When Do Regulators Lean Against the Wind?: The Political Economy of Implementing Macro-prudential Regulatory Tools: Preliminary results

Jeffrey Chwieroth and Christopher Gandrud

22 March, 2016

This document contains **preliminary** results. Comments welcome.[1]

Abstract

In the aftermath of the global financial crisis, macro-prudential regulatory (MPR) tools, which aim to limit the build-up of systemic risk and the macroeconomic costs of financial instability, have gained widespread attention. An important element of MPR tools involves implementing new counter-cyclical regulatory measures to dampen credit cycles. Yet the political dynamics of MPR tools are complicated in that their implementation involves moving against market and public sentiment during boom periods as well as affecting who can obtain access to financing and who cannot. In this sense, the use of MPR tools can be highly and conspicuously distributional, thus potentially constraining their use and effectiveness. In many cases, the allocation of MPR responsibilities to hitherto independent central banks creates additional concerns about the nature of their accountability relationship with the rest of the political process and the public at large. To shed light on these critical issues, we provide the first cross-national statistical political economy analysis of MPR implementation. Our analysis assesses the relative importance of political credit cycles, institutional demands, and societal demands for credit tightening and easing. **Preliminary results** from democracies indicate that independent central banks are important for overcoming the political credit cycles that would hamper effective MPR tightening. Conversely, [GET]

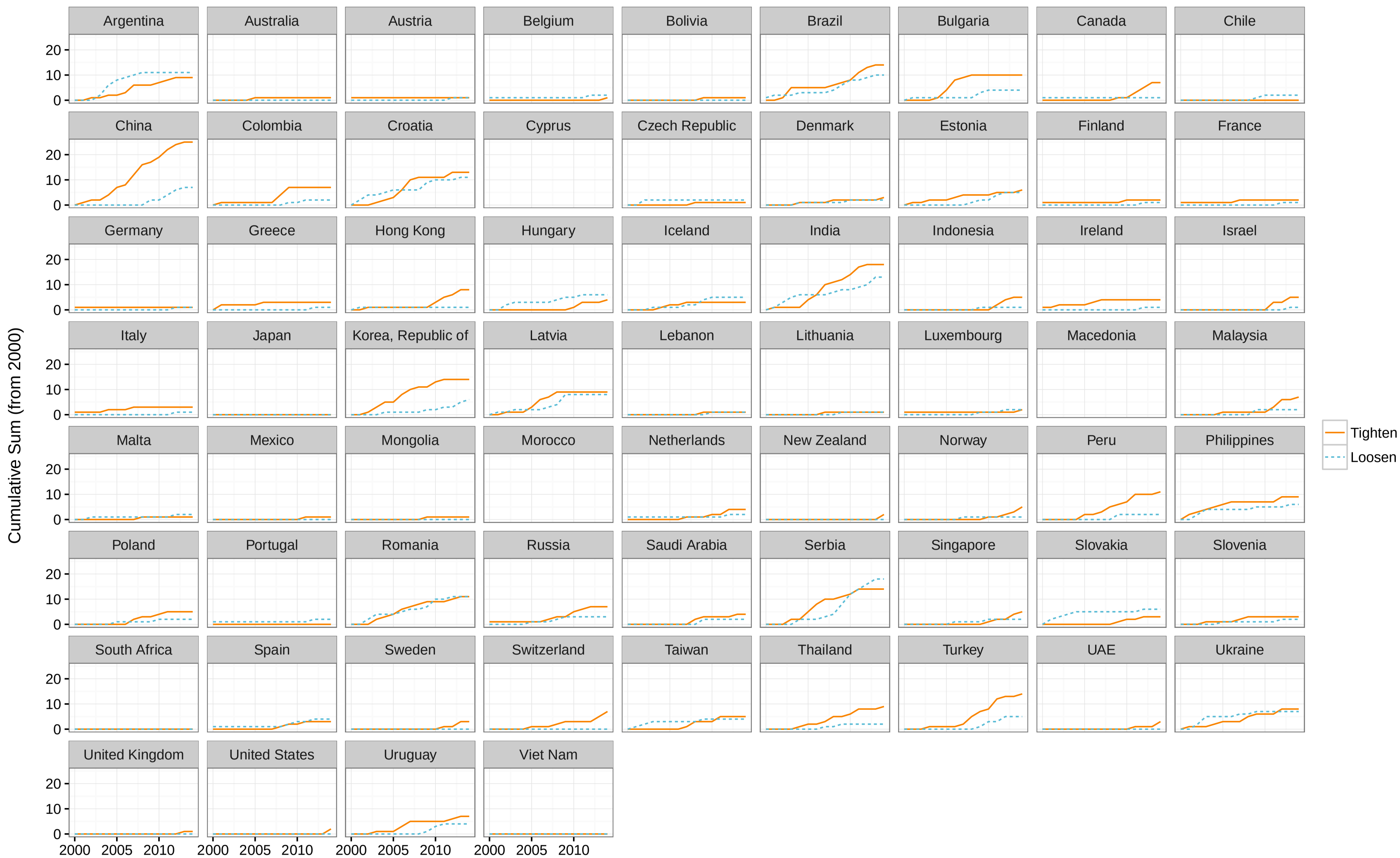
[1]Jeffrey Chweiroth is a Professor of International Political Economy at the London School of Economics (j.m.chwieroth@lse.ac.uk). Christopher Gandrud is a Lecturer of Quantitative International Political Economy at City University London and Post-doctoral Fellow at the Hertie School of Governance (christopher.gandrud@city.ac.uk).

Dependent variables

Our two dependent variables are derived from a new data set of macro-prudential regulatory (MPR) actions created by Reinhardt and Sowerbutts (2015). Aggregating a number of sources, mostly from IMF staff economists, and supplemented with additional hand-coded incidents, they generated binary quarterly indicators of MPR tightening and loosening for 70 countries between 1990 and 2014. They created dummies for a range of individual MPR instruments including lending standards, reserve requirements, capital regulation, risk weights, underwriting standards, profit distribution, and loan to value ratios.

Given that in the sample the use of some of these policies is rarely observed, we created two summary dummy variables from the Reinhardt and Sowerbutts (2015) data to use as our dependent variables. One variable captured if a country took an action that Reinhardt and Sowerbutts (2015) classified as MPR tightening in a given quarter. The other dependent variable captures loosening. These variables equal one for each country-year that any macro-prudential policy was tightened or loosened, respectively, and zero otherwise. Figure 1 shows the cumulative sum (from the year 2000) of these policies for each country-year in our sample.

Figure 1: Cumulative Decisions to Loosen and Tighten Macro-prudential Regulatory Policy (from 2000)



Right-hand variables

We examined how a number of political and economic factors may affect decisions to tighten and loosen macro-prudential policy.

We examined a number of economic indicators from the World Bank's Development Indicators (World Bank 2016).[2] These included the **GDP growth** and **domestic credit growth**. GDP growth is our focus. Macro-prudential policy may be used to calm asset price bubbles, as such we would expect more tightening when growth is high. We may expect that governments would loosen MPR when growth and specifically domestic credit growth is low in order to stimulate the economy. Unfortunately domestic credit growth data is not widely available and so we have a limited ability to directly examine this mechanism. Additionally, from the World Bank Development Indicators, we include **inflation rate** as a control. All World Bank Development Indicators are recorded at the annual level.[3]

Governments may feel a need to tighten macro-prudential policy when asset prices are rising. A key asset prices, often discussed regarding macro-prudential policy, are **residential property prices**. Measuring national-level residential property prices is notoriously difficult (see Scatigna, Szemere, and Tsatsaronis 2014). We use the 57 national series selected by the Bank of International Settlements (Bank of International Settlements 2016) to be as comparable as possible. The indices are at quarterly intervals and in terms of real year-on-year percentage change.

As macro-prudential policy is broadly an attempt to strengthen financial markets, it is important to include the financial market stress policy-makers perceived in real-time. To do this we use the **FinStress** measure from Gandrud and Hallerberg (2015). They created a real-time indicator of financial market stress for over 180 countries between 2003 and 2011 using a text analysis of *Economist Intelligence Unit* monthly country reports. The value ranges from zero (low stress) to one (high stress). We converted this monthly variable to country-quarter averages.

Elected politicians may find it difficult to tighten macro-prudential policy generally as this may slow economic growth in the short-term, even if it promotes stability in the future. Countries with more **central bank independence** (CBI) suffer less from such a time inconsistency problem. Independent central banks were created under the rational that they would not suffer from the electorally induced time-inconsistency problems in monetary policy-making faced by elected politicians. So, countries with independent central banks may be

[2] The indicator IDs are NY.GDP.MKTP.KD.ZG, FS.AST.DOMS.GD.ZS, and FP.CPI.TOTL.ZG, respectively. Note that we created the domestic credit growth variable by finding the year-on-year percentage change in domestic credit as a percentage of GDP.

[3] We also examined models with one year lags of these variables. In general these lags were not statistically significant.

more likely to tighten MPR. We use a standard measure of CBI first devised by Cukierman, Web, and Neyapti (1992) and recently updated through 2008 for about 80 countries by Bodea and Hicks (2015). It ranges from 0.120 to 0.95 in the sample with higher values indicating more central bank independence. Currently countries in the Eurozone are excluded from regressions with this variable. The vast majority of the data set is from the period prior to the European Central Bank taking on banking supervision. Assigning the high independence of the ECB to Eurozone member state supervisory systems during this period is therefore difficult.

One possibility is that elected politicians are more likely to loosen and less likely to tighten macro-prudential policy if they are close to an **election**. Doing so would spur (slow) credit provision to the economy that voters would like (dislike). To examine this we gathered executive election dates from Hyde and Marinov (2012).[4] Politicians would likely not only loosen or avoid tightening in the immediate election quarter, but also in the quarters leading up to the election. As such, we created a binary executive election variable that was one in the election quarter and the three previous quarters. It was zero otherwise.

Perhaps politicians' **economic ideology** may play a role in macro-prudential decisions. To test this we include the government executive's economic policy orientation from the Database of Political Institutions (DPI, Beck et al. 2001 updated through 2012), It is one for right-leaning, two for centre-leaning, and three for left-leaning.

We also included various measures of economic inequality from Solt (2014). [JEFF FINISH WRITE UP]

Preliminary results

One possible estimation method for examining our binary dependent variables would be logistic regression. However, our data does not fit nicely into this modeling technique. Many of "independent" variables are strongly correlated with one another presenting issues of multicolinearity (see the Online Appendix) and likely violate the assumptions of the logistic and similar regression models. We also have many predictors (due to including country fixed effects) relative to our name of observed monetary policy decisions. All of these issue point to the usefulness of random forest classification (Breiman 1996; Breiman 2001).

A random forest is a non-parametric method that allows us to include many correlated variables in the same estimation model (Jones and Linder 2015). Simply, the algorithm builds on a method know as Classification and Regression Trees (CART). A CART algorithm starts with the complete data set (root node) "searches

[4]We used Version 4 of the data set.

through all unique values of [explanatory variables] and calculates the number of cases that would be misclassified if a split would be made at that value" (Jones and Linder 2015, 4). CART creates problems of overfitted 'trees'. Random forests help overcome this problem by finding trees for a bootstrap sample of the data and then averaging over these trees. This method allows us to explore our data set to find potential non-linearities and interactions that would be difficult in a logistic regression context.

We also ran confirmatory analyses using logistic regression models with stepwise included right-hand variables and minimally informative prior information (Gelman et al. 2008) to avoid creating unreasonably large coefficient estimates. The results of these models are presented following the random forests.

Random Forests: MPR Tightening

We first examined random forests with macro-prudential regulatory policy tightening as the response variable. To assess the relative predictive performance of each of the variables we used to try to classify country-quarters as experiencing MPR tightening or now we first examined the variables' minimal depth. Figure 2 shows the minimal depths for each variable included in this model. The assumption behind this plot is that variables have a higher impact on predicting MPR policy tightening if they more frequently split nodes closest to the "trunk" of the tree, i.e. the root node (Ehrlinger 2015, 11). So a lower minimal depth indicates that the variable is more important for predicting MPR policy tightening. Using the optimistic rule developed by [**?**] minimum depth values below the mean minimum depth across the variables indicate variables that are important for predicting MPR policy tightening.

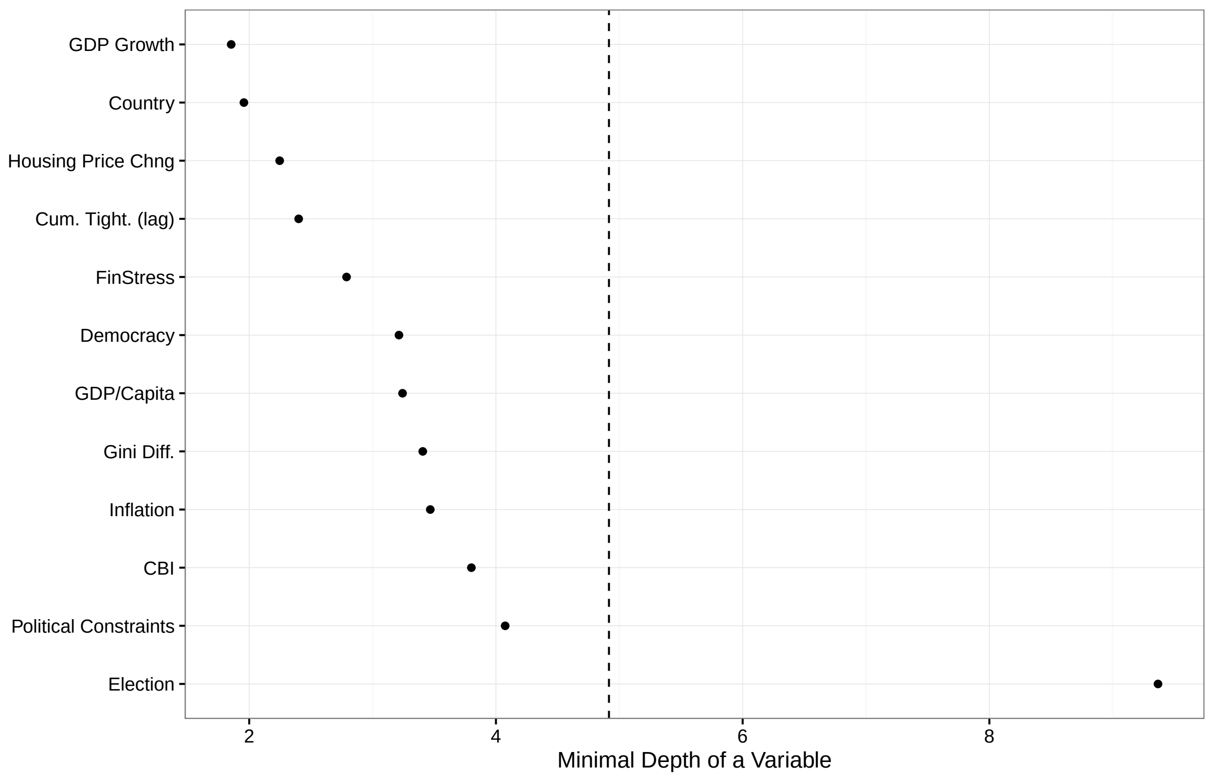
We can see that this rule excludes executive election periods as an important predictor of MPR policy tightening. This suggests against the idea of a macro-prudential electoral cycle.

It is important to note that the country "fixed effect" had a very low minimal depth (see Figure 2). This suggests that there are likely important unobserved factors contributing to MPR policy tightening decisions.

To get a sense of the estimated form of other observed variables' effect on MPR policy tightening, we created found their partial dependence. These are shown in Figure 3. Partial dependence is found by calculating the average prediction from the random forest for each value of $X = x$ variable of interest over all other covariates in X using:

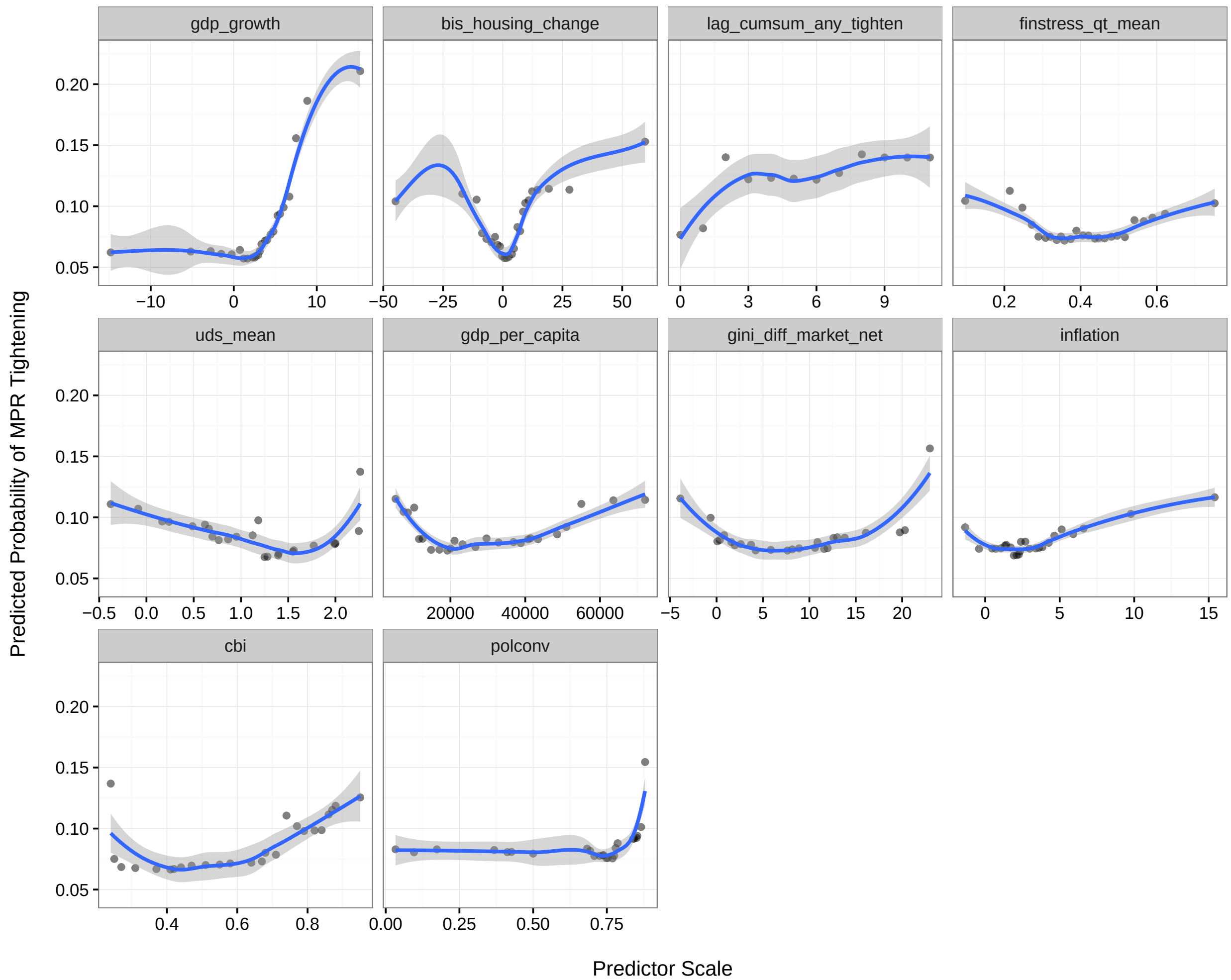
$$\bar{f}(x) = \frac{1}{n}\sum_{i=1}^{n}\hat{f}(x,\ x_{i,o}).$$

Figure 2: Minimal Depth For Trees Classifying Macro-prudential Policy Tightening



The dashed vertical line indicates mean minimum depth across the variables. Minimum depths below the mean depth are considered to be important in forest prediction.

Figure 3: Partial Dependence Plot for Macro-prudential Regulatory Policy Tightening



Note that predictions are for policy change per quarter.

$\hat{f}$ is the predicted MPR policy tightening decision. $x_{i,o}$ is the value for all other covariates than $X = x$ (see Friedman 2000; Ehrlinger 2015, 16).

Random Forests: MPR Loosening

Conclusions

Online Appendix

	Cum. Tight. (lag)	GDP Growth	GDP/Capita	Inflation	FinStress	Housing Chng	CBI	Election Period	Gini Diff.	UDS
Cum. Tight. (lag)	1.00	-0.19	-0.36	0.19	0.09	-0.12	0.17	0.20	-0.12	-0.21
GDP Growth	-0.19	1.00	-0.08	0.07	-0.35	0.61	-0.10	0.05	-0.29	-0.28
GDP/Capita	-0.36	-0.08	1.00	-0.43	0.02	0.04	-0.38	-0.20	0.48	0.51
Inflation	0.19	0.07	-0.43	1.00	-0.20	-0.08	0.12	0.05	-0.26	-0.28
FinStress	0.09	-0.35	0.02	-0.20	1.00	-0.32	0.10	0.01	0.06	-0.09
Housing Chng	-0.12	0.61	0.04	-0.08	-0.32	1.00	-0.14	-0.06	0.01	0.03
CBI	0.17	-0.10	-0.38	0.12	0.10	-0.14	1.00	0.12	0.00	0.09
Election Period	0.20	0.05	-0.20	0.05	0.01	-0.06	0.12	1.00	-0.12	-0.12
Gini Diff.	-0.12	-0.29	0.48	-0.26	0.06	0.01	0.00	-0.12	1.00	0.77
UDS	-0.21	-0.28	0.51	-0.28	-0.09	0.03	0.09	-0.12	0.77	1.00

References

Bank of International Settlements. 2016. "Residential Property Prices Selected Series."

Beck, Thorsten, George Clarke, Alberto Groff, Philip Keefer, and and Patrick Walsh. 2001. "New Tools in Comparative Political Economy: The Database of Political Institutions." *World Bank Economic Review*, no. 1, 15.

Bodea, Cristina, and Raymond Hicks. 2015. "International Finance and Central Bank Independence: Institutional Diffusion and the Flow and Cost of Capital." *The Journal of Politics* 77 (1): 268–84.

Breiman, Leo. 1996. "Bagging Predictors." *Machine Learning* 24 (2): 123–40.

———. 2001. "Random Forests." *Machine Learning* 45 (1): 5–32.

Cukierman, Alex, Steven B. Web, and Bilin Neyapti. 1992. "Measuring the Independence of Central Banks and Its Effect on Policy Outcomes." *The World Bank Economic Review* 6 (3): 353–98.

Ehrlinger, John. 2015. "ggRandomForests." *Arxiv Working Paper*, February, 1–30.

Friedman, JH. 2000. "Greedy Function Approximation: A Gradient Boosting Machine." *Annals of Statistics* 20: 1189–1232.

Gandrud, Christopher, and Mark Hallerberg. 2015. "What Is a Financial Crisis? Efficiently Measuring Real-Time Perceptions of Financial Market Stress with an Application to Financial Crisis Budget Cycles." *CESIfo Working Paper*, no. 5632.

Gelman, Andrew, Aleks Jakulin, Maria Grazia Pittau, and Yu-Sung Su. 2008. "A weakly informative default prior distribution for logistic and other regression models." *The Annals of Applied Statistics* 2 (4): 1360–83.

Hyde, Susan D., and Nikolay Marinov. 2012. "Which Elections Can Be Lost?" *Political Analysis* 20 (2): 191–201.

Jones, Zachary, and Fridolin Linder. 2015. "Exploratory Data Analysis Using Random Forests." *Paper Presented at the Annual MPSA Conference*.

Reinhardt, Dennis, and Rhiannon Sowerbutts. 2015. "Regulatory arbitrage in action: evidence from banking flows and macroprudential policy." *Bank of England Staff Working Paper*, September, 1–37.

Scatigna, Michela, Robert Szemere, and Kostas Tsatsaronis. 2014. "Residential Propoerty Price Statistics

Across the Globe." *BIS Quarterly Reivew* September.

Solt, Frederick. 2014. "The Standardized World Income Inequality Database." *Working Paper*.

World Bank. 2016. "The Global Financial Development Database."