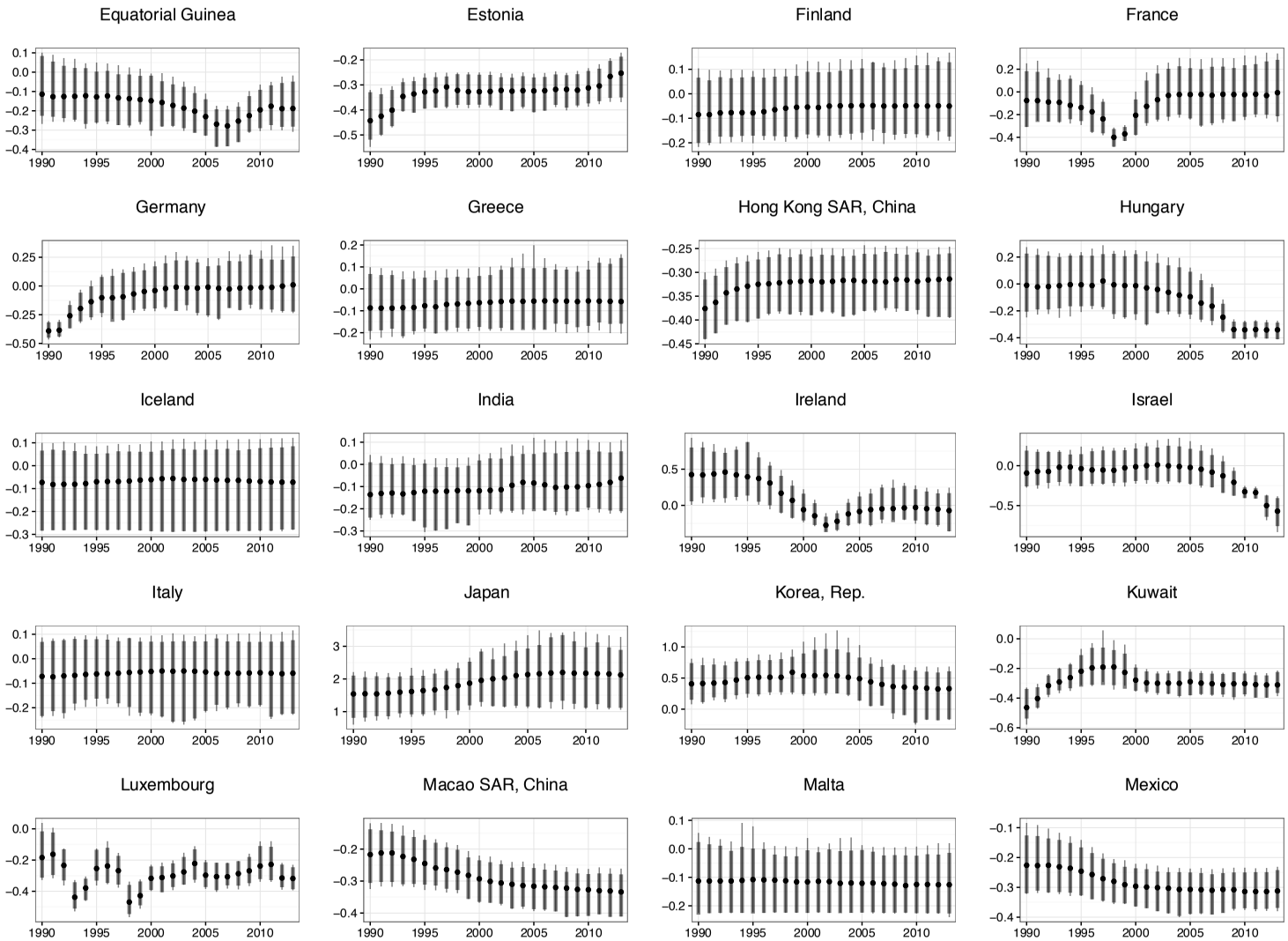


Figure A-10: Individual Countries' FDT Scores Over Time (3)

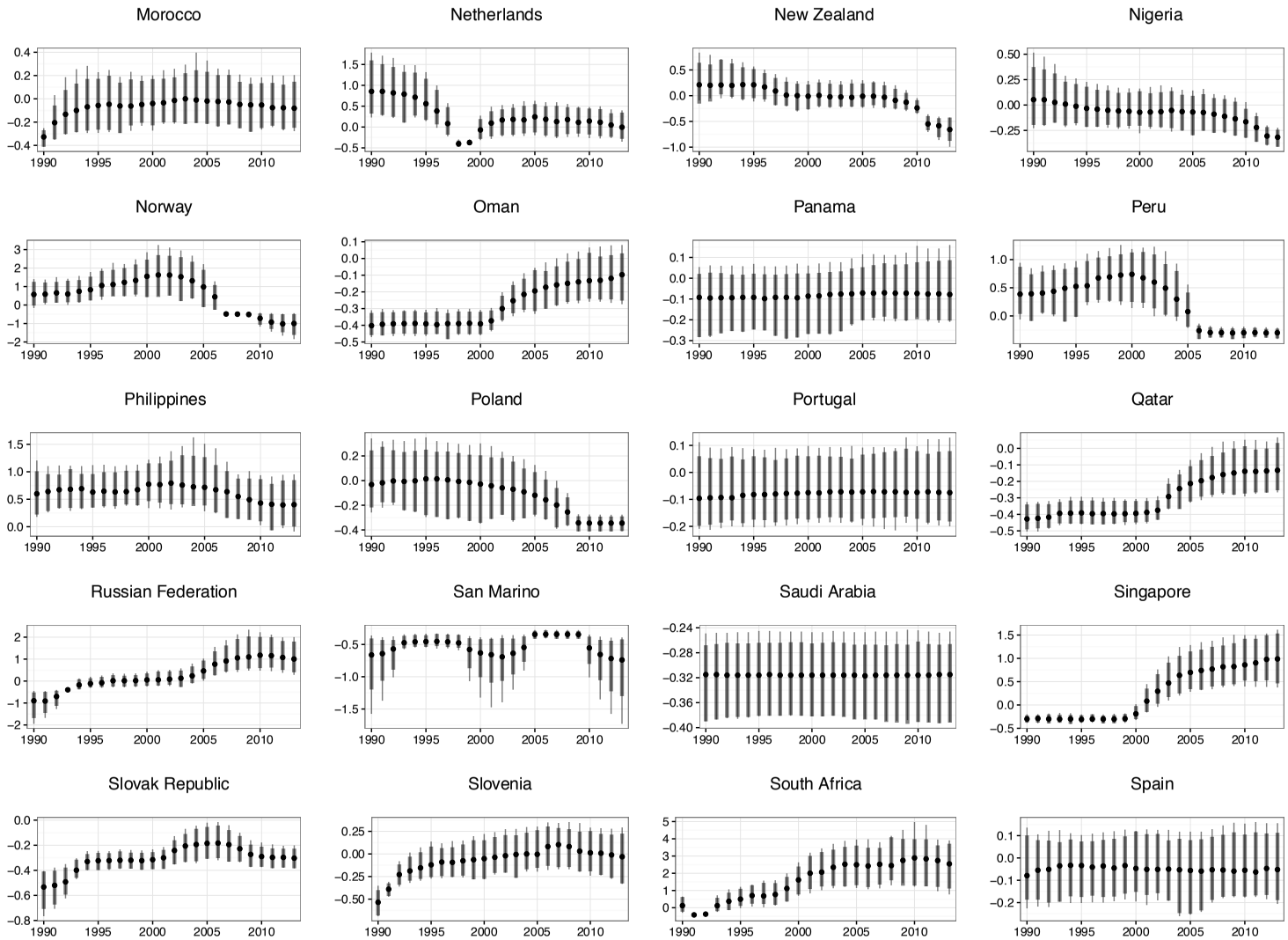


Figure A-11: Individual Countries' FDT Scores Over Time (4)

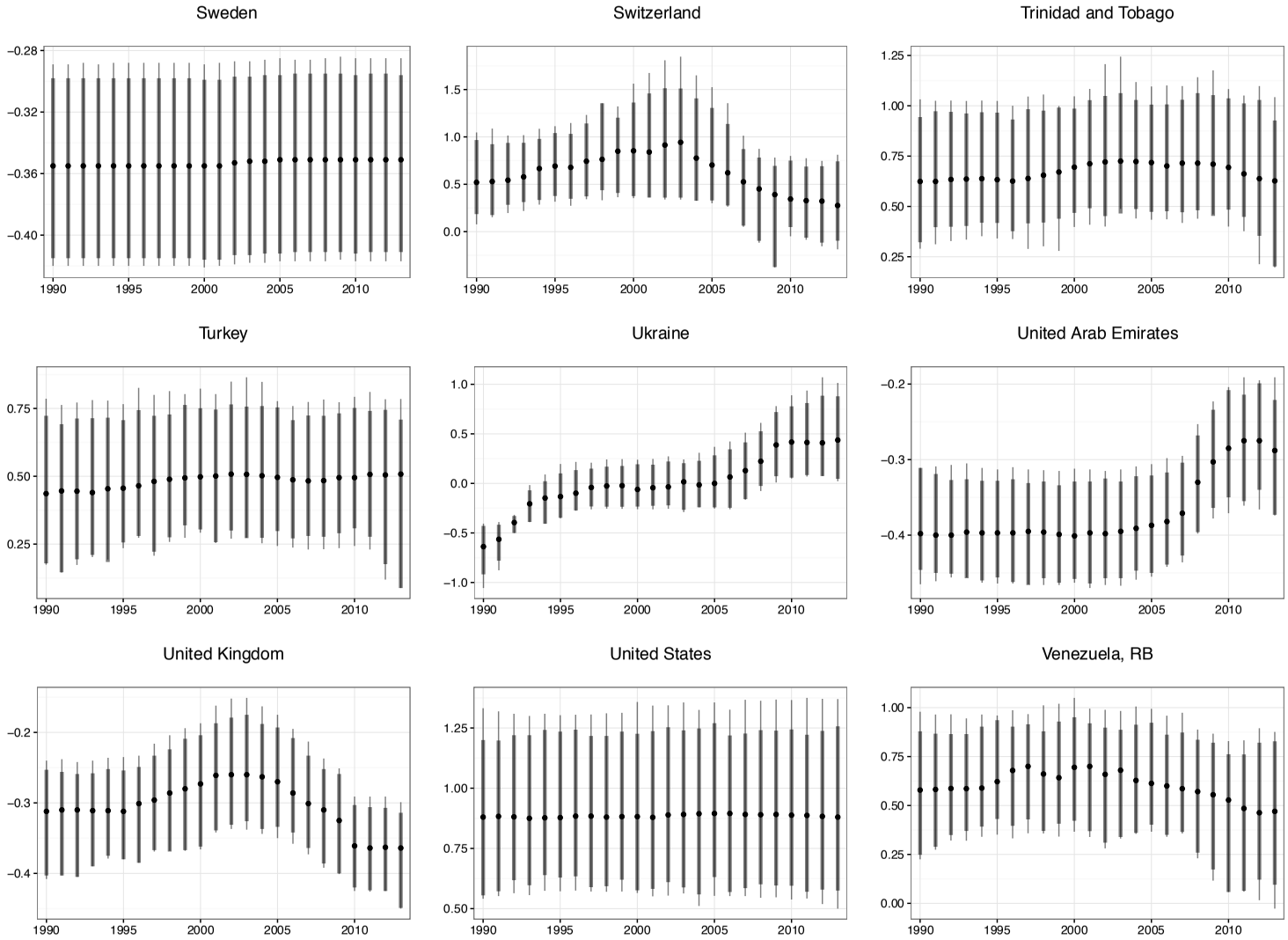


Figure A-12: Individual Countries' Proportions of Items Reported Over Time (1)

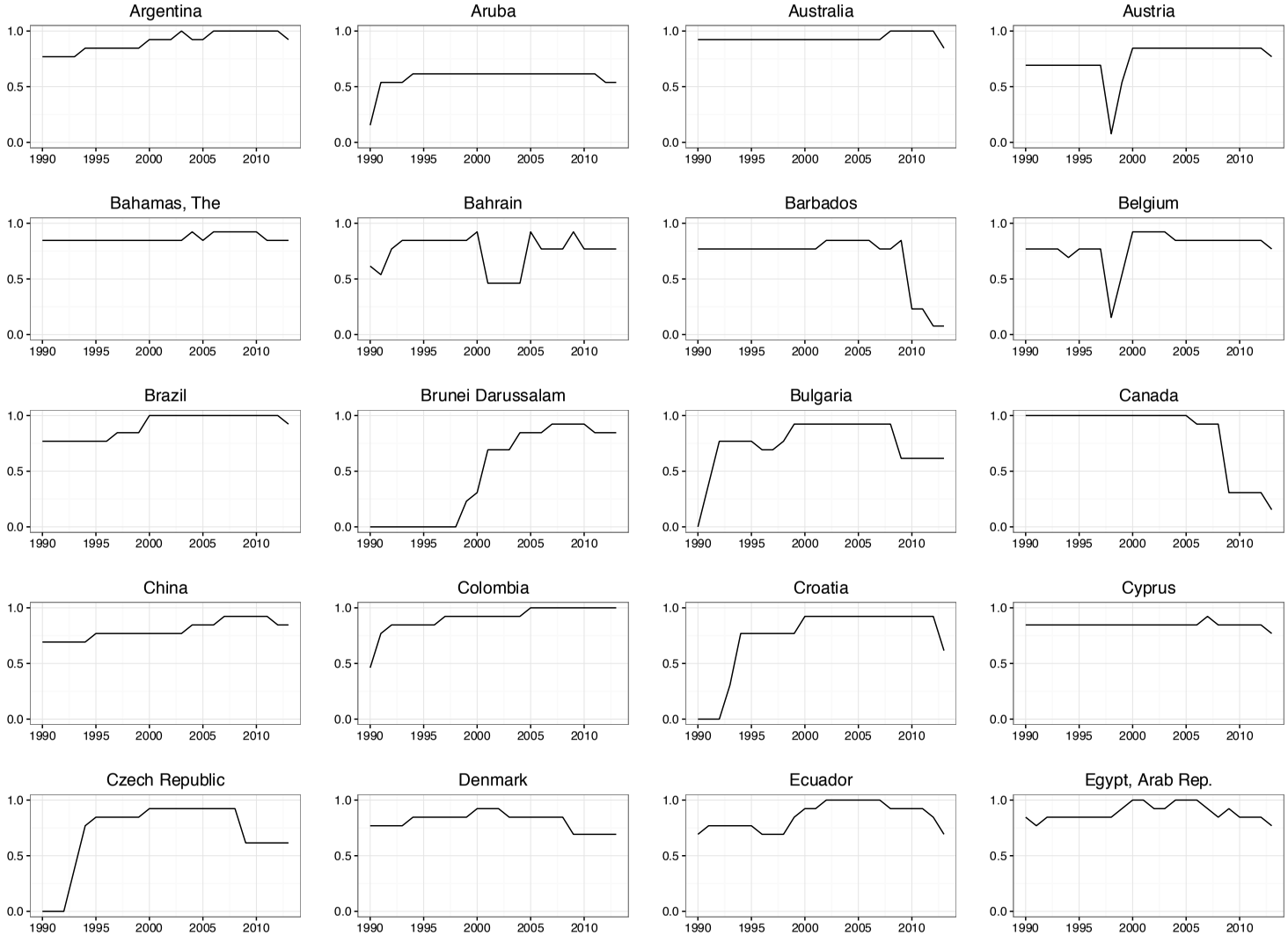


Figure A-13: Individual Countries' Proportions of Items Reported Over Time (2)

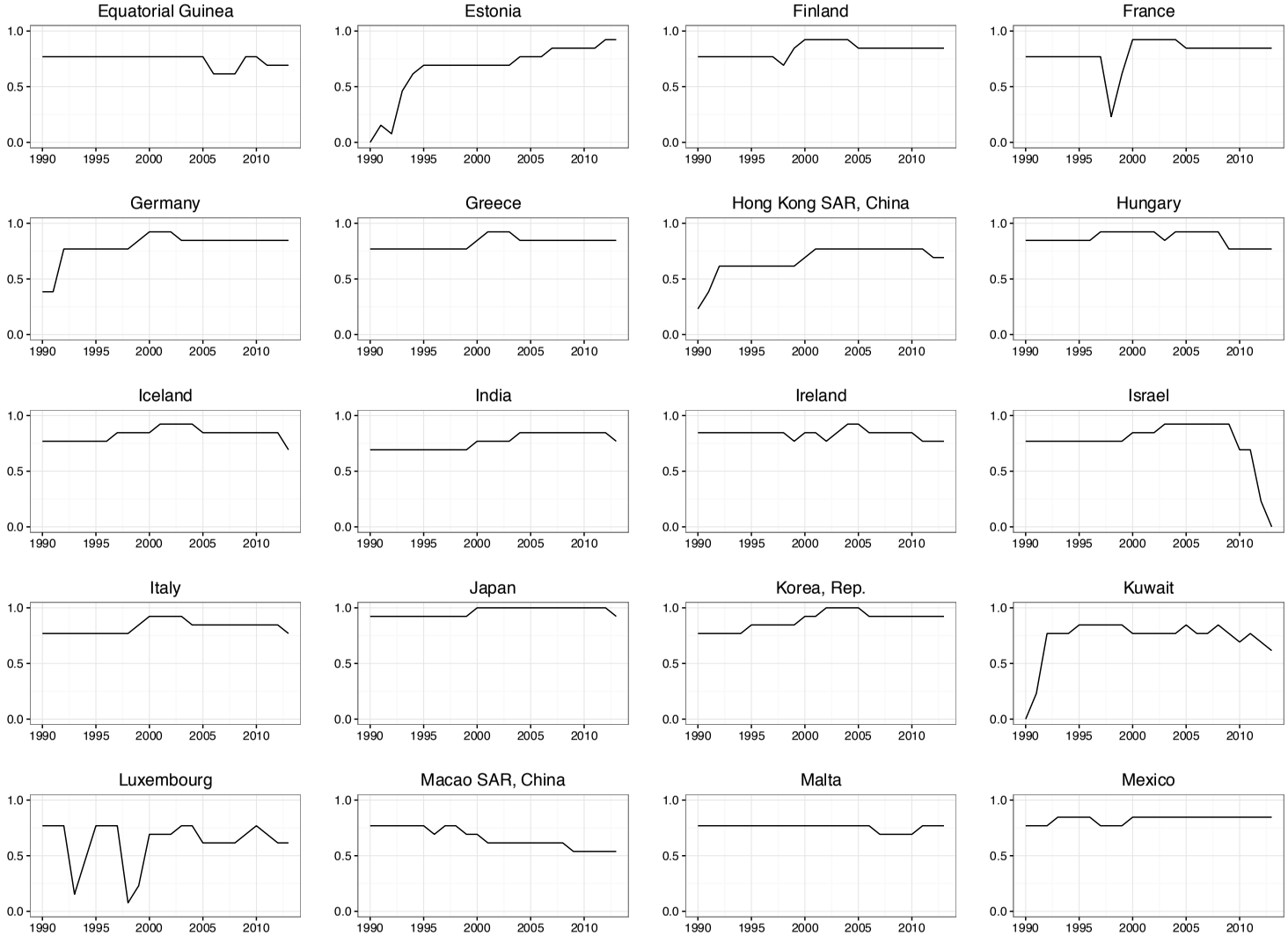


Figure A-14: Individual Countries' Proportions of Items Reported Over Time (3)

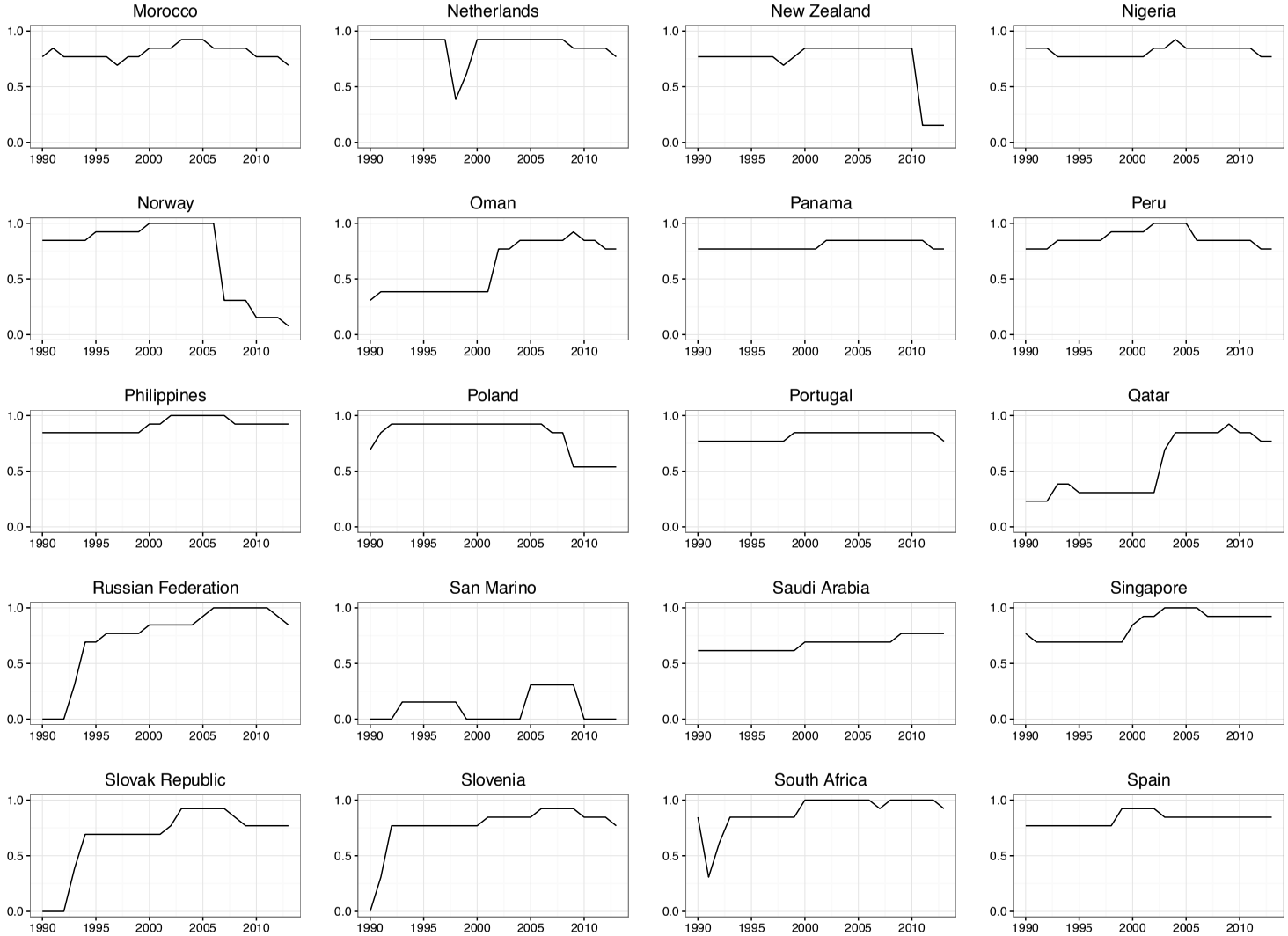
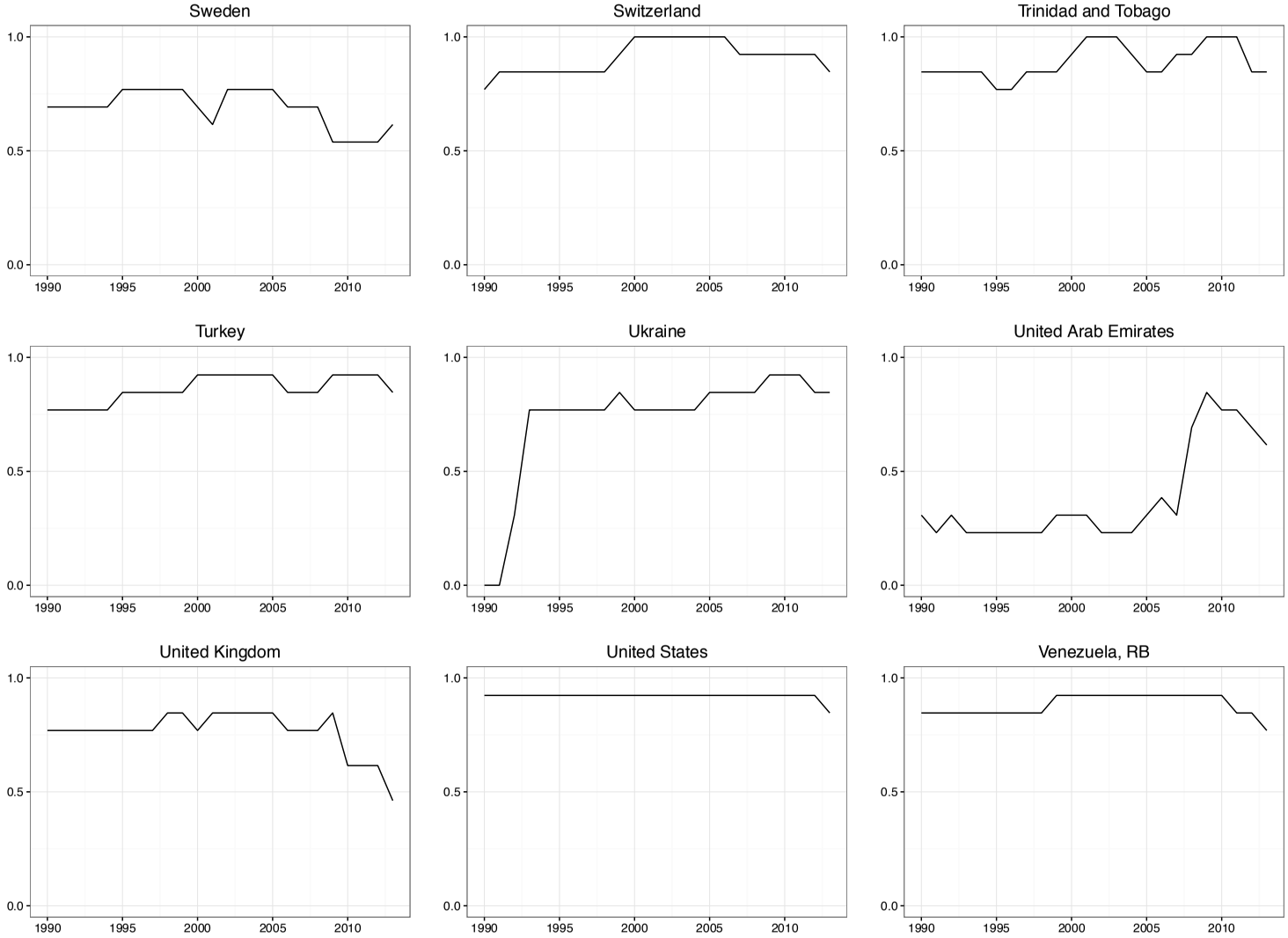


Figure A-15: Individual Countries' Proportions of Items Reported Over Time (4)



Regression model country sample

Note that the United States is excluded from models with bond spreads as the dependent variable and Japan is excluded from all models. Please see the main text for details.

Table A-2: Country sample for OECD countries (as of 2016) for which there is complete data

Country	First Year	Last Year
Australia	1991	2011
Austria	1991	2011
Belgium	1991	2011
Canada	1991	2011
Czech Republic	2001	2011
Denmark	1991	2011
Finland	1992	2011
France	1991	2011
Germany	1993	2011
Greece	1998	2011
Hungary	2000	2011
Iceland	1993	2011
Ireland	1991	2011
Israel	1998	2011
Italy	1992	2011
Japan	1991	2011
Korea, Republic of	2001	2011
Luxembourg	1994	2006
Mexico	2003	2006
Netherlands	1991	2011
New Zealand	1991	2011
Norway	1991	2011
Poland	2002	2011
Portugal	1994	2011
Slovakia	2001	2011
Slovenia	2003	2011
Spain	1991	2011
Sweden	1991	2011
Switzerland	1991	2011
United Kingdom	1991	2011
United States	1991	2011

Table A-3: Re-examining Sovereign Bond Prices Including Executive Election Year & Executive Economic Ideology

	Δ Long-term (10-year) bond spread (US 10-year bond, %)	Δ Long-term (10-year) bond spread (US 10-year bond, %)	Δ Coefficient of variation, LT bond yields (annual, based on monthly data)	Δ Coefficient of variation, LT bond yields (annual, based on monthly data)
Bond Spread$_{t-1}$	-0.33***	-0.33***		
	(0.06)	(0.06)		
LT rate COV$_{t-1}$			-0.74***	-0.73***
			(0.06)	(0.05)
FDT$_{t-1}$	-0.04	-0.22*	-0.70*	-3.87***
	(0.06)	(0.12)	(0.35)	(0.88)
Δ FDT	0.35**	0.30	0.27	-1.98
	(0.14)	(1.14)	(1.13)	(6.06)
Public debt/GDP (%)$_{t-1}$	0.01**	0.01*	0.05**	0.06***
	(0.01)	(0.01)	(0.02)	(0.02)
Δ Public debt/GDP	0.04*	0.04**	0.15***	0.18***
	(0.02)	(0.02)	(0.05)	(0.05)
Inflation (%) $_{t-1}$	0.07	0.07	0.00	-0.08
	(0.04)	(0.04)	(0.17)	(0.16)
Δ Inflation (%)	0.17***	0.17***	-0.09	-0.08
	(0.04)	(0.04)	(0.14)	(0.14)
GDP Growth$_{t-1}$	-0.18**	-0.19**	0.07	0.06
	(0.08)	(0.08)	(0.17)	(0.20)
Δ GDP Growth	-0.16**	-0.16**	-0.11	-0.12
	(0.07)	(0.07)	(0.15)	(0.18)
Per Capita GDP$_{t-1}$	0.00	0.00	-0.10	-0.06
	(0.01)	(0.01)	(0.06)	(0.04)
Δ Per Capita GDP	0.27***	0.28***	0.27	0.41
	(0.07)	(0.07)	(0.28)	(0.36)
OECD average GDP growth$_{t-1}$	0.08	0.09	-0.09	0.16
	(0.08)	(0.08)	(0.19)	(0.17)
Δ OECD average GDP growth	0.00	0.00	0.43**	0.38**
	(0.06)	(0.06)	(0.20)	(0.18)
US 3-month interest rate (%)$_{t-1}$	-0.07**	-0.07**	-0.84***	-0.74***
	(0.03)	(0.03)	(0.18)	(0.16)
Δ US 3-month interest rate (%)	-0.20***	-0.20***	-0.45**	-0.76***
	(0.03)	(0.03)	(0.20)	(0.18)
VIX index$_{t-1}$	-0.02	-0.02	0.03	
	(0.01)	(0.01)	(0.04)	
Δ VIX index	-0.00	-0.01	0.22***	
	(0.01)	(0.01)	(0.05)	
Exec. Election$_{t-1}$	0.01	0.02	-0.25	-0.19
	(0.07)	(0.07)	(0.42)	(0.44)
Left Executive$_{t-1}$	0.04	0.02	-0.42	-0.60
	(0.07)	(0.07)	(0.45)	(0.52)
FDT$_{t-1}$ * Public debt/GDP (%)$_{t-1}$		0.00*		0.03***
		(0.02)		(0.10)
Δ FDT * Δ Public debt/GDP		0.05*		0.33***
		(0.00)		(0.01)
FDT$_{t-1}$ * Δ Public debt/GDP		-0.00		0.03*
		(0.02)		(0.10)
Δ FDT * Public debt/GDP (%)$_{t-1}$		0.00		0.03
		(0.00)		(0.02)
Constant	-0.31	-0.28	8.74**	6.38**
	(0.94)	(0.94)	(3.44)	(2.82)
Countries	29	29	30	30
Observations	499	499	529	529
Adjusted R-squared	0.37	0.37	0.39	0.38

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

All regressions include country fixed effects and robust standard errors.

Japan outlier excluded.

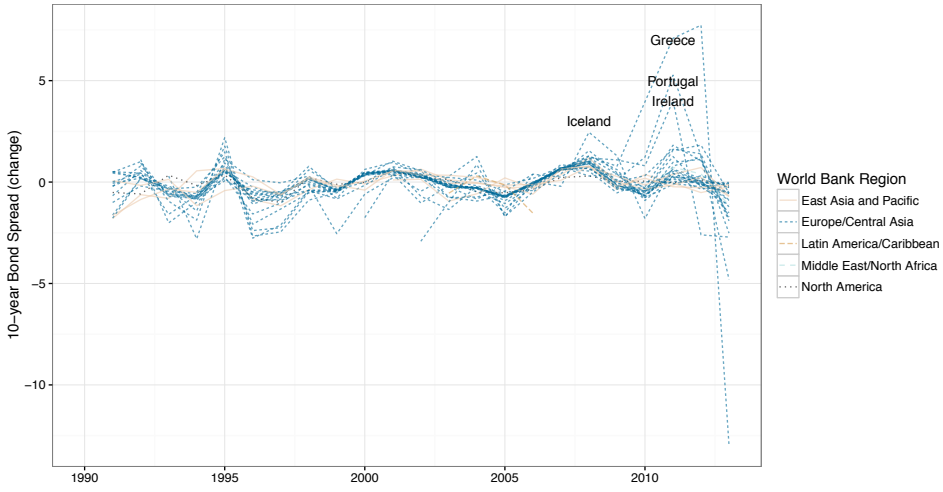
Table A-4: Moran's I Test Statistic of Spatial Autocorrelation, Δ Long-term (10-year) bond spread (US 10-year bond, %)

Year	Observed Moran's I	P-Value
1991	-0.01	0.638
1992	0.46	6.66e-07
1993	-0.05	0.965
1994	-0.04	0.887
1995	-0.00	0.562
1996	0.05	0.24
1997	-0.07	0.83
1998	-0.09	0.634
1999	0.06	0.0307
2000	-0.01	0.559
2001	0.03	0.289
2002	-0.01	0.587
2003	-0.10	0.308
2004	-0.06	0.678
2005	0.32	8.26e-09
2006	0.08	0.0327
2007	-0.00	0.523
2008	-0.03	0.847
2009	-0.03	0.924
2010	-0.05	0.82
2011	0.03	0.237
2012	-0.04	0.94
2013	-0.02	0.617

Table A-5: Moran's I Test Statistic of Spatial Autocorrelation, Δ Coefficient of variation, LT bond yields (annual, based on monthly data)

Year	Observed Moran's I	P-Value
1991	-0.15	0.53
1992	0.19	0.0708
1993	0.16	0.114
1994	-0.03	0.894
1995	-0.26	0.0598
1996	-0.17	0.286
1997	0.17	0.0672
1998	-0.20	0.179
1999	0.05	0.363
2000	0.20	0.0324
2001	0.04	0.397
2002	-0.15	0.192
2003	0.03	0.294
2004	-0.16	0.0372
2005	0.25	0.00202
2006	-0.02	0.873
2007	0.09	0.123
2008	-0.09	0.602
2009	-0.06	0.815
2010	-0.01	0.831
2011	-0.02	0.881
2012	0.12	0.0986
2013	0.19	0.0148

Figure A-16: Change in Long-Term Bond Spreads Grouped by World Bank Geographic Region (OECD Sample)



Countries highlighted with unusually large spread increases in a given year.

Table A-6: Re-examining Sovereign Bond Prices using the Hollyer et al. (2014) Transparency Index (HRV)

	Δ Long-term (10-year) bond spread (US 10-year bond, %)	Δ Long-term (10-year) bond spread (US 10-year bond, %)	Δ Coefficient of variation, LT bond yields (annual, based on monthly data)	Δ Coefficient of variation, LT bond yields (annual, based on monthly data)	Δ Long-term (10-year) bond spread (US 10-year bond, %)
Bond Spread$_{t-1}$	-0.40***	-0.40***			-0.40***
	(0.04)	(0.04)			(0.04)
LT rate COV$_{t-1}$			-0.84***	-0.84***	
			(0.06)	(0.06)	
HRV$_{t-1}$	-0.02	-0.04	-0.12	-0.21	
	(0.02)	(0.05)	(0.15)	(0.34)	
Δ HRV	-0.04	0.00	0.23	0.49	
	(0.08)	(0.07)	(0.66)	(1.33)	
Public debt/GDP (%)$_{t-1}$	0.01*	0.01	0.03	0.02	0.01*
	(0.00)	(0.01)	(0.02)	(0.02)	(0.00)
Δ Public debt/GDP	0.05***	0.05	0.15**	0.11	0.05***
	(0.01)	(0.04)	(0.06)	(0.12)	(0.02)
Inflation (%) $_{t-1}$	0.14***	0.14***	-0.22	-0.23	0.14***
	(0.04)	(0.04)	(0.17)	(0.17)	(0.04)
Δ Inflation (%)	0.21***	0.21***	-0.09	-0.10	0.22***
	(0.05)	(0.05)	(0.13)	(0.14)	(0.05)
GDP Growth$_{t-1}$	-0.06	-0.06	-0.30	-0.30	-0.06
	(0.05)	(0.05)	(0.20)	(0.22)	(0.05)
Δ GDP Growth	-0.07	-0.07	-0.23	-0.23	-0.06
	(0.05)	(0.06)	(0.22)	(0.24)	(0.06)
Per Capita GDP$_{t-1}$	0.00	0.00	-0.15**	-0.14**	0.00
	(0.01)	(0.01)	(0.06)	(0.06)	(0.01)
Δ Per Capita GDP	0.18*	0.18*	0.35	0.40	0.17
	(0.09)	(0.10)	(0.50)	(0.55)	(0.10)
OECD average GDP growth$_{t-1}$	-0.02	-0.01	-0.16	-0.20	-0.01
	(0.06)	(0.06)	(0.30)	(0.29)	(0.06)
Δ OECD average GDP growth	-0.04	-0.03	0.42	0.38	-0.03
	(0.05)	(0.05)	(0.25)	(0.22)	(0.05)
US 3-month interest rate (%)$_{t-1}$	-0.03	-0.04	-0.37**	-0.35**	-0.04
	(0.04)	(0.04)	(0.17)	(0.17)	(0.04)
Δ US 3-month interest rate (%)	-0.19***	-0.20***	-0.05	-0.03	-0.20***
	(0.04)	(0.04)	(0.20)	(0.19)	(0.04)
VIX index$_{t-1}$	-0.02*	-0.02*	0.06	0.07*	-0.02*
	(0.01)	(0.01)	(0.04)	(0.04)	(0.01)
Δ VIX index	-0.01	-0.01	0.24***	0.24***	-0.02
	(0.01)	(0.01)	(0.04)	(0.03)	(0.01)
Democracy (UDS)$_{t-1}$	-0.05	-0.04	0.36	0.47	-0.03
	(0.16)	(0.17)	(1.02)	(1.04)	(0.17)
Δ Democracy (UDS)	-0.33*	-0.33	-0.09	-0.02	-0.32
	(0.19)	(0.21)	(0.74)	(0.80)	(0.20)
HRV$_{t-1}$ * Public debt/GDP (%)$_{t-1}$		0.00		0.00	
		(0.00)		(0.02)	
Δ HRV * Δ Public debt/GDP		-0.01		0.05	
		(0.00)		(0.00)	
HRV$_{t-1}$ * Δ Public debt/GDP		0.00		0.01	
		(0.02)		(0.10)	
Δ HRV * Public debt/GDP (%)$_{t-1}$		-0.00		-0.00	
		(0.01)		(0.02)	
FDT Residuals$_{t-1}$					-0.04
					(0.05)
Δ FDT Residuals					-0.01
					(0.08)
FDT Residuals$_{t-1}$ * Public debt/GDP (%)$_{t-1}$					0.00
					(0.00)
Δ FDT Residuals * Δ Public debt/GDP					-0.01
					(0.00)
FDT$_{t-1}$ * Δ Public debt/GDP					0.00
					(0.02)
Constant	-0.06	0.01	11.44***	11.06***	-0.10
	(0.83)	(0.90)	(3.68)	(3.67)	(0.84)
Countries	23	23	24	24	23
Observations	395	395	421	421	395
Adjusted R-squared	0.45	0.44	0.49	0.49	0.45

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

All regressions include country fixed effects and robust standard errors. Japan outlier excluded. The IMF Program Start variable was also omitted because of collinearity. The results are substantively similar when we exclude the UDS democracy level.

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