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

Jeffrey Chwieroth and Christopher Gandrud

16 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]

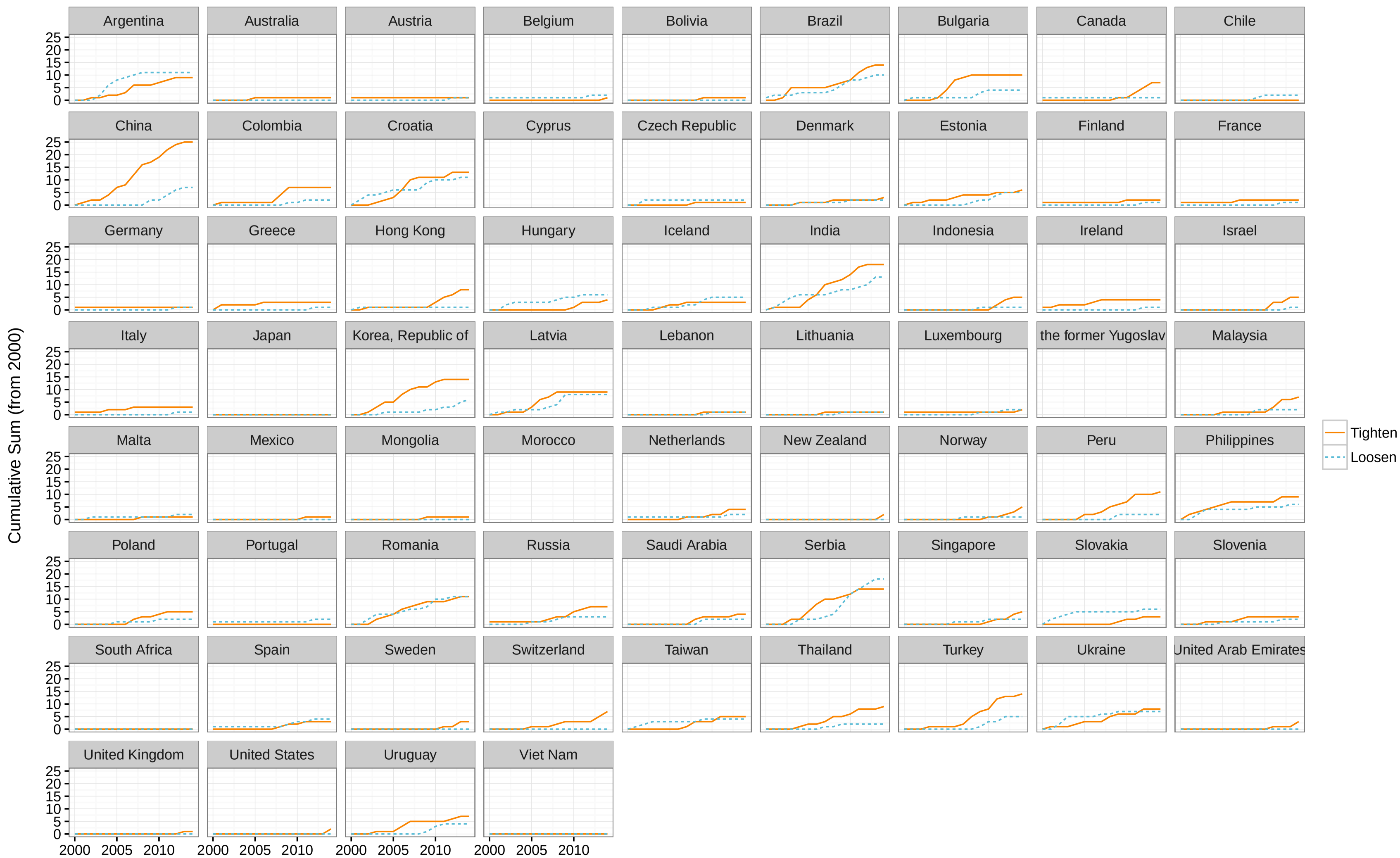
[1]Jeffrey Chweiroth is a Professor of International Political Economy at the London School of Economics (j.m.chwieroth@lse.ac.uk). Christopher Gandrud is a Lecturer of Quantitative International Political Economy at City University London and Post-doctoral Fellow at the Hertie School of Governance (christopher.gandrud@city.ac.uk).

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 (democratic) 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.

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Preliminary results

Because we are primarily interested in how politicians with electoral incentives choose macro-prudential policies, in the following regressions we focus on county-years with a Polity 2 score greater than five (Marshall and Jaggers 2009 updated through 2012). This is the threshold at which the index's authors decide whether a country is democratic or not.

The following tables are from logistic regressions with country and quarter fixed effects.[2] To avoid problem well known problems of unrealistic logistic regression coefficient sizes and, in the extreme case, complete separation we include minimal prior information suggested by Gelman et al. (2008).[3] Additionally, we may expect that countries that a country that has already tightened has a higher propensity to tighten again and having previously tightened is necessary to be able to loosen. As such we include a variable of **cumulative observed macroprudential policy tightening**. This variable simply sums the number of observed instances of tightening by a country up to, but not including the present quarter. Results were largely substantively the same regardless of whether or not we include this variable.[4]

References

Gelman, Andrew, and Yu-Sung Su. 2015. *Arm: Data Analysis Using Regression and Multilevel/Hierarchical Models*. https://CRAN.R-project.org/package=arm.

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.

Marshall, Monty G., and Keith Jaggers. 2009. "Polity IV Project: Dataset Users' Manual," February. Center

[2] We consistently found that policies (both tightening and loosening) were more likely to be recorded by Reinhardt and Sowerbutts (2015) as occurring in the first quarter of the year.

[3] We implemented this with the `bayesglm` function from the **arm** package (Gelman and Su 2015) in R (R Core Team 2016).

[4] Only results from regressions including the variable are show.

Table 1: Logistic Regression Estimates For Macro-prudential Policy **Tightening**

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
(Intercept)	-3.63^{***}	-1.28	-5.67^{***}	-6.57^{***}	-5.27^{***}	-4.72^{***}
	(0.86)	(1.16)	(0.92)	(1.18)	(1.07)	(1.09)
lag_cumsum_any_tighten	0.11	0.07^{*}	0.07^{*}	0.07	0.04	-0.02
	(0.07)	(0.03)	(0.03)	(0.04)	(0.04)	(0.04)
gdp_growth	0.21^{***}	0.24^{***}	0.21^{***}	0.29^{***}	0.22^{***}	0.13^{**}
	(0.06)	(0.04)	(0.04)	(0.06)	(0.04)	(0.04)
inflation	0.11	-0.00	0.01	0.04	0.02	0.01
	(0.07)	(0.02)	(0.02)	(0.03)	(0.03)	(0.02)
finstress_qt_mean	-0.11					
	(1.35)					
bis_housing_change	0.01					
	(0.02)					
‘_1_gini_market‘		-0.05				
		(0.03)				
cbi			3.55^{**}	4.35^{**}	2.86^{*}	3.06^{*}
			(1.23)	(1.51)	(1.43)	(1.51)
execrlc				-0.25		
				(0.18)		
executive_election_4qt1				0.05		
				(0.35)		
fiscal_trans_gfs					0.00	
					(0.01)	
domestic_credit_change						0.00
						(0.01)
AIC	528.70	1107.17	923.46	593.45	777.32	654.40
BIC	844.75	1466.46	1262.46	915.63	1101.79	961.75
Log Likelihood	-200.35	-490.58	-398.73	-231.72	-324.66	-263.20
Deviance	400.70	981.17	797.46	463.45	649.32	526.40
Num. obs.	1031	2215	1605	1050	1176	900

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

All models include country and quarter fixed effects.

Table 2: Logistic Regression Estimates For Macro-prudential Policy **Loosening**

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
(Intercept)	-4.51^{***}	-2.26	-1.32	-1.63	-4.76^{***}	-2.28
	(1.10)	(1.40)	(0.85)	(1.06)	(1.22)	(1.24)
lag_cumsum_any_tighten	0.27^{**}	0.07	0.08^{*}	0.05	0.24^{***}	0.14^{*}
	(0.08)	(0.04)	(0.04)	(0.04)	(0.06)	(0.06)
gdp_growth	-0.17^{**}	-0.07^{**}	-0.06^{**}	-0.08^{*}	-0.07^{*}	-0.05
	(0.06)	(0.02)	(0.02)	(0.04)	(0.03)	(0.03)
inflation	0.22^{***}	-0.00	-0.01	0.00	0.09^{*}	-0.05
	(0.06)	(0.02)	(0.02)	(0.03)	(0.04)	(0.04)
finstress_qt_mean	-0.91					
	(1.97)					
bis_housing_change	0.03					
	(0.02)					
‘_1_gini_market‘		-0.03				
		(0.03)				
cbi			-2.38^{*}	-2.50	1.09	-0.95
			(1.16)	(1.34)	(1.57)	(1.70)
execrlc				0.17		
				(0.21)		
executive_election_4qt1				-0.52		
				(0.47)		
fiscal_trans_gfs					0.01	
					(0.01)	
domestic_credit_change						0.00
						(0.01)
AIC	333.28	767.14	709.07	512.17	505.42	461.59
BIC	649.33	1126.43	1048.07	834.35	829.89	768.94
Log Likelihood	-102.64	-320.57	-291.53	-191.09	-188.71	-166.79
Deviance	205.28	641.14	583.07	382.17	377.42	333.59
Num. obs.	1031	2215	1605	1050	1176	900

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

All models include country and quarter fixed effects.

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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.