MEMORANDUM

FROM: Patrick Cavanaugh and Eric Elizes
TO: Ms. Gopinath, Chief Economist of the IMF
SUBJECT: Results of Economic Freedom analysis
DATE: February 19, 2023

SUMMARY

Table 1: Regressions Legend

Abbreviation	Full
MR	Multivariate Regression
FE	Fixed Effects Estimator
IVE	Instrumental Variable Estimator
DID	Difference-in-Difference

These results are summarized in the following table:

Table 1: Regression Results

	Dependent variable:		
	MR	FE	DID
	(1)	(2)	(3)
gov_size	-4.595***	-3.762***	0.844
	(0.380)	(0.511)	(0.560)
property_rights	-13.951***	-4.861***	-0.187
	(0.386)	(0.668)	(0.519)
sound_money	-5.802***	-4.068***	-1.147
	(0.452)	(0.424)	(1.410)
trade	-2.290***	2.835***	-0.967**
	(0.620)	(0.536)	(0.414)
regulation	-0.041	2.921***	-1.552***
	(0.548)	(0.717)	(0.467)
treated			2.412***
			(0.844)
year_dum			0.235
			(0.749)
did			4.117***
			(1.229)
Constant	232.395***	104.422***	30.393**
	(4.097)	(5.937)	(13.152)
Note:			*p<0.1; **p<0.05; ***p<0.01

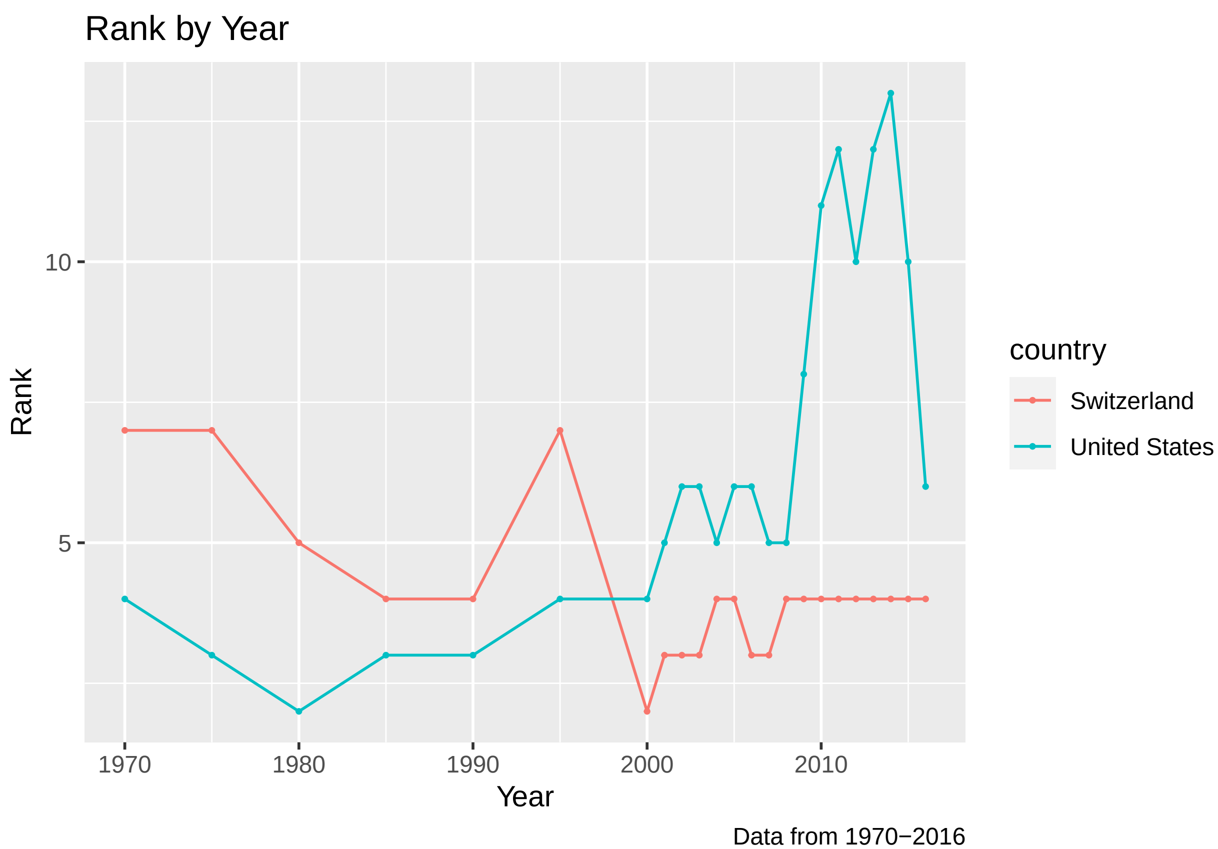
Instrumental Variables Estimator

The relationship between government size and rank can be analyzed using an instrumental variables estimator.

Difference-in-Difference Estimator

On November 4, 2008, Americans elected Illinois senator Barack Obama to be the 44th President of the United States. The result was historic, as Obama, a first-term U.S. senator, became, when he was inaugurated on January 20, 2009, the country's first African American president. The following analysis will use difference-in-difference to investigate whether this had a causal impact on rank in the United States.

The difference-in-differences method is an experimental research design that is often used to estimate the causal effect of a treatment or intervention on an outcome variable. The basic idea behind the difference-in-difference method is to compare the change in the outcome variable over time for a treatment group and a control group, and then take the difference between these changes as the estimate of the treatment effect. In order to obtain unbiased estimates of the treatment effect using the this method, several assumptions need to be met. The first is the parallel trends assumption, which requires that the trend in the outcome variable for the treatment and control groups would have been the same in the absence of the treatment. The following graph shows that there are parallel trends between the United States and Second is the common shocks assumption, which requires that there are no unobserved factors that affect the treatment and control groups differently over time, and that are also related to the outcome variable. Third is that there are no spillover effects. Finally, the last assumption is that there is a sufficiently long post-treatment period. Since these assumptions are met, our estimate is a valid unbiased estimate of the causal effect of the treatment on the outcome variable.

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##
## Table 2: Difference-in-Difference
## ===========================================
##                     Dependent variable:
##                 ---------------------------
##
## -------------------------------------------
## gov_size                   0.844
##                           (0.560)
## property_rights           -0.187
##                           (0.519)
## sound_money               -1.147
##                           (1.410)
## trade                     -0.967**
##                           (0.414)
## regulation                -1.552***
##                           (0.467)
## treated                   2.412***
##                           (0.844)
## year_dum                   0.235
```

```
##                              (0.749)
## did                         4.117***
##                              (1.229)
## Constant                    30.393**
##                             (13.152)
## ===========================================
## ===========================================
## Note:           *p<0.1; **p<0.05; ***p<0.01
```

Obama's presidency increases rank in the United States by 4.117 on average. The difference-in-difference estimator is significant at the 0.01 significance level. It is economically significant because this is a large increase in rank

Regression Discontinuity Estimator

The local average treatment effect refers to the average effect of a treatment on the population of individuals who are "induced" to receive the treatment due to being close to a pre-specified threshold or cutoff. This is a particular type of treatment effect that only pertains to those individuals who are affected by the threshold, and not to the entire population. In this context, the average effect of polling centers being located in a place with cell phone coverage on fraudulent votes is explored. The most important assumption for the regression discontinuity design is that the treatment is assigned based on a threshold or cutoff value. Here, the cutoff in both panels is 0 meters of distance to boundary and the treatment is being located in an area with cell service. This model also satisfies continuity, exogeneity, local independence, monotonicity and common support. Since all of these conditions are met, unbiased estimates can be obtained using the regression discontinuity design. The regression discontinuity plots in Figure 3 show that there is a clear drop in the levels of fraud for centers located on the coverage side. The likelihood of a polling center reporting fraud drops by about 5 percentage points and the average share of fraudulent votes drops by about 2.5 percentage points. These are economically significant drops when looking at the average values in centers on the noncoverage side.