Measuring Transparency, Again: Updating and Extending the HRV Transparency Index

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Abstract

This paper describes an updated version of the HRV Transparency Index first introduced in Hollyer, Rosendorff and Vreeland (2014). This measure of transparency captures governments' tendency to disclose credible information on the functioning of the economy and society to international organizations – and, by extension, to the general public. It does so by fitting an item response model to a data matrix representing the reporting/missingness of 228 variables drawn from the World Development Indicators data series, released by the World Bank. The current version of the index is not a direct replication of its predecessor, owing to changes in reporting policies at the Bank. It expands the temporal coverage, which previously ended in 2010, to 2015. And it expands the cross-sectional coverage (previously 125 countries from 1980-2010) to include 24 additional countries that enter the dataset in 1993. In addition to describing the new index, we compare it to its predecessor (HRV1) and replicate the results of Hollyer, Rosendorff and Vreeland (2018) using the updated index.

Government transparency refers to the openness of the informational environment in a given polity. The term term has been used to refer to citizens' ease of access to government deliberations (e.g., Broz, 2002; Prat, 2005; Stasavage, 2004), government records (Berliner, 2014; Berliner and Erlich, 2015), or the details of government regulations and laws (Li, 2022). Elsewhere, it refers to the reach or freedom of the media (e.g. Adserà, Boix and Payne, 2003; Besley and Burgess, 2002; Brunetti and Weder, 2003).[1] Hollyer, Rosendorff and Vreeland (2014) define a particular facet of transparency: governments' collection and dissemination of information about the state of the economy and society to the mass public. They develop a novel measure of this dimension of transparency – a latent index reflecting governments' disclosure of information to the World Development Indicators (WDI), covering 125 countries from 1980-2010. They (immodestly) dub this measure the HRV Transparency Index.

The HRV Index has become a widely used cross-national measure of the richness of states' informational environments. Hollyer, Rosendorff and Vreeland (2018) demonstrate that this measure (1) predicts the collapse of autocratic regimes by mass protest or processes leading to democratization, (2) is negatively correlated with the frequency of coups in autocracies, (3) predicts the survival of democratic regimes – in particular, under-performing democratic leaders are more likely to be ousted by elections in transparent countries and by irregular methods in opaque ones, and (4) predicts higher levels of investment (both domestic and foreign). Others have used this measure to investigate the effects of government disclosures on areas as diverse as governments choices across debt instruments (Mosley and Rosendorff, 2023), the ownership structures of firms engaged in FDI (Betz and Pond, 2023), on reporting of human rights violations (Creamer and Simmons, 2019), the decisions by MNCs to invest in risky environments (Barry and DiGiuseppe, 2019). The measurement strategy employed in the HRV Index may also be modified to develop measures of information availability tailored to particular research questions, as in Copelovitch, Gandrud and Hallerberg (2015).

The HRV Index is, however, constrained in its coverage. To ensure that the data matrix was rectangular, Hollyer, Rosendorff and Vreeland (2014) restrict the set of countries in the analysis to 125.[2] The authors also drop the last two years of the raw data, terminating the analysis in 2010, to reduce the risk that reporting delays might influence the structure of the measure. The index thus had coverage from 1980-2010, for 125 countries, with no missing observations.

We extend this dataset, and do so in two dimensions. First, we extend coverage temporally through 2015. We find that reporting delays influence the index well beyond the two year period the initial index adjusts for, and so we drop the last six years from the date the data were initially downloaded. Second, we expand the index cross-sectionally. Specifically, we allow for another 'round' of countries to enter into the index in 1993, expanding coverage by 24 (mostly post-Soviet) states. As a consequence, the data are no

[1]For a simple conceptual model of different forms of government transparency and their relation to government accountability, see Hollyer, Rosendorff and Vreeland (2018, chapter 2).

[2]The WDI reports information on countries in existence at the time the data are accessed – in this instance, in late-2012. To ease the coding of the autoregressive priors in the estimation model, the authors drop all countries that came into existence after the start of their index, in 1980. And all micro-states with populations that fall below 500,000 during the estimation window are dropped.

longer rectangular: the new HRV2 Index covers 125 countries from 1980-2015 and 24 additional countries from 1993, leading to a total of 149 countries from 1993 to 2015.

However, this is not merely an extension of the original HRV dataset. The HRV index is built on a measurement model, and we must revise and refit the HRV algorithm to the new (as of 2020) underlying data from the World Bank's World Development Indicators (WDI) (World Bank, N.d.).

Moreover, the WDI are not merely appended together each year, with a new set of observations one year being added to a series stretching back in time. To a degree not often appreciated by applied researchers, the WDI are living data, subject to constant revision and updating by the World Bank (Goes, 2023, 2024). Over time, whole data series (variables) are added and removed from the WDI collection. Observations are revised, or changed from missing to reported, as more information becomes available. Processes such as GDP re-basing (Kerner and Crabtree, 2018) often lead to substantial changes in basic national accounts statistics. Whole countries may be deleted or added, since the WDI includes only presently existing states in its database. These changes, particularly the backfilling of previously unreported data, mean that the correlation between the updated index (HRV2) and the original (HRV1) is 0.78, rather than 1.00.[3]

In what follows, we outline the construction of the HRV2 index in greater detail. We then discuss the departures in coding from the original HRV1 and compare the systematic discrepancies between the two measures. We then replicate the results in Hollyer, Rosendorff and Vreeland (2018), and demonstrate that these overwhelmingly hold when the HRV2 index is used in place of HRV1. We conclude with a reflection on the implications of the WDI's revision process for scholarly work.

Measurement Model

As with the original HRV1 index, we treat 'transparency' as the latent (unobserved) tendency for a given country in a given year to report economic information to the World Bank. This information is typically collected by a given country's national statistical offices, before being disclosed to international organizations (IOs). For instance, both the IMF and ILO collect information related to national accounts, financial flows, and labor statistics. The WDI mostly consists of data the World Bank compiles from these and similar organizations.[4] During the reporting process, these data are subject to some degree of vetting by the collecting organizations (by the World Bank and by intermediary IOs); data that fail to meet basic international standards are deleted. We thus use the reporting of information that makes it into the WDI as a proxy for the tendency for governments to make available valid information pertaining to the economy and society to a broader range of actors. This assumes that countries are unlikely to be making information available at

[3]The WDI is not alone in this process of revision, deletion and addition of data. See, for instance Horn et al. (2024) on backfilling and revisions to the World Bank International Debt Statistics.

[4]Some WDI data are collected directly by the World Bank – e.g., the World Governance Indicators, or (formerly) the Doing Business Survey. We omit both these series from our estimates. We also omit international debt statistics, many of which are reported only for developing economies.

home that they are unwilling to report to the World Bank, and *vice versa*.[5]

To help ensure that the common tendency to report any two variables to the WDI is driven only by this latent transparency term, Hollyer, Rosendorff and Vreeland (2014) trim the WDI dataset of measures of common concepts in different currencies and eliminate terms that are simple transformations of other variables. They also drop any series that isn't reported by at least one country in every year between 1980 and 2010. This leaves them with a set of 240 variables to analyze.

We attempt to match the 240 variables in the HRV1 analysis to data downloaded from the World Bank in 2020. Changes to the WDI over time ensure that some of these terms have either been dropped or significantly redefined. We find 228 close matches for the initial 240 terms in HRV1.[6]

The second dimension of change between HRV1 and HRV2 is that of time: Where the estimation window for HRV1 runs from 1980-2010, that for HRV2 runs from 1980-2015. These windows imply that considerably more annual observations are dropped from the HRV2 estimation window, relative to when the underlying data were accessed (5 years dropped) than was the case for HRV1 (two years dropped). As we discuss in greater detail below, this is because our investigations reveal that the gradual revelation of data and backfilling of information by the World Bank influences observations far beyond the 2 year window allowed for in the HRV1 estimates. This process artificially deflates countries' transparency scores in the final years of the estimation window when fewer than five years are trimmed from the underlying data. This also implies that HRV1 estimates show an artificial decrease in the years running up to 2010. We demonstrate that this trend is mostly an artifact of the data collection process, and not driven by the (contemporaneous) global financial crisis.

Finally, we extend the set of countries included in our analysis. We include all 125 countries in the original HRV1 analysis. This set included all countries in the 2012 WDI which (1) existed continuously from 1980, and (2) never had a population fall below 500,000. Hollyer, Rosendorff and Vreeland (2014) omit countries that experience serious fractures or which are the product of unions (both Germany and Yemen are omitted). Though, in some instances, countries from which smaller units separate are allowed to continue in the index – Indonesia remains in the data despite the secession of Timor Leste, Ethiopia despite that of Eritrea, and the Russian Federation is treated as the successor of the Soviet Union.

We expand this list of states by allowing an additional 'round' of new entrants into our dataset. Using the list of independent states over time from Gleditsch and Ward (1999), we find that including an additional set of states that have been in continuous existence since 1993 substantially expands the analysis (by 24 states). We choose this date to maximize both the number of states covered by the data and, given the autoregressive nature of the priors, to maximize the number of years each is observed. Moving the cut-off date forward from 1993 (slightly) increases the number of states in our sample, but reduces the period each is observed. Moving it back (substantially) reduces the number of states, but expands the period

[5]Other works that makes use of reporting of information to IOs as a measure of government transparency includes, *inter alia*, Bueno de Mesquita et al. (2003); Islam (2006); Williams (2009).

[6]If we confine ourselves to 'exact' matches on variable names, this number drops to 142. We have also fit an expanded index using only these exact matches. Results look qualitatively similar to using the broader pool of 228 'close' matches. Exact match data are available from the authors on request.

each is observed.[7]

As in HRV1, the transparency score for any given country $c \in \{1, ..., 149\}$ in any given year $t \in \{1980, ..., 2015\}$ is a latent term predicting the reporting of data. Each data point $y_{j,c,t} \in \{0, 1\}$ is a binary indicator equal to one when a given item $j \in \{1, ..., 228\}$ is reported by country c in year t and zero otherwise. We can then estimate

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

where δ_j is an item-specific difficulty parameter, capturing the frequency with which any given variable is reported in the data, and β_j is an item-specific discrimination parameter, capturing the extent to which the reporting of any given item j predicts the reporting of others $k \neq j$. This process adjusts for the possibility that reporting some terms is easier – requiring fewer resources or political costs – than others, and for the possibility that some items may be omitted for idiosyncratic reasons unrelated to the general tendency to disclose economic and social information of the type predominant in the WDI.[8]

This model is identified only up to a positive affine transformation. To fix the scale and location of the index, we adopt the same approach as in HRV1 and re-center the transparency estimates in 1980 at each stage of the MCMC sampling (Knorr-Held, 1999). That is, we draw scores from a diffuse normal prior $transparency_{c \in \{1,...,125\}, t=1980} \sim N(0, 100)$ and then subtract the mean value of the sample and divide by the standard deviation. We then use half-normal priors to constrain Cuba to have a negative and Sweden a positive transparency score.

Subsequent transparency scores evolve according to an AR(1) process. That is, we place a prior of $transparency_{c,t} \sim N(transparency_{c,t-1}, \frac{1}{\tau_c})$ for $t > 1980$ and $c \in \{1, ..., 125\}$. checking this is the right number, not 149? This set of priors acts, in essence, as a non-parametric inter-temporal smoother, wherein each country's transparency score tends to shrink back toward that of the prior year. The degree of shrinkage is inversely proportional to the information contained in the likelihood function and directly proportional to the smoothing parameter τ_c Jackman (2009). τ_c is itself a country-specific parameter, drawn from the distribution $\tau_c \sim Gamma(20, 0.25)$.[9] Similar dynamic priors are used elsewhere in the literature (Martin and Quinn, 2002).

Notice, however, that $transparency_{c,t=1980}$ is defined only for the 125 countries present in the data from 1980 onward. (For simplicity, we index these countries $c \in \{1, ..., 125\}$. The additional 24 countries are indexed $c \in \{126, ..., 149\}$.) All countries that appear first in the data following the expansion 'round' in 1993 require an alternative definition. To accommodate this, we include the following set of priors for the

[7]One could also incorporate multiple 'rounds' of new entrants. But, doing so expands the dataset only slightly, while increasing the complexity of the model.

[8]Item-specific discrimination parameters may also adjust for procedural differences in the collection of the data. If most items in the data require substantial input from national statistical agencies, but a few can be imputed from other sources, presumably the reporting of the latter will correlate poorly with the reporting of the former. This would then imply the discrimination parameters on the latter terms are close to zero, their reporting has little effect on the overall index.

[9]This implies a distribution mean of 5 and variance of 1.25.

new entrants:

$$\begin{aligned} transparency_{c\in\{126,\ldots,149\},t=1993} &\sim N(\bar{t}_{1992}, 100) \\ \bar{t}_{1992} &= \frac{1}{125}\sum_{c\in\{1,\ldots,125\}} transparency_{c,t=1992} \\ transparency_{c\in\{126,\ldots,149\},t>1993} &\sim N(transparency_{c\in\{126,\ldots,149\},t-1}, \frac{1}{\tau_c}) \end{aligned} \tag{2}$$

where the prior on τ_c is identical to that of the first 125 countries. Hence, the transparency scores for the 'new' countries in the dataset are centered on the average values in 1992 for the countries in the existing dataset, via a weak prior. All subsequent observations evolve according to the same AR(1) process as the original 125 in HRV1.

We additionally place diffuse priors on the discrimination and difficulty parameters,

$$\begin{pmatrix} \delta_j \\ \beta_j \end{pmatrix} \sim N\left(\begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} 100 & 0 \\ 0 & 100 \end{pmatrix} \right).$$

We estimate the above model in JAGS, using two MCMC chains run for 10,000 iterations each. The first 5,000 iterations serve as a burn-in period.

HRV1 vs HRV2

The resultant HRV2 index correlates strongly, but not perfectly, with the original HRV measure; the raw correlation is 0.77. The two indices are also in broad agreement on the cross-sectional rankings of countries in any given year. Since the bulk of variation in transparency scores is cross-sectional, rather than temporal, this tends to produce a strong relationship between the two measures.

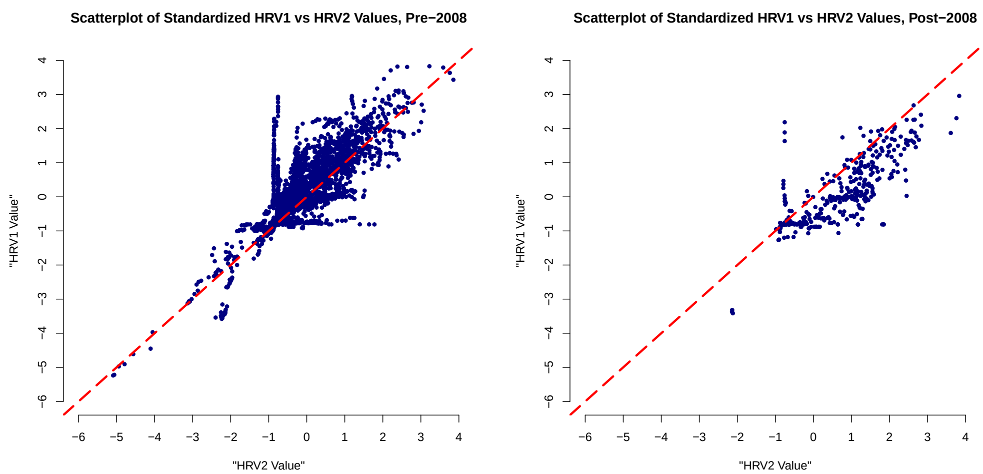
The two indices are also in broad agreement regarding dynamic patterns in the data. The country-by-country correlation between HRV1 and HRV2 scores captures the extent of the two measures' temporal covariance. While, as may be expected, there is considerable variation in these correlation coefficients across the 125 countries common to both indices, most indicate a high level of agreement. The median correlation coefficient in this sample of all 125 countries is 0.76 (the country is Burundi). For 26 of those countries the temporal correlation across the two indices is greater than or equal to 0.9; for 57 it is greater than or equal to 0.8.

However, for a handful of countries, the temporal correlation across the two indices is poor – in some instances, it is even negative. The single worst performer in this regard is Denmark. Perhaps this is unsurprising, since Hollyer, Rosendorff and Vreeland (2014) note that Denmark's original HRV scores demonstrated puzzling patterns, fluctuating wildly from one year to the next. Other countries that demonstrate low levels of temporal agreement in HRV1 and HRV2 scores are predominantly sub-Saharan African states (e.g., the Republic of Congo, Madagascar, Burkina Faso), which exhibited low, and largely time-invariant, HRV scores in the original dataset.

While the two indices are in broad agreement when pooling observations across the full dataset, there are some discrepancies between the two measures. HRV1 reports a marked decline in worldwide transparency scores from a peak in 2005, with notable declines in 2008, 2009, and 2010, coinciding with the global financial crisis. No such decline is evident in HRV2.

This discrepancy can be most readily be seen graphically. Figure 1 displays two scatterplots of normalized HRV1 and HRV2 scores.[10] The plot to the left depicts the relationship before 2008. The one to the right depicts it after 2008.

Figure 1: Scatterplots of Standardized HRV1 and HRV2



Note: While both are highly correlated, HRV1 scores are systematically lower post-2008 than are HRV2 scores.

Before 2008, most points are closely – and symmetrically – distributed around the 45 degree line depicting a perfect correlation. By contrast, the bulk of observations on the rightmost graph are below the dashed line – indicating a higher score on the HRV2 index (the x-axis) than the HRV1 index (the y-axis). While the two indices correlate highly in both samples, there is a clear pattern where in which – on average – HRV1 scores are systematically lower post-2008 than HRV2 scores.

The pre-/post-2008 discrepancies between HRV1 and HRV2 scores are also evident in within-country temporal comparisons. If we split the sample in 2008, and look at the within-country correlation coefficients between the HRV1 and HRV2 measures, the median pre-2008 correlation coefficient is 0.90 (France). With a very few exceptions, the correlation in the temporal patterns between the two measures within all countries in the sample is very high. Post-2008, however, these correlations become markedly worse. Indeed, the median within-country correlation coefficient is negative (-0.64, Korea). With a few exceptions, the temporal patterns over the 2008-2010 period picked up in HRV2 bear little resemblance to those documented in HRV1.

[10] Scores have been normalized by subtracting the full sample mean and dividing by the standard deviation.

A final way of documenting this trend is simply to regress the standardized HRV1 score against the standardized HRV2 values and an indicator variable for the post-2008 period. As can be seen in Table 1, the correlation between the two indices is strong – the regression coefficient on the standardized measures is 0.91. But, a marked departure between the two values arises in 2008, after which the average HRV1 score drops by 0.72 standard deviations relative to its HRV2 counterpart.

Table 1: Regression of HRV1 on HRV2

	Estimate	Std. Error	t value	Pr(>|t|)
Intercept	0.2044	0.0103	19.90	0.0000
HRV 2 Index	0.9098	0.0107	85.22	0.0000
Post-2008	-0.7213	0.0334	-21.62	0.0000

Note: Correlation between HRV1 and HRV2 is very high but falls after 2008.

The post-2008 discrepancies between HRV1 and HRV2 arise from a simple cause – the data included in the WDI are subject to a continuous process of vetting and updating by World Bank staff. Additionally, countries often experience significant reporting delays in relaying information to the Bank, which subsequently backfills missing observations as new data comes to light.

When compiling HRV1, Hollyer, Rosendorff and Vreeland (2014) anticipated that reporting delays might affect their measure. As an ad hoc way of adjusting for this, they dropped the last two years of reported observations from the World Development Indicators (downloaded in late-2012), such that the HRV1 index is available only from 1980-2010. In our re-analysis, we find a similar drop-off in the HRV2 measures when these are extended through 2018 (downloaded in late-2020). Indeed, to limit these reporting effects, we had to drop five years worth of data (to 2015) from the estimation. (Noticeably, some downward trend in average scores is still present.)

Evidence for this reporting effect can also be seen in the raw data. In the sample of WDI variables from 1980-2010 included in both HRV1 and HRV2, roughly 10 percent of cells report conflicting missing/present values. That is, 10 percent of observations are listed as present in one set of raw data, but missing in the other. It is roughly equally likely that a variable will be listed as reported in the data used to construct HRV1 (and missing in that used to construct HRV2), as the reverse (missing in HRV1 reported in HRV2). Before 2008, this pattern holds – when the two sets of raw data conflict about the missingness of a given item, it is roughly equally likely that the item is reported in the HRV1 data (and is missing in HRV2) as the reverse (present in HRV2, but missing in HRV1). But, post-2008, the proportion of changed cells jumps up to 12 percent of the sub-sample, from 10 percent pre-2008. Of these conflicting values, roughly three-quarters are reported as missing in HRV1 (and reported as present in HRV2). This is clear evidence of the influence of backfilling on these indices.

Cross-Sectional Expansion

The most substantial change in HRV2, relative to HRV1 – other than shifts generated by the backfilling of the underlying World Development Indicators data series – is its expanded temporal and cross-sectional coverage. As noted above, the HRV2 index pushes the end-date for its coverage to 2015 (from 2010). And it increases the set of countries included in the analysis by 24, to 149.

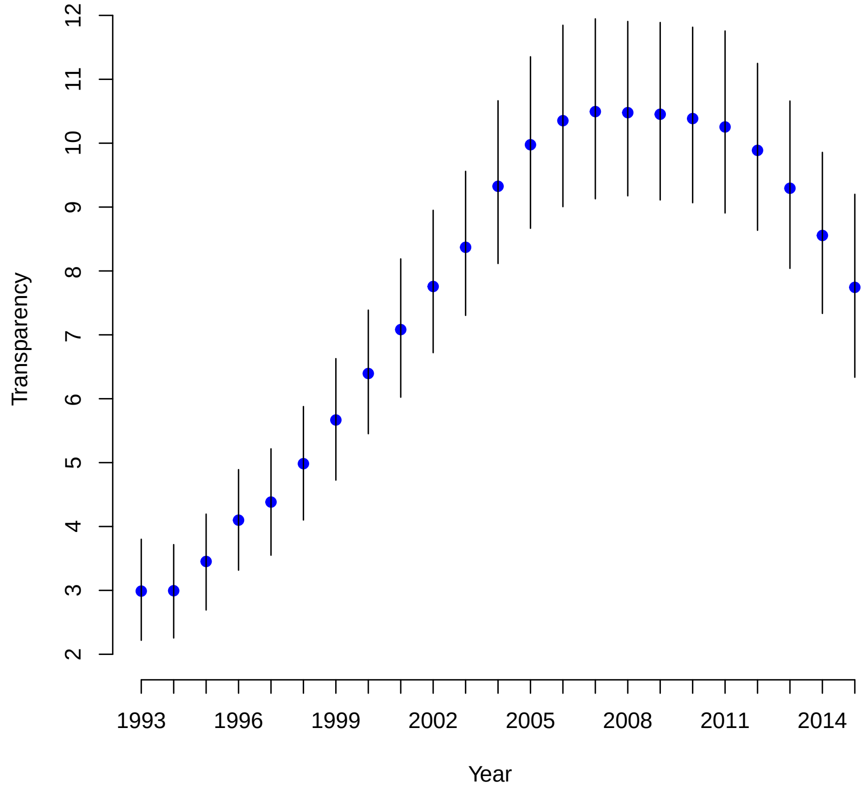
This latter move is accomplished by including a second 'wave' of countries in the index, all of which enter in 1993. Thus, the 24 expanded countries are observed for the 1993-2015 period. This procedure facilitates fitting the dynamic priors used as an inter-temporal smoother in the HRV index's algorithm. And the choice of the year 1993 is motivated by the desire maximize both the number of countries covered and the period of time during which they are assigned HRV scores.[11]

Given the choice of timing, the bulk of new entrants to the dataset are former Soviet states. Though, some (e.g., Czechia, Slovakia, former Yugoslav states) are other post-Communist countries that experienced fractures after the fall of the Iron Curtain. Still others (Eritrea, Namibia) are newly independent states from other parts of the world. And some (Germany, Yemen) are products of mergers between pre-existing states during the 1980-1992 window. A full list of the expanded set of countries is presented in Table 8.

Most countries in this set of expanded observations – particularly former Eastern Bloc countries – experience a clear upward trend in transparency scores over time, with some signs of tapering or reversal in the mid-2010s. (Though, these downturns should be treated with caution. It is possible that these observations are more prone to reporting delays and backfilling than the overall sample.) These patterns are, perhaps, unsurprising given the process of state formation following the collapse of communist rule in the early-1990s, and are consistent with patterns observed for post-communist states present in both HRV1 and HRV2 releases. For some observations, the rise in transparency scores is quite dramatic, and – at their peak – these countries disclose information at rates that are among the highest in the world. This is consistent with governments adopting international statistical standards wholesale, and is particularly common for states that wind up entering the EU. Figure 2 plots the mean transparency estimates, and 95 percent credible intervals, annually for Czechia from 1993-2015, which serves as a useful representative case.

[11] One could, of course, expand both temporal and cross-sectional coverage still further by adding additional 'waves' of entrants either before or after 1993. However, doing so would increase index coverage only slightly while significantly complicating the construction of the algorithm.

Figure 2: HRV2 Scores: Czechia



Some examples follow the same general trend as Czechia, but do so in a less-smooth, more-disjoint, manner. For instance, Croatia's HRV2 scores (plotted in Figure 3) follow the same general upward trend through the early 2010s. But, there is distinct break in the time series between 1999 and 2000, corresponding the death of Franjo Tudman and the ousting of his Croatian Democratic Union party from power. Similarly, a time-series plot of Georgia's HRV2 scores (Figure 4) reveals a discontinuous jump in transparency scores from 2009 to 2010. This likely relates to the rebuilding of the country following the 2008 war with Russia over the breakaway provinces of Abkhazia and South Ossetia.

Figure 3: HRV2 Scores: Croatia

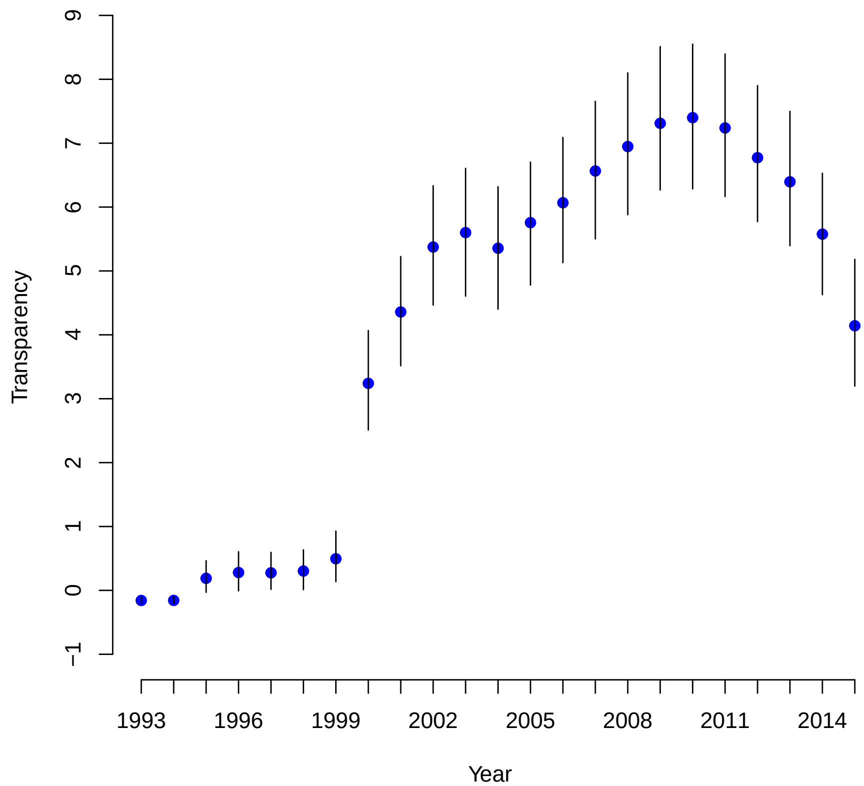
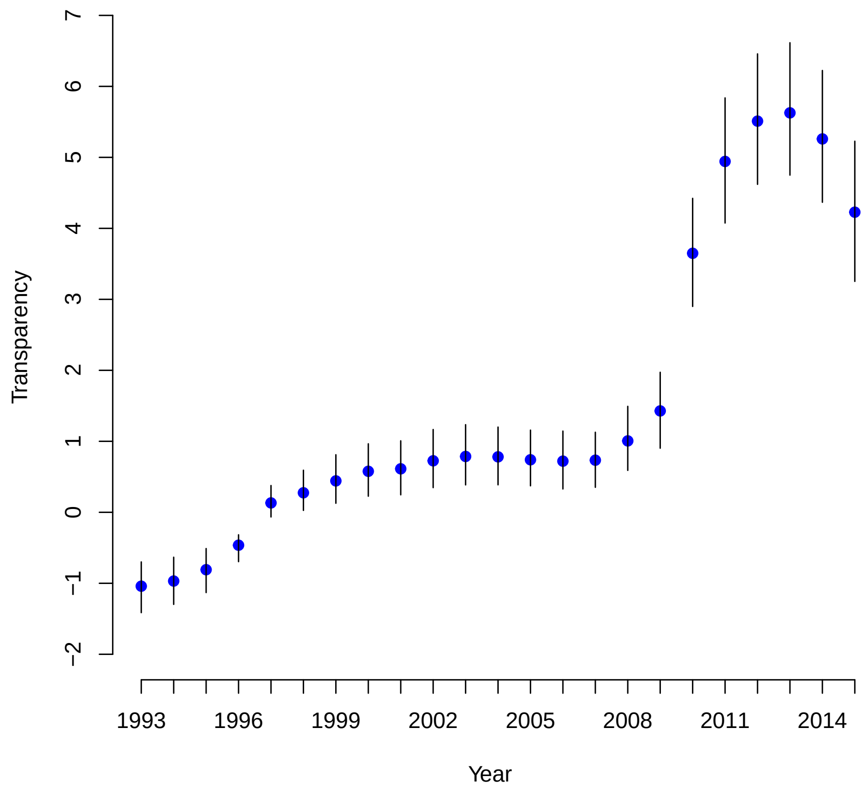


Figure 4: HRV2 Scores: Georgia



However, not all states in the expanded sample demonstrate strong patterns of rising transparency. Figure 5 plots the time-series of Eritrea's HRV2 scores, and 95 percent credible intervals, from 1993-2015. In keeping with Eritrea's status as one of the most repressive governments in the world, its scores are consistently poor, and deteriorate over time. In an interesting contrast with Georgia, Eritrea's transparency scores fall markedly after the resolution of its 1998-2000 border war with Ethiopia (after, somewhat surprisingly, rising during the conflict). They fall again in the years after Eritrea's conflict with Djibouti in 2009 and the resultant imposition of sanctions by the UN Security Council.

Figure 5: HRV2 Scores: Eritrea

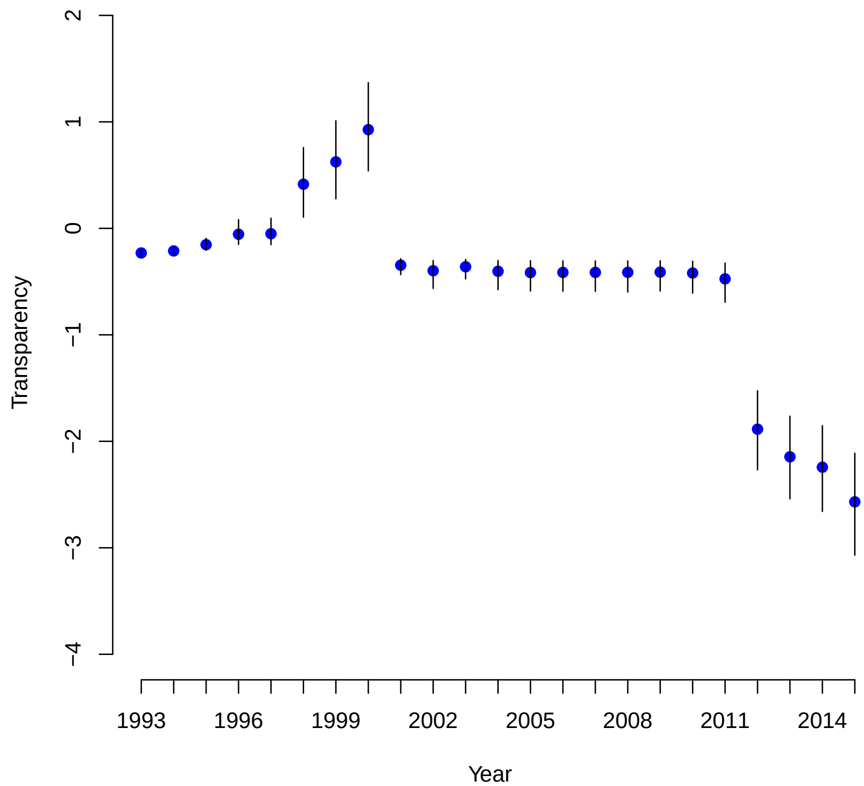
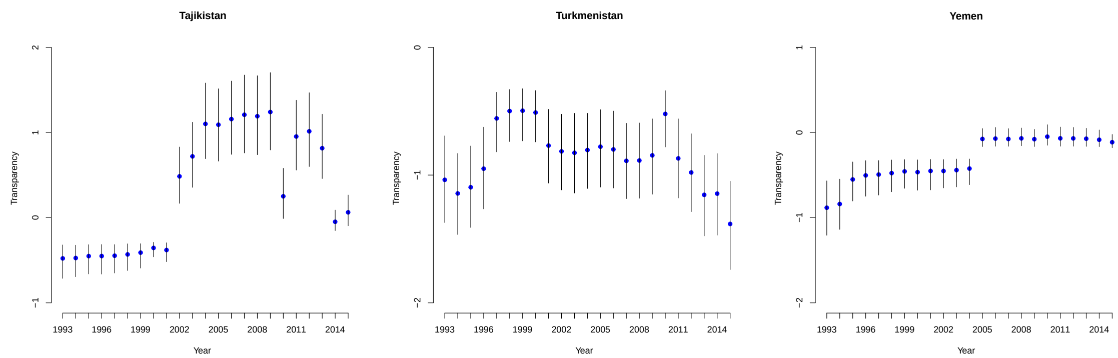


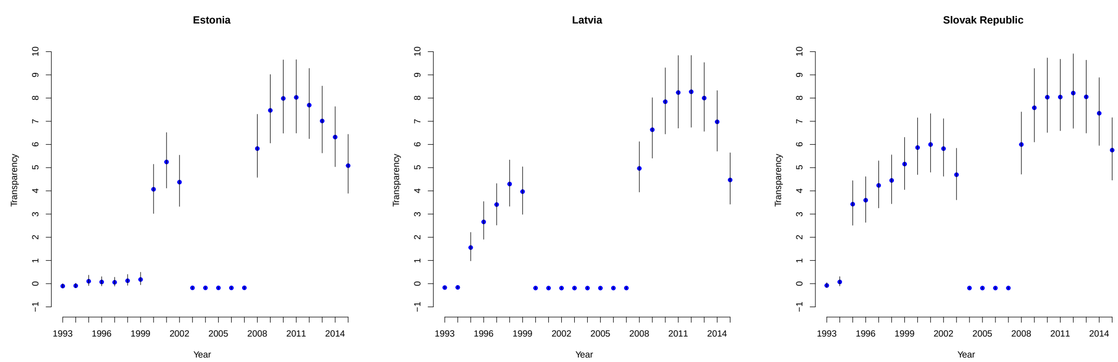
Figure 6 plots the time series for several additional (unsurprisingly) poor performers on the HRV transparency measure. The post-Soviet Central Asian states of Tajikistan and Turkmenistan receive consistently poor transparency scores. (Though, Tajikistan shows statistically significant, if substantively small, uptick in scores around the time it started serving as a base for US troops in Afghanistan.) Analogously, Yemen's HRV scores are largely time-invariant and consistently poor. The time-series ends more or less contemporaneously with the Houthi seizure of power and the Saudi-led military campaign to reverse this take-over. We would anticipate a substantial decline in these scores were the time-series extended further.

Figure 6: HRV2 Scores: Poor Peformers



While most of the examples provided thus far are consistent with typical narratives about the countries in question and so are indicative of the face validity of the expanded HRV measure, there are examples of some surprising patterns in transparency scores among the set of newly added countries. In particular, several EU-accessor states evidence a striking drop in HRV2 scores right around the moment of accession (or soon thereafter) only for scores to jump back to trend levels (all quite high) soon thereafter. This pattern is evident in Estonia, Latvia, and the Slovak Republic.[12] These outliers are plotted in Figure 7.

Figure 7: HRV2 Scores: Odd EU Applicants



Replications

We conclude our examination of the properties of the HRV2 index by replicating the results of an existing set of papers that make use of HRV1. That is, we swap the HRV1 scores for the 125 countries observed from 1980-2010 with the corresponding HRV2 scores.[13] This analysis thus assesses whether the discrepancies between HRV1 and HRV2 introduced by the backfilling process in the WDI affects existing results.

[12] Interestingly, Lithuania does not demonstrate the same odd pattern as the other Baltic states.

[13] As several of the data series used in these prior papers terminate in 2008, we leave extensions of these analyses using broader coverage of HRV2 to a future exercise.

We specifically focus on existing findings linking transparency to autocratic instability (particularly originating from mass demonstrations and democratization from Hollyer, Rosendorff and Vreeland (2015)), and linking transparency to democratic stability (particularly to more frequent ousting of under-performing leaders through regular, as opposed to extra-constitutional, channels, from Hollyer, Rosendorff and Vreeland (2019)).

Below, we report the results of 40 different regression specifications drawn from the main results of Hollyer, Rosendorff and Vreeland (2015) and Hollyer, Rosendorff and Vreeland (2019).[14] In 39 of these 40 specifications, the estimates using HRV2 fall within the confidence intervals reported when using the original measure. The lone exception comes from the fixed-effects negative binomial regression examining the relationship between transparency and the number of general strikes reported in Banks (1979) in a given year. Whereas HRV1 found a positive and significant relationship between transparency and general strikes, HRV2 returns a null result.

Tables 2 and 3 report the empirical core results from Hollyer, Rosendorff and Vreeland (2015) relating transparency to the collapse of autocratic regimes (via processes of mass revolt or that lead to democratization) and to the hazard of democratic transition. The unit of observation is the autocratic regime year, and both tables report the results of Cox proportional hazards regressions. (Coefficient values, rather than hazard ratios, are reported – so a positive coefficient implies an increase in the hazard rate and a negative coefficient the reverse.) In Table 2, the model is a competing risks model, wherein autocratic regimes may fall for a variety of reasons (notably because of coups) other than popular uprisings or democratization. These alternative forms of collapse are treated as competing risks, and autocratic regimes that succumb to these risks are censored from the data (Gordon, 2002). The definitions of forms of regime collapse are drawn from Svolik (2012) and those for democratic transitions (Table 3) are from Cheibub, Gandhi and Vreeland (2010).

[14]For reasons of space, we omit the expanded negative binomial regressions in Table 3 of Hollyer, Rosendorff and Vreeland (2015) and the (mostly null) results in the regression of transparency against the hazard of regular leader removal in Table 4 of Hollyer, Rosendorff and Vreeland (2019). These results are substantively similar to those reported below and are available from the authors on request.

Table 2: Replication of *APSR*, (2015) "Transparency, Protest, and Autocratic Instability" – Table 1: Regime Collapse by Mass Revolution or Democratization

	Cond. Past Collapse			**Cond. Hist. Instability**			**Control Past Collapse**		
ORIGINAL: HRV1									
Transparency	0.234	0.278*	0.259**	0.245	0.245*	0.239*	0.221	0.265*	0.262*
	[-0.076,0.543]	[-0.025,0.581]	[0.005,0.513]	[-0.056,0.545]	[-0.045,0.534]	[-0.040,0.517]	[-0.087,0.530]	[-0.041,0.572]	[-0.008,0.531]
Growth	-0.034*	-0.033*	-0.028*	-0.050**	-0.049**	-0.042*	-0.036*	-0.034*	-0.029
	[-0.069,0.001]	[-0.068,0.002]	[-0.061,0.005]	[-0.099,-0.002]	[-0.096,-0.002]	[-0.086,0.002]	[-0.075,0.003]	[-0.073,0.005]	[-0.065,0.007]
Transparency	-0.004	-0.006	-0.006	-0.002	-0.005	-0.007	-0.002	-0.005	-0.005
× Growth	[-0.041,0.033]	[-0.043,0.030]	[-0.036,0.025]	[-0.047,0.043]	[-0.051,0.041]	[-0.042,0.028]	[-0.043,0.038]	[-0.046,0.035]	[-0.040,0.030]
Full Controls	✓			✓			✓		
Partial Controls		✓						✓	
REPLICATION: HRV 2									
Transparency	0.235	0.246	0.282**	0.318**	0.295*	0.312**	0.248*	0.260*	0.307**
	[-0.055, 0.525]	[-0.052, 0.544]	[0.035, 0.528]	[0.024, 0.613]	[-0.015, 0.605]	[0.027, 0.597]	[-0.045, 0.540]	[-0.037, 0.556]	[0.057, 0.557]
Growth	-0.042**	-0.039**	-0.035**	-0.052**	-0.051**	-0.045**	-0.044**	-0.040*	-0.037*
	[-0.080, -0.004]	[-0.075, -0.003]	[-0.068, -0.002]	[-0.098, -0.006]	[-0.095, -0.006]	[-0.087, -0.003]	[-0.087, -0.001]	[-0.080, 0.001]	[-0.074, 0.000]
Transparency	-0.016	-0.016*	-0.014*	-0.021*	-0.021**	-0.017*	-0.016	-0.015	-0.014
× Growth	[-0.036, 0.003]	[-0.034, 0.003]	[-0.030, 0.003]	[-0.044, 0.003]	[-0.043, -0.000]	[-0.036, 0.002]	[-0.039, 0.006]	[-0.036, 0.005]	[-0.033, 0.004]
Full Controls	✓			✓			✓		
Partial Controls		✓						✓	
# of Subjects	137	137	143	137	137	143	137	137	143
# of Failures	30	30	31	30	30	31	30	30	31

Cox competing hazards regressions of the hazard of autocratic removal via revolt or democratization. The first three columns report a conditional gap time model where the baseline hazard is separately estimated for regimes that experience a prior regime failure and for those that did not. The next two columns estimate separate baseline hazards based on the number of prior collapses. The final three columns control for prior collapses. 95 percent confidence intervals are presented in brackets. All standard errors have been clustered by autocratic regime. The results using HRV1 and HRV2 are substantively the same.

* p<0.1, ** p<0.05, *** p<0.01.

Table 3: Replication of *APSR* (2015), "Transparency, Protest, and Autocratic Instability" – Table 2: Regime Transitions

	Cond. Prior Tranition		Cond. Num. Transitions		No Prior Transition	
ORIGINAL: HRV1						
Transparency	0.231**	0.214**	0.284**	0.255**	0.317**	0.237*
	[0.030,0.431]	[0.035,0.394]	[0.057,0.511]	[0.044,0.466]	[0.059,0.575]	[-0.002,0.476]
Growth	-0.039*	-0.034**	-0.038*	-0.035**	-0.039*	-0.034*
	[-0.079,0.000]	[-0.068,-0.001]	[-0.079,0.003]	[-0.070,-0.000]	[-0.084,0.007]	[-0.070,0.003]
Transparency	-0.014	-0.013	-0.014	-0.015	-0.019**	-0.019**
× Growth	[-0.033,0.005]	[-0.032,0.005]	[-0.034,0.007]	[-0.036,0.007]	[-0.035,-0.003]	[-0.036,-0.002]
Controls	✓		✓		✓	
REPLICATION: HRV2						
Transparency	0.288**	0.226**	0.256**	0.241**	0.290**	0.221**
	[0.043, 0.414]	[0.054, 0.399]	[0.048, 0.464]	[0.047, 0.435]	[0.055, 0.525]	[0.006, 0.435]
Growth	-0.042**	-0.035**	-0.042**	-0.036**	-0.043*	-0.036*
	[-0.083, -0.002]	[-0.070, -0.001],	[-0.083, -0.000]	[-0.072, -0.000]	[-0.091, 0.004]	[-0.074, 0.002]
Transparency	-0.029***	-0.029***	-0.030***	-0.031***	-0.033***	-0.033***
× Growth	[-0.049, -0.009]	[-0.047, -0.012]	[-0.050, -0.010]	[-0.050, -0.012]	[-0.053, -0.013]	[-0.052, -0.014]
Controls	✓		✓		✓	
# of Subjects	106	106	106	106	80	80
# of Failures	52	52	52	52	34	34

Cox proportional hazards regressions of the hazard of transition to democracy. The first two columns report a conditional gap time model where the baseline hazard is separately estimated for regimes that experience a prior regime failure and for those that did not. The next two columns estimate separate baseline hazards based on the number of prior collapses.The final two columns control for prior collapses. 95 percent confidence intervals are presented in brackets. All standard errors have been clustered by autocratic spell.
The results using HRV1 and HRV2 are substantively the same.
* p<0.1, ** p<0.05, *** p<0.01.

As is evident from the two tables, the results using HRV1 and HRV2 are substantively the same. The point estimates on all coefficients are very similar across both sets of specifications, regardless of the transparency measure used. In Table 2 the precision of the estimates on the *Transparency* coefficients is sometimes greater when using HRV1, and sometimes greater when using HRV2, but there doesn't appear to be any systematic pattern to this variation. In Table 3, the results are even more similar. The most substantial departure between the two models arises from the *Transparency* × *Growth* interaction, which is more precisely estimated (and somewhat larger in magnitude) when HRV2 is used in place of HRV1.

Table 4 reports the results of the replication exercise reproducing Table 4 from Hollyer, Rosendorff and Vreeland (2015). These results are obtained from fixed-effects negative binomial regressions of counts the number of annual instances of various forms of unrest – drawn from Banks (1979) – against transparency.

Theoretically, transparency should be associated with more frequent forms of mobilization involving coordination (strikes, protests) against authoritarian governments. But, the original paper argues, there is little reason to suspect it will be associated with other forms of anti-regime mobilization (e.g., assassinations, organized violent revolutions). This table reports the results of these regression making use of a limited set of controls. The results from Table 3 in the original paper, which use an expanded set, are substantively similar.

Table 4: Replication of *APSR* (2015), "Transparency, Protest, and Autocratic Instability" – Table 4: Forms of Unrest

	General Strikes	Riots	Demonstrations	Revolutions	Guerrilla	Coups	Assassinations
ORIGINAL: HRV 1							
Lag Unrest	0.302***	0.087***	0.085***	0.216***	0.548***	-0.196	0.065*
	[0.102,0.502]	[0.043,0.130]	[0.053,0.116]	[0.139,0.292]	[0.359,0.736]	[-1.009,0.618]	[-0.010,0.139]
Transparency	0.610***	0.176**	0.359***	-0.031	-0.019	-0.179	0.085
	[0.204,1.016]	[0.007,0.346]	[0.210,0.508]	[-0.137,0.075]	[-0.127,0.089]	[-0.606,0.248]	[-0.106,0.275]
Growth	-0.029*	0.002	-0.010	0.005	0.003	-0.063***	-0.037***
	[-0.058,0.000]	[-0.019,0.024]	[-0.028,0.008]	[-0.008,0.018]	[-0.011,0.017]	[-0.110,-0.017]	[-0.062,-0.013]
Transparency	-0.012	-0.006	0.004	0.004	0.001	-0.022***	-0.009
× Growth	[-0.038,0.014]	[-0.018,0.006]	[-0.008,0.016]	[-0.002,0.009]	[-0.005,0.007]	[-0.039,-0.006]	[-0.023,0.005]
REPLICATION: HRV2							
Lag Unrest	0.308***	0.088***	0.092***	0.211***	0.552***	-0.195	0.066*
	[0.110, 0.507]	[0.045, 0.131]	[0.061, 0.122]	[0.132, 0.291]	[0.363, 0.742]	[-1.009, 0.618]	[-0.008, 0.139]
Transparency	0.190	0.133*	0.290***	-0.014	-0.070	-0.240	0.056
	[-0.075, 0.456]	[-0.023, 0.289]	[0.154, 0.426]	[-0.125, 0.097]	[-0.190, 0.049]	[-0.726, 0.246]	[-0.125, 0.236]
Transparency	-0.011	-0.009	-0.004	0.003	0.000	-0.023**	-0.010
× Growth	[-0.029, 0.008]	[-0.019, 0.002]	[-0.016, 0.008]	[-0.002, 0.008]	[-0.006, 0.007]	[-0.040, -0.005]	[-0.022, 0.002]
#Obs	590	986	1014	1002	671	514	635
#Countries	42	66	70	65	43	33	41

Fixed-effects negative binomial regressions of counts the number of annual instances of various forms of unrest.
Only "General Strikes" from the original model fails to replicate when the HRV2 measure is substituted for HRV1.
* p<0.1, ** p<0.05, *** p<0.01.

All but one of the results from the original model replicate when the HRV2 measure is substitute for HRV1. As in the original, anti-government demonstrations are significantly and positively associated with transparency (as are riots); whereas, revolutions, guerrilla movements, coups, and assassinations are not. (The point estimate on the frequency of coups is sharply negative using both measures.) For all of these outcome terms, the coefficients using HRV2 lie within the confidence intervals of the original estimates.

However, one result fails to replicate from the original model: General strikes are positively and significantly associated with transparency when the HRV1 score is used as a measure. But, the result is null (though the point estimate still positive) when the HRV2 score is used instead. Indeed, the coefficient in the replication falls outside of the confidence interval from the original model.

We now turn our attention to the results from Hollyer, Rosendorff and Vreeland (2019) relating transparency to the survival of democratic rule. Table 5 presents the main results of this paper, which finds that rising levels of transparency is associated with a reduced hazard of democratic collapse and a reversion to autocracy. We find that the coefficient estimates on all key parameters of interest – transparency, economic growth, and their interaction – derived using the HRV2 measure (the replication) lie within the confidence intervals of the original model (using HRV1). In this sense, the model replicates. However, the point estimates on these coefficients are consistently (slightly) closer to zero when HRV2 is used in place of HRV1. And the confidence intervals around these estimates are wider. As a consequence, the majority of specifications using the HRV2 measure return null results; whereas, all but one of the original specifications returned estimates with p-values of 0.10 or below.

The statistical significance of these findings is, therefore, fragile. The replication is partial. Given the relatively small number of democratic to autocratic transitions (as coded from Cheibub, Gandhi and Vreeland (2010)) in the sample, this is perhaps unsurprising. The fragility of these results may also arise from the inclusion of controls for past instability (either through a direct control for prior transitions or a stratification of the baseline hazard rate), and – in some specifications – an additional control for the level of economic development. Gassebner, Lamla and Vreeland (2013) find that, once these terms are included, few other covariates are capable of systematically predicting democratic collapse as defined in the Cheibub, Gandhi and Vreeland (2010) dataset.

Hollyer, Rosendorff and Vreeland (2019) additionally find that higher levels of transparency are associated with a reduced risk of the 'irregular' removal of democratic leaders, as defined in Goemans, Gleditsch and Chiozza (2009). Leaders are less likely to be ousted via extra-constitutional means when transparency is high and when the economy is performing well.[15] Other forms of leader exit are treated as competing hazards. Table 6 reports both the original results using HRV1, and our replication using HRV2.

As before, the point estimates on all coefficients of interest from the replication lie within the confidence intervals of the original models. However, in contrast to the the results in Table 5, here the precision of these estimates is – if anything – slightly enhanced relative to the original. Though, the point estimates on the transparency term shrink slightly toward zero. Of nine specifications, only one sees a loss of statistical significance resulting from the substitution of HRV2 for HRV1.

Since the interpretation of coefficients – particularly interaction terms – in non-linear models is not straightforward (Berry, DeMeritt and Esarey, 2010), Hollyer, Rosendorff and Vreeland (2019) also include a simulation of the effect of a one standard deviation increase in economic growth on the hazard of leader removal, both when transparency is one standard deviation below (not transparent) and one standard deviation above (transparent) its mean value in the sample. They also include estimates from the hazard of regular leader removal (here unreported). We replicate these simulations in Table 7. Theoretically, they argue that – in transparent democracies – poor economic performance should be punished at the ballot box, i.e., through regular methods. In opaque democracies, by contrast, poor performance is more likely to be punished through irregular removal. Hence, an increase in growth should reduce the hazard of irregular removal for opaque democracies and reduce the hazard of regular removal for transparent democracies.

[15] They also examine the risk of regular leader removal as a function of the same factors. These results are mostly null. We have also replicated these findings, but omit their inclusion for reasons of space.

Table 5: Replication of *BJPS* (2019), "Transparency, Protest, and Democratic Stability" – Table 2: Democratic Collapse

ORIGINAL: HRV 1

	Cond. Prior Transition			**Cond. Num. Transitions**			**Prior Transition Control**		
Transparency	-0.642**	-0.697***	-0.703***	-0.545*	-0.634***	-0.621***	-0.335	-0.586***	-0.611***
	[-1.227,-0.057]	[-1.121,-0.273]	[-1.114,-0.291]	[-1.095,0.006]	[-1.028,-0.241]	[-1.036,-0.206]	[-0.796,0.127]	[-0.965,-0.207]	[-0.967,-0.255]
Growth	-0.141***	-0.109***		-0.127***	-0.103***		-0.123***	-0.117***	
	[-0.208,-0.073]	[-0.165,-0.054]		[-0.193,-0.060]	[-0.158,-0.048]		[-0.185,-0.062]	[-0.176,-0.058]	
Transparency ×	0.031	0.037		0.060***	0.055**		0.027	0.033	
Growth	[-0.047,0.109]	[-0.059,0.132]		[0.015,0.105]	[0.003,0.107]		[-0.051,0.106]	[-0.053,0.119]	
Controls	✓			✓			✓		

REPLICATION: HRV 2

	Cond. Prior Transition			**Cond. Num. Transitions**			**Prior Transition Control**		
Transparency	-0.402	-0.548	-0.652**	-0.387	-0.556	-0.636	-0.301	-0.464*	-0.581**
	[-1.197, 0.393]	[-1.205, 0.108]	[-1.298, -0.006]	[-1.012, 0.237]	[-1.299, 0.186]	[-1.429, 0.157]	[-0.807, 0.205]	[-0.979, 0.051]	[-1.103, -0.059]
Growth	-0.132***	-0.109***		-0.126***	-0.106***		-0.124***	-0.116***	
	[-0.200, -0.064]	[-0.174, -0.045]		[-0.198, -0.055]	[-0.175, -0.036]		[-0.193, -0.055]	[-0.180, -0.051]	
Transparency	0.017	0.009		0.054	0.034		0.017	0.007	
× Growth	[-0.074, 0.108]	[-0.060, 0.078]		[-0.029, 0.137]	[-0.020, 0.088]		[-0.066, 0.101]	[-0.064, 0.078]	
Controls	✓			✓			✓		
# of Subjects	88	88	88	88	88	88	88	88	88
# of Failures	19	19	19	19	19	19	19	19	19

Cox proportional hazards regressions of the hazard of democratic collapse. Thefirst two columns report a conditional gap time model, where the baseline hazard is separately estimated for regimes that experience a prior transition and for those that did not. The next two columns estimate separate baseline hazards based on the number of prior transitions. The final two columns examine only autocratic spells that did not experience a prior transition. We present estimates of coefficient values, not hazard ratios, with 95 percent confidence intervals are presented in brackets. All standard errors have been clustered by democratic spell.
While results replicate when using HRV2 (compared to HRV1), the point estimates are consistently closer to zero with wider confidence intervals with HRV2.
* p<0.1, ** p<0.05, *** p<0.01.

Table 6: Replication of *BJPS* (2019), "Transparency, Protest, and Democratic Stability" – Table 3: Irregular Leader Removal

	Cond. Prior Transition			Cond. Num. Transitions			Prior Transition Control		
ORIGINAL: HRV 1									
Transparency	-0.407*	-0.666***	-0.614***	-0.404*	-0.654***	-0.626***	-0.409*	-0.673***	-0.624***
	[-0.815,0.001]	[-0.997,-0.336]	[-0.893,-0.336]	[-0.846,0.038]	[-1.011,-0.297]	[-0.931,-0.322]	[-0.823,0.004]	[-1.012,-0.334]	[-0.911,-0.337]
Growth	-0.069**	-0.064**		-0.064**	-0.058*		-0.062**	-0.059*	
	[-0.121,-0.016]	[-0.119,-0.008]		[-0.123,-0.006]	[-0.121,0.006]		[-0.121,-0.003]	[-0.118,0.000]	
Transparency ×	0.045	0.051*		0.042	0.049		0.042	0.048	
Growth	[-0.019,0.109]	[-0.009,0.112]		[-0.029,0.113]	[-0.018,0.117]		[-0.026,0.110]	[-0.017,0.112]	
Controls	✓			✓			✓		
REPLICATION: HRV 2									
Transparency	-0.288*	-0.457***	-0.496***	-0.244	-0.456**	-0.502***	-0.296*	-0.464***	-0.508***
	[-0.612, 0.037]	[-0.789, -0.125]	[-0.792, -0.199]	[-0.580, 0.091]	[-0.804, -0.109]	[-0.821, -0.183]	[-0.626, 0.034]	[-0.803, -0.124]	[-0.816, -0.200]
Growth	-0.076**	-0.091***		-0.073**	-0.091***		-0.071**	-0.087**	
	[-0.142, -0.010]	[-0.158, -0.025]		[-0.134, -0.012]	[-0.153, -0.029]		[-0.140, -0.002]	[-0.155, -0.020]	
Transparency	0.014	0.022		0.001	0.020		0.011	0.018	
× Growth	[-0.055, 0.083]	[-0.050, 0.093]		[-0.071, 0.073]	[-0.054, 0.094]		[-0.059, 0.080]	[-0.055, 0.091]	
Controls	✓			✓			✓		
# of Subjects	442	442	442	442	442	442	442	442	442
# of Failures	27	27	27	27	27	27	27	27	27

Cox competing hazards regressions of the hazard of irregular leader removal in democratic regimes. The first two columns report a conditional gap time model wherein the baseline hazard is separately estimated for regimes that experience a prior transition and for those that did not. The next two columns estimate separate baseline hazards based on the number of prior transitions. The final two columns examine only autocratic spells that did not experience a prior transition. We present estimates of coefficient values, not hazard ratios, with 95 percent confidence intervals presented in brackets. All standard errors have been clustered by leader.

The point estimates of the replication lie within the confidence intervals of the original models, and shrink slightly toward zero. Of nine specifications, only one sees a loss of statistical significance resulting from the substitution of HRV2 for HRV1.

* p<0.1, ** p<0.05, *** p<0.01.

Table 7: Replication of *BJPS* (2019), "Transparency, Protest, and Democratic Stability" – Table 5: Estimates Marginal Effects of a One Standard Deviation Increase in Growth

	Transparent	Not Transparent	Difference
ORIGINAL: HRV 1			
Irregular Removal	0.09	-0.14	0.23***
	(0.11)	(0.09)	(0.10)
Regular Removal	-0.22*	-0.02	-0.20
	(0.13)	(0.06)	(0.14)
REPLICATION: HRV 2			
Irregular Removal	-0.03	-0.27***	0.24
	(0.13)	(0.07)	(0.16)
Regular Removal	-0.16*	-0.004	-0.15
	(0.1)	(0.06)	(0.13)

Estimated marginal effects of a one standard deviation increase in the growth rate, reported as percentage changes in the hazard (divided by 100). Transparency levels are set one standard deviation above and below the sample mean. Growth rates are set at their mean and one standard deviation plus the mean, to assess the marginal effect. Standard errors from simulations are reported in parentheses.

The results are stronger than those using the HRV1 measure.

* denotes significance at the 90 percent level, ** denotes significance at the 95 percent level, *** denotes significance at the 99 percent level.

As is overwhelmingly true of our other replications, all of our point estimates from the replication lie within the 95% confidence intervals from the original models (using HRV1). Substantively, the results of our simulations look quite similar – perhaps somewhat stronger – than those making use of the HRV1 measure. As in the original, a one standard deviation increase in growth is associated with a reduced hazard of regular removal in transparent democracies, with an associated p-value below 0.1 but above 0.05. In the replication, in contrast to the original, an increase in growth is associated with a large and significant decline in the hazard of irregular removal in opaque democracies, but no such effect in transparent ones. Though, the discrepancy in the effect of growth between transparent and opaque regimes is slightly less precisely estimated in the replication than the original.

Conclusion

We have introduced a new and expanded version of the HRV Transparency Index. This new measure expands the temporal coverage of the original (by five years). It also expands the cross-sectional coverage (by 24 countries, over the 1993-2015 period). We urge scholars to make use of the expanded version of the index to test theories about the causes, effects, and non-causal relationships they expect to arise involving government disclosures and the broader informational environment.

While our replication makes use of an identical methodology to the original HRV index construction and – to the extent possible – defines the items (the reporting of statistical indicators to the WDI data series) in an identical way, the two measures are not identical to one another in all instances where their coverage overlaps. These discrepancies arise primarily because of the revision and backfilling of the underlying WDI data over time. Notably, while the HRV1 index finds a substantial decline in transparency scores across most countries during the years 2008-2010, the HRV2 index finds no such pattern. This decline in transparency seems to be a statistical artifact resulting from reporting patterns by national statistical agencies and the World Bank, and not a symptom of the 2008 global financial crisis.

This result has a broader implication: Social scientists should be aware that the data that underly many of their analyses are living objects subject to constant revision. This is particularly true of data reported for the recent past. Such records are likely to be incomplete and, information that is released, is likely to be subject to revision as more information becomes available. Over time, such revisions are likely to become less frequent, as agencies gradually incorporate all information that is likely to ever to be available on that period. While sensitivity to such reporting issues is common when dealing with quarterly or monthly time-series, we find that lags in reporting affect annual cross-national data series over a period of years. Statistical analysis that make use of such series, therefore, should be robust to these systematic patterns. When using time-series cross-sectional data, our results argue in favor of steps like flexible controls for time trends, or tests to see if broader patterns hold when only looking at temporally defined subsets of the data.

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List of Post-1993 Countries Added to the Index

Table 8: Countries Added to the HRV2 Index

	Countries Available from 1993-2015
1	Armenia
2	Azerbaijan
3	Bosnia and Herzegovina
4	Belarus
5	Czech Republic
6	Germany
7	Eritrea
8	Estonia
9	Georgia
10	Croatia
11	Kazakhstan
12	Kyrgyz Republic
13	Lithuania
14	Latvia
15	Moldova
16	North Macedonia
17	Namibia
18	Slovak Republic
19	Slovenia
20	Tajikistan
21	Turkmenistan
22	Ukraine
23	Uzbekistan
24	Yemen, Rep.