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

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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]

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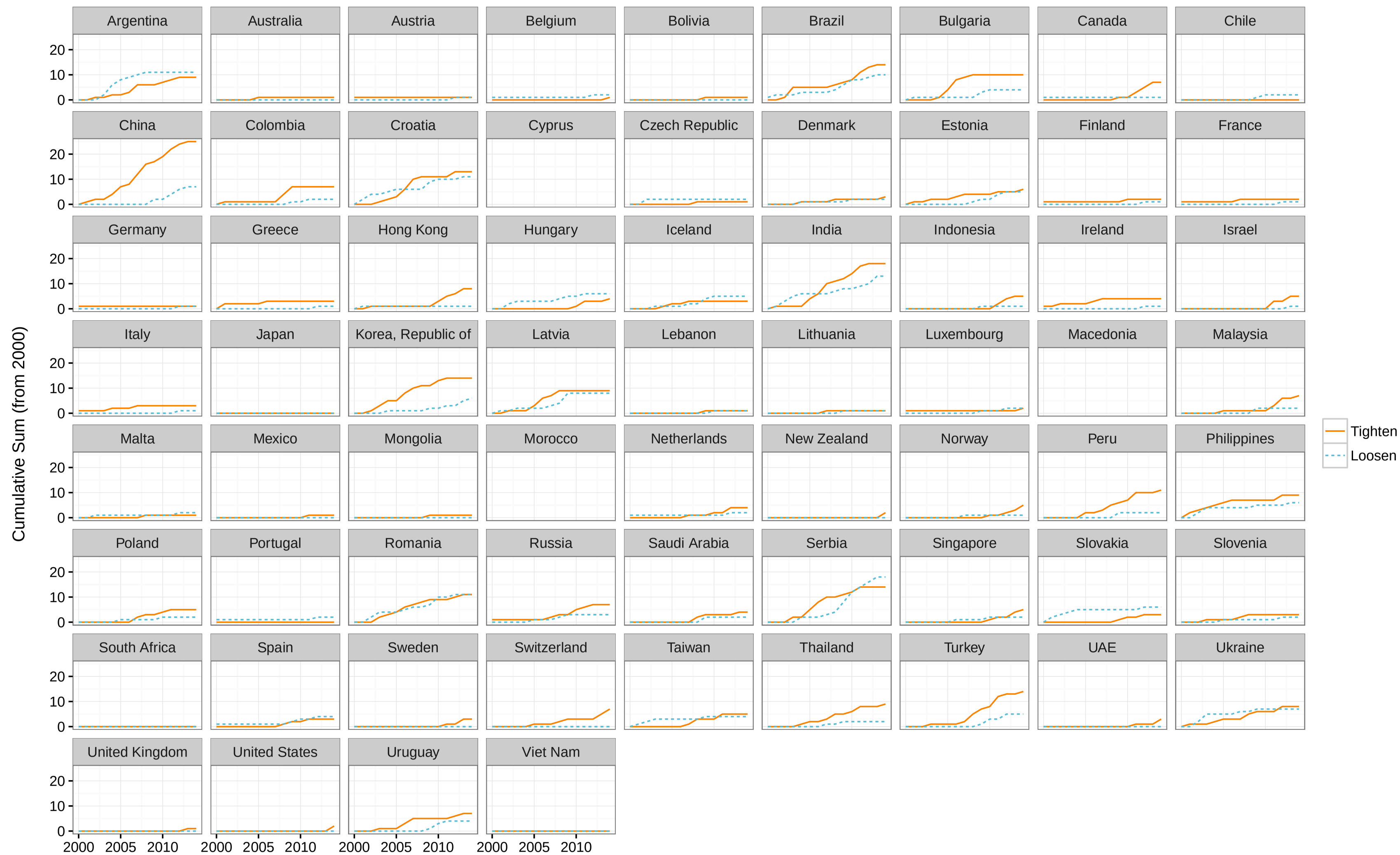
Dependent variables

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). [FINISH WRITE UP]

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. Note that the results are substantively the same when using the full sample.

The following tables are from logistic regressions with country and quarter fixed effects.[5] 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).[6] Additionally, we may expect that countries that a country that has already tightened has a higher propensity to tighten

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

[5] 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.

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

again and having previously tightened is necessary to be able to loosen. As such we include a variable of **cumulative observed macro-prudential 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.[7]

A consistent finding is that GDP Growth is associated with macro-prudential regulatory policy change. The effect is in the expected direction as more growth is associated with more tightening, likely because the factors causing the GDP growth are also causing bubbles that governments are trying to manage. Conversely, lower GDP growth is associated with MPR loosening. Governments may be easing up on the supply of credit to spur more growth. Another fairly consistent finding is the role that central bank independence appears to play.

CBI is also in the expected direction for both loosening and tightening. More independent central banks are more likely to tighten and less likely to loosen MPR policy. To explore the size and estimation uncertainty of these effects we followed King, Tomz, and Wittenberg (2000) and Gandrud (2015) by simulating and plotting predicted probabilities of MPR tightening and loosening. Figure 3 shows the predicted probabilities in two contrasting scenarios. The left-panel shows predicted probabilities of instituting a tightening policy in a quarter when GDP growth is at the 90th percentile in our sample–7.4 percent.

Conclusions

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.

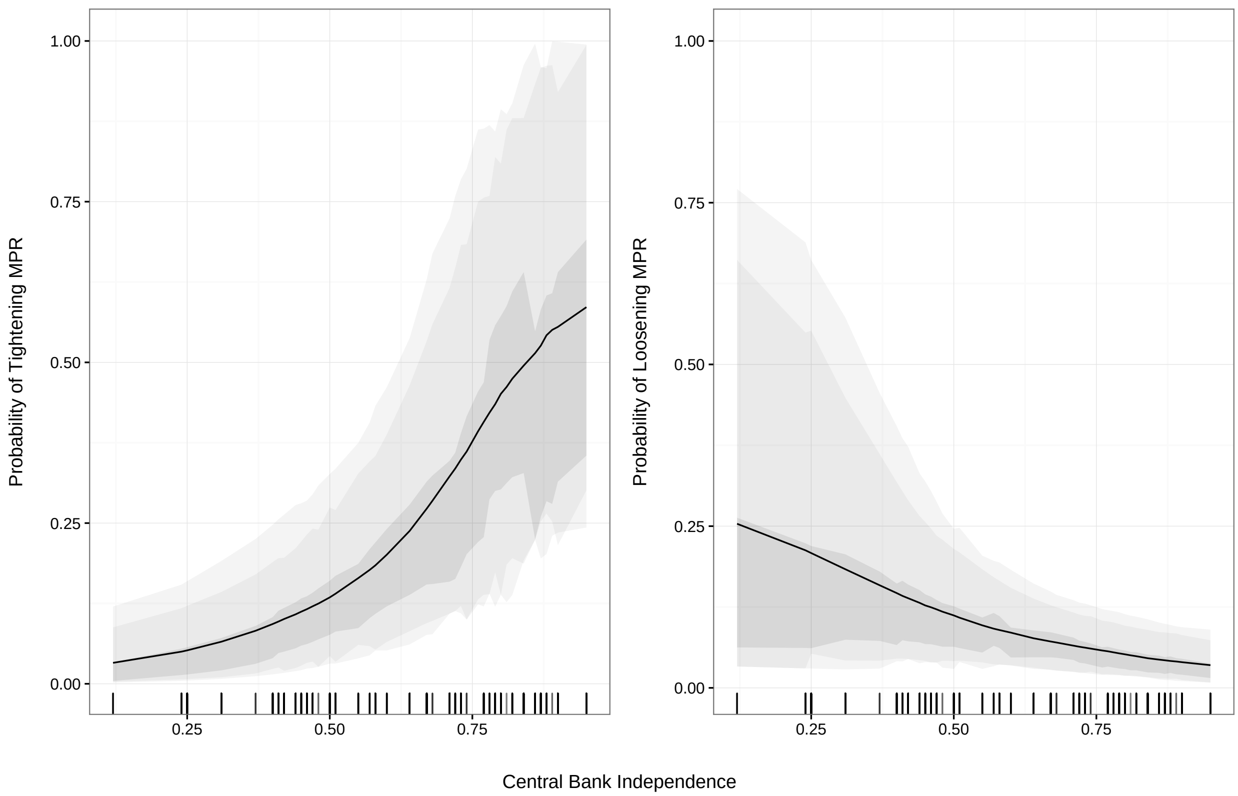
Bodea, Cristina, and Raymond Hicks. 2015. "International Finance and Central Bank Independence: Institutional Diffusion and the Flow and Cost of Capital." *The Journal of Politics* 77 (1): 268–84.

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.

Gandrud, Christopher. 2015. "SimPH: An R Package for Illustrating Estimates from Cox Proportional

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

Figure 2: Predicted Probability of Macro-prudential Regulatory Policy Tightening and Loosening at Various Fitted Values of Central Bank Independence



The figures show the median and highest probability density intervals (50%, 90%, and 95%) of 1000 simulations.

The figures were created using estimates from the fourth models show in Tables 1 and 2. In the left-panel GDP growth was fitted at the democratic sample's 90th percentile–7.4 percent. In the right-panel GDP growth was fitted at the 10th percentile—0.85 percent. Inflation and the cumulative number of previous tightening moves were fitted at the sample mean.

Figure 3: Predicted Probability of Macro-prudential Regulatory Policy Tightening Various Fitted Values of Housing Price change and GDP Growth

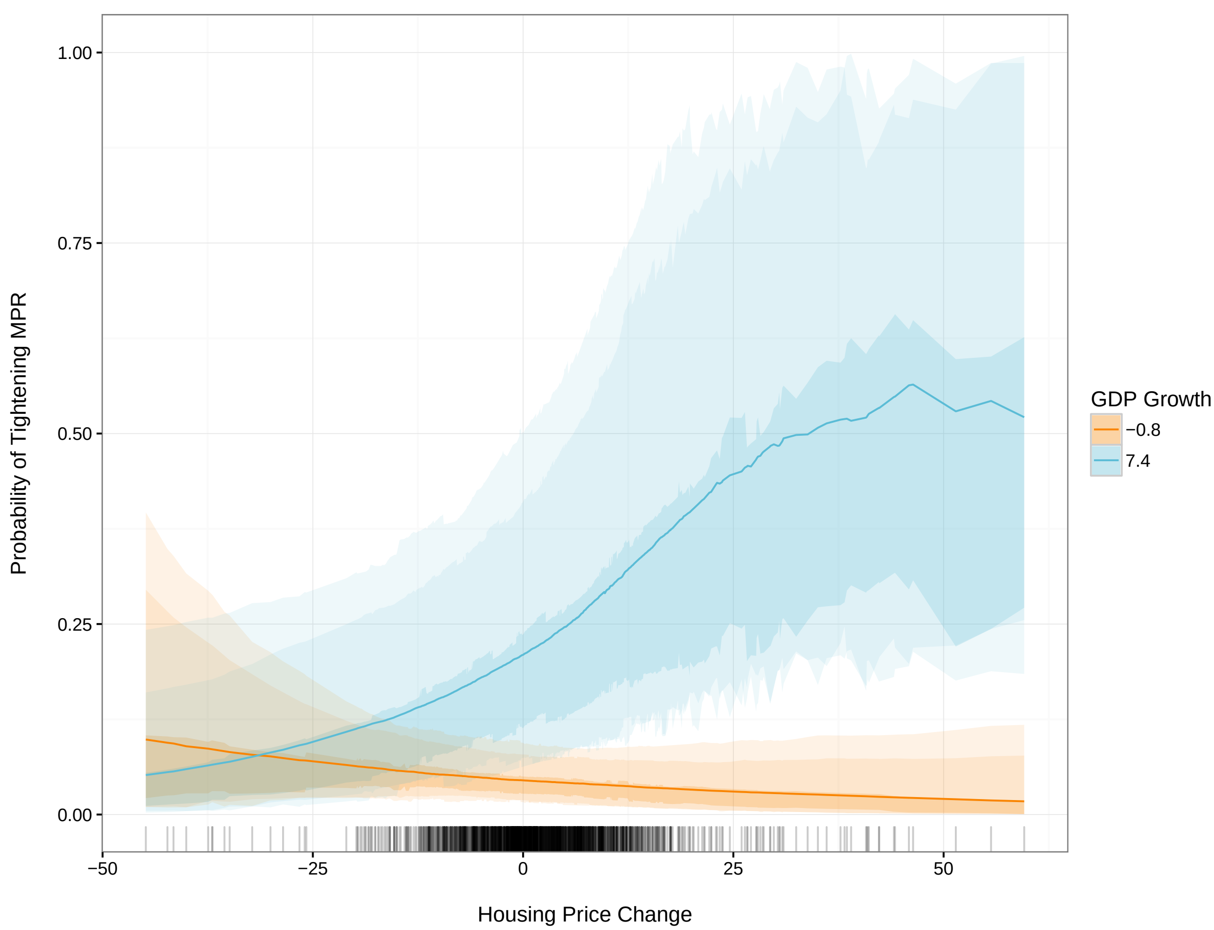


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Table 1: Logistic Regression Estimates For Macro-prudential Policy **Tightening**

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
(Intercept)	-3.63^{***}	-3.52^{***}	-1.28	-5.67^{***}	-6.57^{***}	-5.27^{***}	-4.72^{***}
	(0.86)	(0.46)	(1.16)	(0.92)	(1.18)	(1.07)	(1.09)
Cumulative Tightening (lag)	0.11	0.05	0.07^{*}	0.07^{*}	0.07	0.04	-0.02
	(0.07)	(0.04)	(0.03)	(0.03)	(0.04)	(0.04)	(0.04)
GDP Growth	0.21^{***}	0.17^{***}	0.24^{***}	0.21^{***}	0.29^{***}	0.22^{***}	0.13^{**}
	(0.06)	(0.05)	(0.04)	(0.04)	(0.06)	(0.04)	(0.04)
Inflation	0.11	0.09	-0.00	0.01	0.04	0.02	0.01
	(0.07)	(0.06)	(0.02)	(0.02)	(0.03)	(0.03)	(0.02)
FinStress	-0.11						
	(1.35)						
Housing Price Δ	0.01	-0.01					
	(0.02)	(0.02)					
GDP Growth * Housing Δ		0.01^{**}					
		(0.00)					
Gini			-0.05				
			(0.03)				
CBI				3.55^{**}	4.35^{**}	2.86^{*}	3.06^{*}
				(1.23)	(1.51)	(1.43)	(1.51)
Executive Ideology					-0.25		
					(0.18)		
Executive Election					0.05		
					(0.35)		
Fiscal Transparency						0.00	
						(0.01)	
Credit Growth							0.00
							(0.01)
AIC	528.70	793.62	1107.17	923.46	593.45	777.32	654.40
BIC	844.75	1136.42	1466.46	1262.46	915.63	1101.79	961.75
Log Likelihood	-200.35	-332.81	-490.58	-398.73	-231.72	-324.66	-263.20
Deviance	400.70	665.62	981.17	797.46	463.45	649.32	526.40
Num. obs.	1031	1566	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	Model 7
(Intercept)	-4.51^{***}	-3.62^{***}	-2.26	-1.32	-1.63	-4.76^{***}	-2.28
	(1.10)	(0.47)	(1.40)	(0.85)	(1.06)	(1.22)	(1.24)
Cumulative Tightening (lag)	0.27^{**}	0.22^{***}	0.07	0.08^{*}	0.05	0.24^{***}	0.14^{*}
	(0.08)	(0.05)	(0.04)	(0.04)	(0.04)	(0.06)	(0.06)
GDP Growth	-0.17^{**}	-0.16^{**}	-0.07^{**}	-0.06^{**}	-0.08^{*}	-0.07^{*}	-0.05
	(0.06)	(0.05)	(0.02)	(0.02)	(0.04)	(0.03)	(0.03)
Inflation	0.22^{***}	0.18^{***}	-0.00	-0.01	0.00	0.09^{*}	-0.05
	(0.06)	(0.05)	(0.02)	(0.02)	(0.03)	(0.04)	(0.04)
FinStress	-0.91						
	(1.97)						
Housing Price Δ	0.03	0.02					
	(0.02)	(0.02)					
GDP Growth * Housing Δ		-0.00					
		(0.00)					
Gini			-0.03				
			(0.03)				
CBI				-2.38^{*}	-2.50	1.09	-0.95
				(1.16)	(1.34)	(1.57)	(1.70)
Executive Ideology					0.17		
					(0.21)		
Executive Election					-0.52		
					(0.47)		
Fiscal Transparency						0.01	
						(0.01)	
Credit Growth							0.00
							(0.01)
AIC	333.28	545.53	767.14	709.07	512.17	505.42	461.59
BIC	649.33	888.33	1126.43	1048.07	834.35	829.89	768.94
Log Likelihood	-102.64	-208.76	-320.57	-291.53	-191.09	-188.71	-166.79
Deviance	205.28	417.53	641.14	583.07	382.17	377.42	333.59
Num. obs.	1031	1566	2215	1605	1050	1176	900

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

All models include country and quarter fixed effects.

Hazard Models Including for Interactive and Nonlinear Effects.” *Journal of Statistical Software* 65 (3): 1–20.

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, 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.

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

King, Gary, Michael Tomz, and Jason Wittenberg. 2000. “Making the Most of Statistical Analyses: Improving Interpretation and Presentation.” *American Journal of Political Science* 44 (2): 341–55.

Marshall, Monty G., and Keith Jaggers. 2009. “Polity IV Project: Dataset Users’ Manual,” February. Center for Systemic Peace.

R Core Team. 2016. *R: A Language and Environment for Statistical Computing*. Vienna, Austria: R Foundation for Statistical Computing. https://www.R-project.org/.

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.”