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

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Incomplete working draft containing **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 potentially 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.

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Introduction

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Economic Conditions and Macro-prudential Policy Choices

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Political Conditions and Macro-prudential

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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.

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. We do not include FinStress in all of the models below because it shrinks the time periods of our sample.

Policy-makers may turn to macro-prudential tools when they lack the monetary policy tools needed to constrain bubbles. To test this we included countries annual average standardised **central bank policy interest rate**. This data is from the IMF's International Financial Statistics (International Monetary Funds 2016). Perhaps countries with already high policy rates–and thus little room to maneuver are more likely to turn to MPR policy tools. We also used this variable to create a measure of central bank policy interest rate year-on-year percentage change to examine if the rate of change, not just the level may be important. Macro-prudential and monetary policies may be treated as complementary–countries could tighten monetary policy and macro-prudential policy simultaneously to avoid or quell bubbles–or, conversely, the policies they may be treated as substitutes. This is an empirical question that we examine below.

[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.

We also examined whether or not a countries' **exchange rate regime** impacted their propensity to use macro-prudential tools. Perhaps having a more fixed exchange rate regime would prevent policy-makers from using monetary policy to tame credit cycles. To examine this we used the Ethan Ilzetzki and Rogoff (2010) coarse measure of exchange rate regime. Their measure had six categories, where higher values indicated more a flexible exchange rate regime. It is available through 2010. However, we did not find any meaningful results with this measure and do not include it among the estimates below.

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 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.

Central bank independence should have a more important role on tightening if the central bank plays a larger part in macro-prudential decision-making. To examine this, we included the central bank' and ministry of finance's–who are presumably more attuned to voters and removal pressures–de facto involvement in the macro prudential decision-making. This data was from Lim et al. (2013). Their **MaPP** (measuring central bank involvement) and **MoF** indices range from a low of zero where there is no involvement to 4 where these actors are primarily or solely responsible. Note that surprisingly, these measures were never statistically meaningful in our various estimation models and results with them are not shown below.

It may be that politicians that are more accountable to voters with short-time horizons and who benefit from easy credit would be less likely to tighten monetary policy. To examine this possibility, we used **Unified Democracy Scores** (UDS) from Pemstein, Meserve, and Melton (2010) which they updated through 2012. UDS scores are found using a Bayesian latent variable model of eleven commonly used measures of democracy. We used the posterior mean estimates from this model. The variable ranges from about -2.1 to 2.2 where higher scores indicate a higher level of democracy.

One possible manifestation of electoral accountability effect may be a macro-prudential regulatory policy electoral cycle. Elected politicians may be 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.

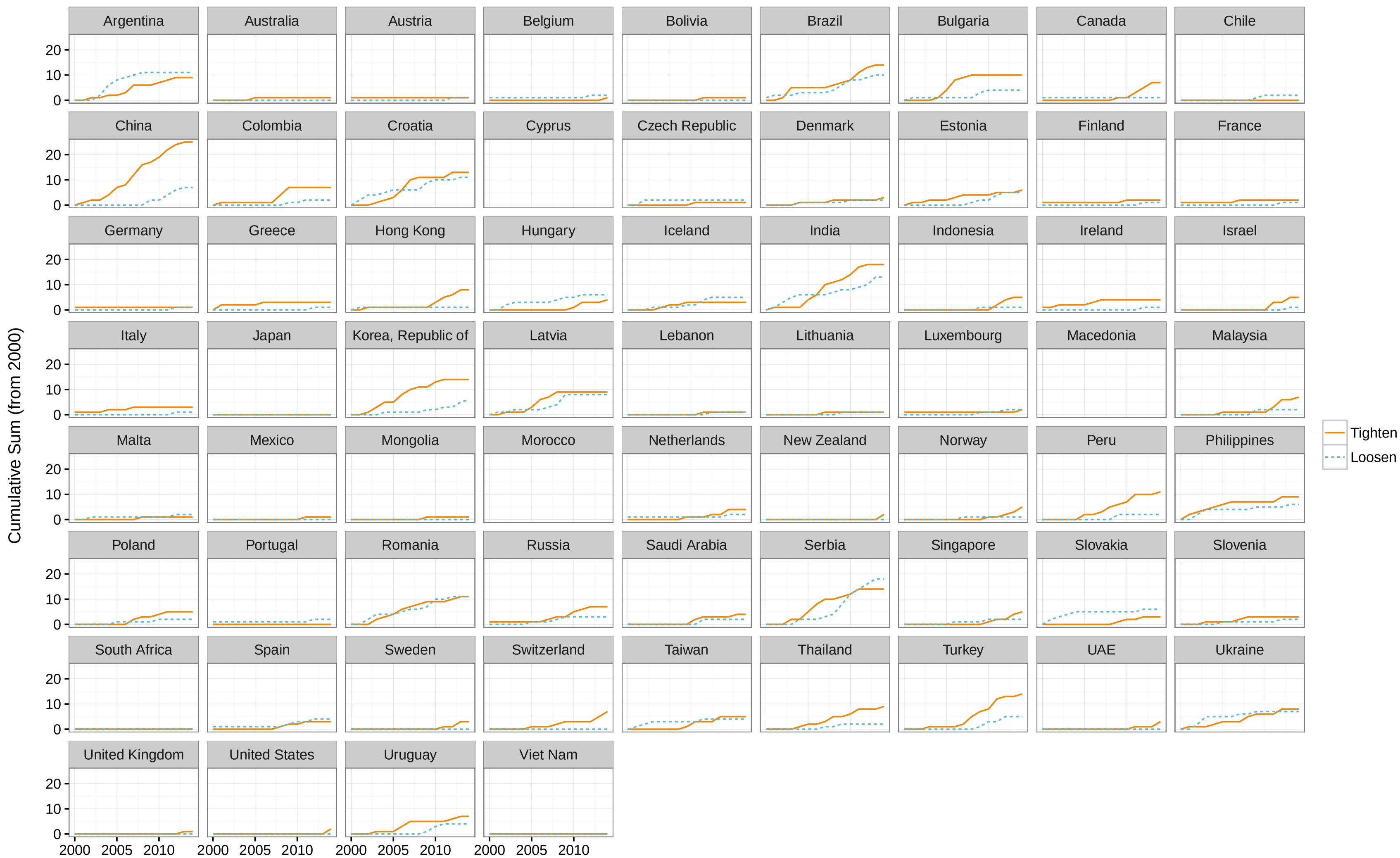
Perhaps politicians' **economic ideology** may play a role in macro-prudential decisions. To test this we include the government executive's economic policy orientation from the Database of Political Institutions (DPI, Beck et al. 2001 updated through 2012), It is one for right-leaning, two for centre-leaning, and three for left-leaning. We never found any support for this variable, so results from models using it are not shown below.

Inequality may also influence the implementation of macro-prudential policy measures. Rajan (2012) and Calomiris and Haber (2014) suggest inequality may be a root cause of credit booms in democracies, especially in societies with limited redistributive capacity or political will. Faced with such conditions, democratic governments may aim to boost the consumption of lower-income households by manufacturing credit booms through less stringent financial regulation. Indeed, Piketty and Saez (2013) show that large increases in private debt before the Great Depression and Great Recession were associated with widening income inequality. Politicians may prefer not to intervene and instead permit credit bubbles to inflate in order to sustain their popularity. To assess the influence of inequality, we use several standard measures of the Gini coefficient, devised by Solt (2008) and later updated in Solt (2014). The measures range from zero to one, with higher values indicating higher income inequality. The first two measures–market-income Gini and net-income Gini–capture the income distribution before and after public redistributive measures are taken into account, respectively. If inequality is an important component of the MPR decision-making process then we would expect that the inequality measure that takes redistribution would be more strongly associated with a low probability of macro-prudential tightening as it would reflect the public's lived level of inequality.

We use these measures to also assess the extent of public **redistribution** on MPR decisions. To do this we created a measure of redistribution relative to market inequality (the difference between the market-income and net-income Gini indices divided by market-income and multiplied by 100); that is, the percentage by which market-income inequality is reduced by redistribution. Perhaps countries that respond to inequality pressures with redistributive policies would be less likely to forestal MPR tightening.

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

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



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 right-hand variables are strongly correlated with one another, presenting issues of multicolinearity (see the Online Appendix for the correlation matrix of our key independent variables) and likely violate the assumptions of the logistic and similar regression models. There are also relatively few events to non-events.[5] We also have many predictors when including fixed effects relative to the number of observed monetary policy decisions. All of these issues point to the usefulness of an alternative modeling strategy: 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). Though previously rarely used, this method is increasingly relied on in political science (e.g. Gandrud and Hallerberg 2015; Hill and Jones 2014; Jones and Linder 2015; Muchlinski et al. 2016; Shellman, Levey, and Young 2013; Spirling 2012). The algorithm builds on a method know as Classification and Regression Trees (CART). A CART algorithm starts with the complete data set (root node) and recursively partitions (branches) the observations into increasingly homogeneous groups on the predictor space based on their values of the predictor variables (see Muchlinski et al. 2016, 92). This creates a single classification tree. However, CART creates problems of overfitted trees. Random forests help overcome this problem by finding multiple trees for bootstrapped samples of the data and then averaging over the trees. This method allows us to explore our data set of relatively rare events and find potential non-linearities and interactions among our correlated variables, which would be difficult in a logistic regression context. It also has high robustness to noise and outliers (Muchlinski et al. 2016, 93), which as we will see, of which there are important instances in the data.

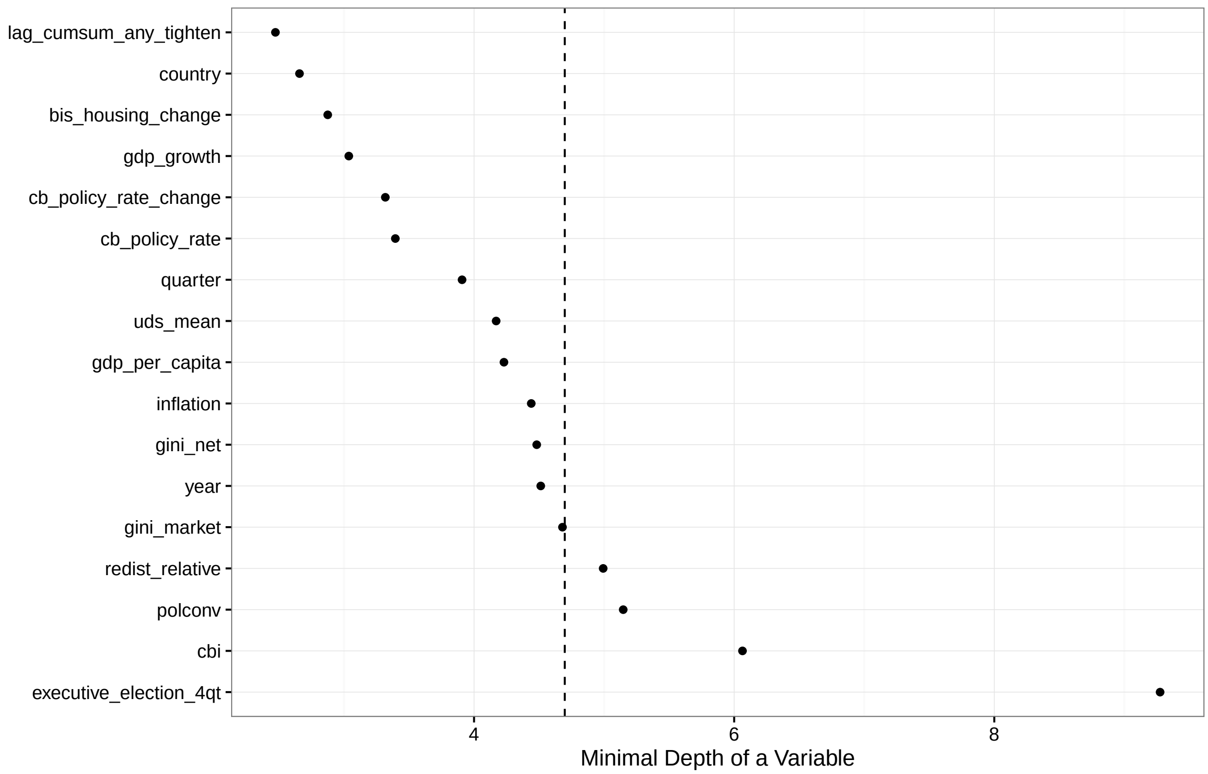
We also ran confirmatory analyses using logistic regression models with stepwise included right-hand variables and minimally informative prior information (Gelman et al. 2008) to avoid creating unreasonably large coefficient estimates. The results of these models will presented in the Online Appendix.

Random Forests: MPR Tightening

We first examined random forests with macro-prudential regulatory policy tightening as the response variable. To assess each variable's relative performance for classifying country-quarters as experiencing MPR tightening

[5] In the full sample there were 5118 country-quarters, 355 observations country-quarters with any MPR policy tightening and 205 instances of loosening. A common way of addressing this type of situation is to use rare events logistic regression (King and Zeng 2001). Muchlinski et al. (2016) show that random forests outperform these types of models in prediction.

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.

or not we first examined the variables' minimal depth. Figure 2 shows the minimal depths for each variable included in our random forest 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 2015b, 11). So a lower minimal depth indicates that the variable is more important for predicting MPR policy tightening. Using the rule developed by Ishwaran et al. (2010), minimum depth values below the mean minimum depth across the variables indicate variables that are important for predicting MPR policy tightening.[6]

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. Additionally central bank independence is not an important predictor using this metric. These two findings complement each other. If there is not a macro-prudential electoral cycle, then countries with and without independent central banks

[6] We used the `ggRandomForests` package (Ehrlinger 2015a) for R to find minimum depths and create partial dependence plots shown below.

would not have meaningful differences in tightening choices as the purported effect of CBI would be to mitigate MPR electoral cycles. We also found that the relative level of redistribution and political constraints are likely not important predictors of MPR tightening.

It is important to note that the country "fixed effect" had a very low minimal depth and the year and quarter effects were also below the minimal depth threshold (see Figure 2). This suggests that there are likely other important unobserved factors that vary by country and time contributing to MPR policy tightening decisions.

To get a sense of the estimated form of the variables' effects on MPR policy tightening, we found their partial dependences with MPR tightening. 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:[7]

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

f is the predicted MPR policy tightening decision. x is the variable for which we want to find the partial dependence and $x_{i,o}$ are the other variables (see Friedman 2000; Ehrlinger 2015b, 16). With binary dependent data the summand here is the log of the fraction of total votes for the classification–the predicted logit–of y defined by:

$$f(x) = \log p_k(x) - \frac{1}{K}\sum_{j=1}^{K} \log p_j(x). \tag{2}$$

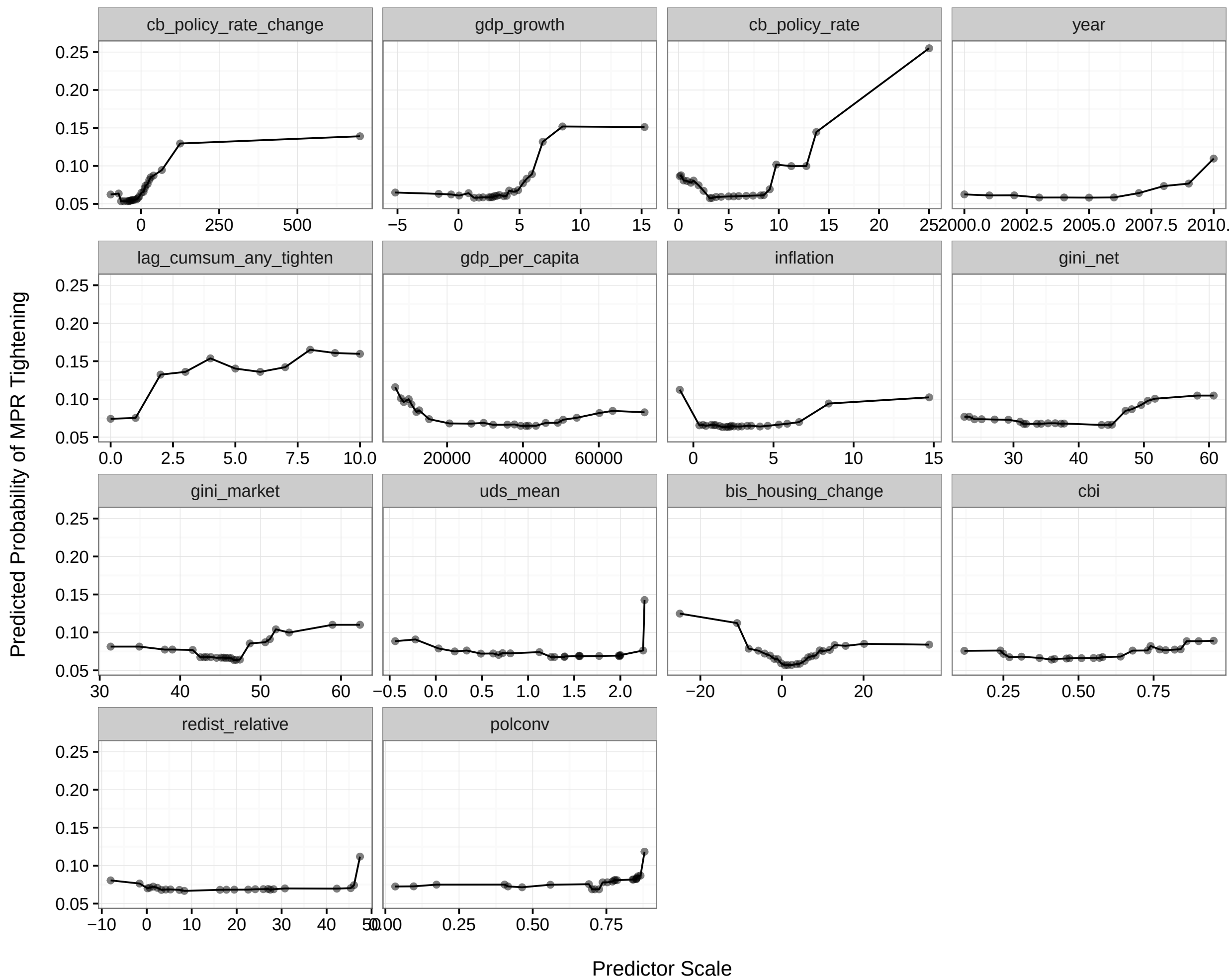
K is the number of classes in y. k is the predicted class. p_j is the proportion of votes for class j (Muchlinski et al. 2016, 99).

In this case, we can think of partial dependence as the average predicted probability of MPR tightening for a value of one explanatory variable averaged within the joint values of the other predictors (Jones and Linder 2015, 8) or possibly in more familiar terms: the marginal effect of a variable on the probability of tightening (Muchlinski et al. 2016, 98).

Countries with higher central bank policy rates have a higher probability of tightening. There does not appear to be much difference in the low probability of tightening if the policy rate is below about 10 percent. Above this point the predicted probability of tightening increases to between 10 to about 25 percent. This result appears to be largely driven by Brazil which tightened in nine quarters between 2002 and 2010. Brazil

[7] Largely for computational reasons, for variables with many values predictions are made for a subset of the values.

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



Variables shown are those that were below the minimal depth threshold. Two of the "fixed effect" variables (country and quarter) are also not show. Note that predictions are for policy change to be made per quarter.

was only one of four countries to have such a high policy rate in the estimation sample. One of the other countries–Columbia in 2000 also tightened.[8] As such it appears that countries with less monetary policy room for maneuver, are more likely to resort to macro-prudential tightening. Interestingly, countries with increasing policy rates are also more likely to tighten. This suggests that macro-prudential tightening may be used as a complement to monetary policy tightening.

GDP Growth appears to have a relationship with MPR tightening in a manner that we would expect from a model of policy-makers tightening in an attempt to calm asset price bubbles. There is a very low probability of MPR policy tightening at growth levels up to about 5 percent of GDP. From this point, the probability of tightening rises somewhat, reaching about 15 percent per quarter when growth is around seven percent of GDP.

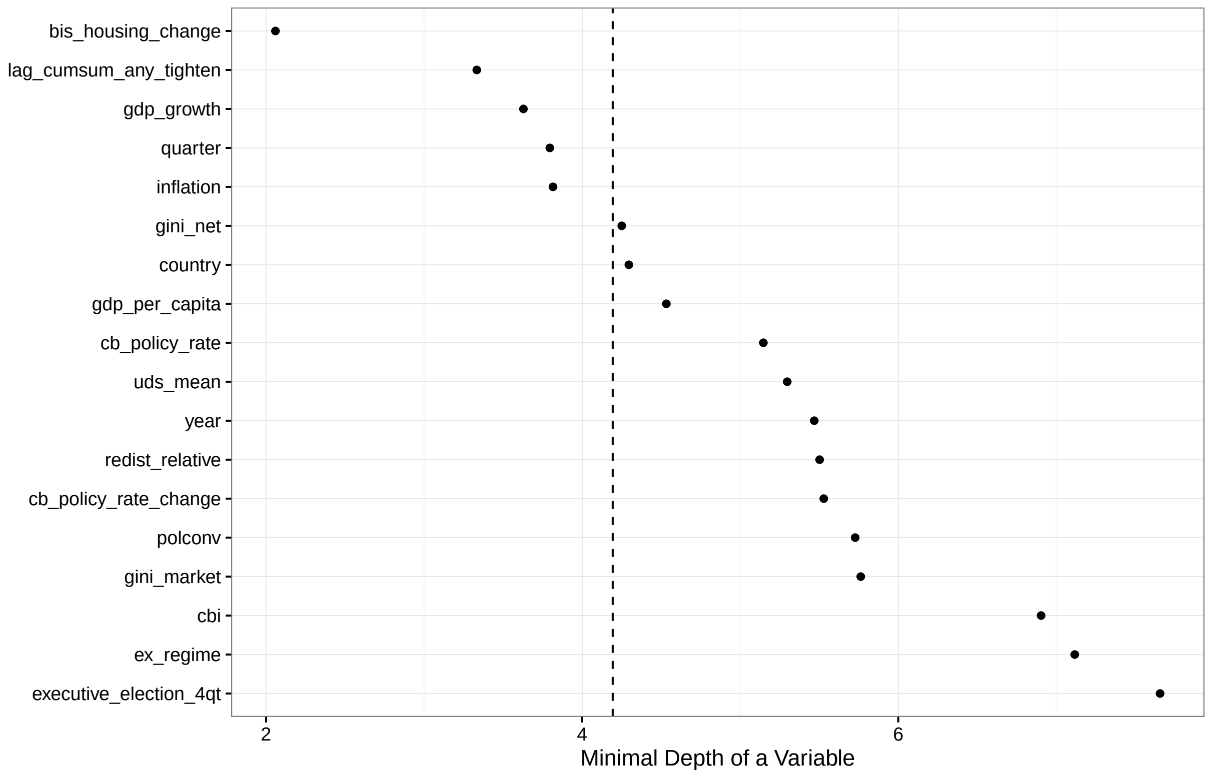
Housing price changes appear to have a U-shaped relationship with MPR tightening. When housing prices are stable–around zero percent change–there is a low average probability of tightening. Large year-on-year quarterly housing price increases bring the probability of tightening to a little under 10 percent per quarter. This is what we would expect from policy-makers using MPR policy tightening to quell property price bubbles. Interestingly, large housing price declines are also associated with tightening. The countries in the model where housing prices declined more than 5 percent and had tightening included Brazil (quarter 1, 2003), Canada (quarter 4, 2008), Hungary (quarters 1 and 2, 2010), Peru (quarter 3, 2006), and Singapore (quarter 3, 2009). Brazil tightened reserve requirements. Canada, Hungary, and Singapore tightened lending standards, despite falling housing prices. Peru tightened capital requirements. Given the wider context of the Global Financial Crisis in which Canada, Hungary, and Singapore tightened it may be that their tightening was a late date measure to prevent banking system contagion from a crisis that was already hitting economic growth and so housing prices. We see a possibly similar Global Financial Crisis effect by looking at the partial dependence for the year variable. The predicted probability of tightening increases noticeably from 2008.

%We can also see that countries appear to be more likely to tighten when there is lower perceived financial market stress as measured by FinStress. This would be the outcome we would expect if policy-makers were using tighter MPR policy to head off future crises, when conditions are still relatively stable.

Inequality appears to affect tightening decisions, though not in the way we initially expected. We anticipated that countries with higher inequality, especially even after redistribution, would be less likely to tighten in order not to alienate less advantaged supporters by reducing their access to credit. However, we found that countries with higher inequality (using both the market and post-redistribution measures) are more likely to tighten. Countries such as Brazil, Colombia, Peru, and Thailand all had Gini scores above 45 (on

[8] The other two countries were Indonesia and South Africa.

Figure 4: Minimal Depth For Trees Classifying Macro-prudential Policy Loosening



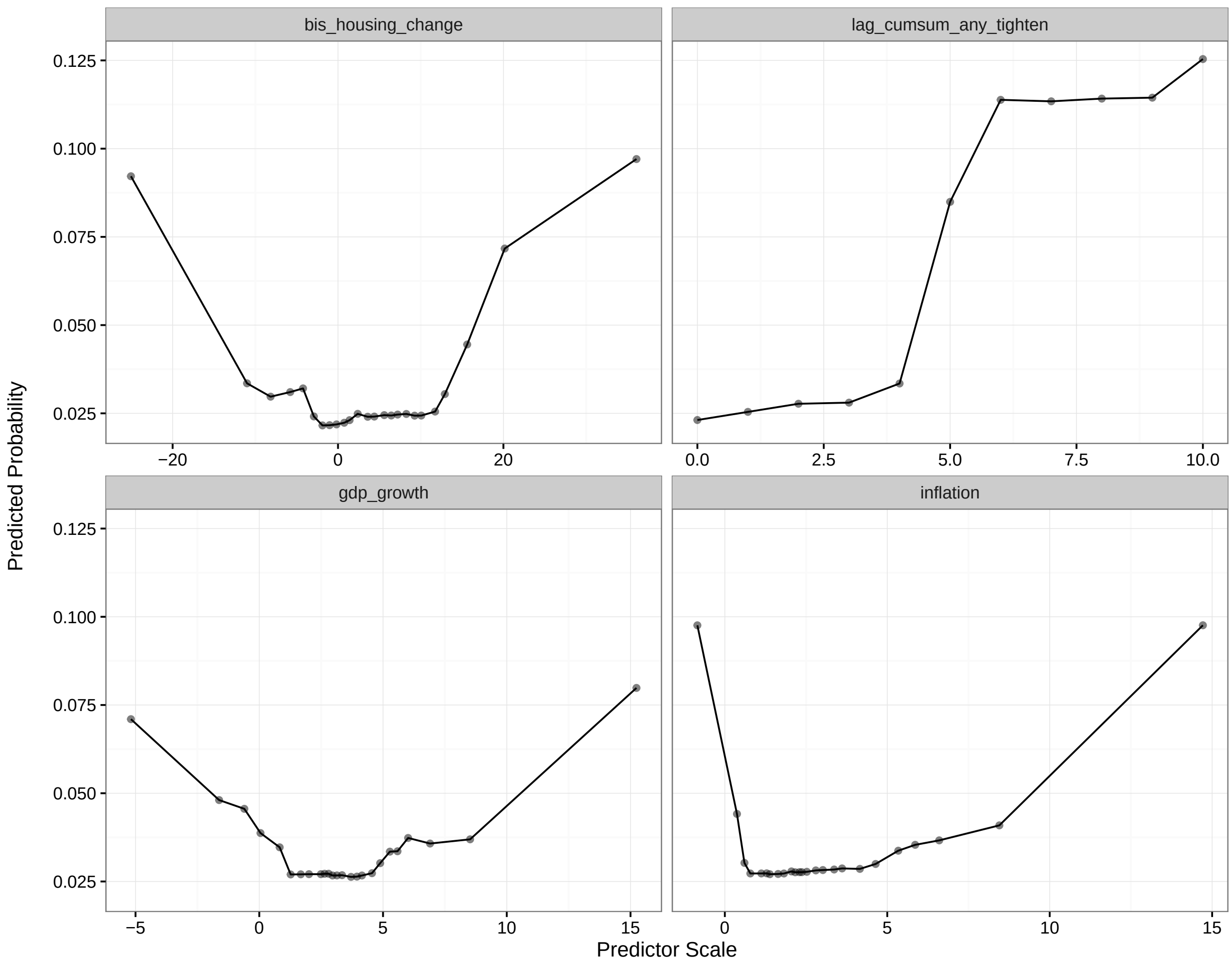
The dashed vertical line indicates mean minimum depth across the variables. Minimum depths below the mean depth are considered to be important in forest prediction.

both measures) and tightened over multiple quarters. Almost all of these countries tightened by increasing reserve requirements. One possible explanation for this seemingly contradictory result is that while there may be political pressures to not tighten in unequal societies, they are also more likely to get into a situation where they need to tighten. They also seem to tighten in such a away–increasing reserve requirements–that does not directly impact borrowers, though presumably such a policy would tighten available credit over the medium-term.

Random Forests: MPR Loosening

Many instances of MPR loosening occurred in the more recent period of our sample as countries began to wind down their responses to the Global Financial Crisis.

Figure 5: Partial Dependence Plot for Macro-prudential Regulatory Policy Loosening



Variables shown are those that were below the minimal depth threshold. The "fixed effects" variables are not shown. Note that predictions are for policy change to be made per quarter.

Conclusions

Online Appendix

Table 1: Country Quarter-Year Sample Included in the Random Forests After Deleting Cases with Missing Values

	Country	First Year	Last Year
1	Australia	2004	2010
2	Brazil	2002	2010
3	Bulgaria	2010	2010
4	Canada	2000	2010
5	Chile	2010	2010
6	Colombia	2000	2010
7	Denmark	2003	2010
8	Indonesia	2003	2010
9	Israel	2000	2010
10	Malaysia	2005	2010
11	Mexico	2009	2010
12	New Zealand	2000	2010
13	Norway	2000	2010
14	Peru	2004	2010
15	Singapore	2000	2010
16	South Africa	2000	2010
17	Sweden	2003	2010
18	Switzerland	2000	2010
19	Thailand	2009	2010
20	United Kingdom	2000	2010
21	United States	2000	2010

Table 2: Predictor Variable Correlations

	Cum. Tight. (lag)	GDP Growth	GDP/Capita	Inflation	FinStress	Housing Chng	CBI	Election	Gini Diff.	Absolute Redist.	UDS
Cum. Tight. (lag)	1.00	0.09	-0.37	0.13	0.11	0.01	0.20	0.19	-0.05	-0.21	-0.21
GDP Growth	0.09	1.00	-0.20	0.13	0.32	0.02	0.14	0.21	0.32	-0.40	-0.43
GDP/Capita	-0.37	-0.20	1.00	-0.57	0.03	-0.35	-0.20	-0.53	0.02	0.58	0.49
Inflation	0.13	0.13	-0.57	1.00	-0.14	0.05	0.15	0.70	-0.06	-0.43	-0.35
FinStress	0.11	0.32	0.03	-0.14	1.00	-0.11	-0.06	0.07	0.11	0.06	0.05
Housing Chng	0.01	0.02	-0.35	0.05	-0.11	1.00	0.06	-0.16	0.06	-0.15	0.10
CBI	0.20	0.14	-0.20	0.15	-0.06	0.06	1.00	0.19	0.02	-0.16	-0.14
Election	0.19	0.21	-0.53	0.70	0.07	-0.16	0.19	1.00	0.05	-0.32	-0.23
Gini Diff.	-0.05	0.32	0.02	-0.06	0.11	0.06	0.02	0.05	1.00	-0.06	0.04
Absolute Redist.	-0.21	-0.40	0.58	-0.43	0.06	-0.15	-0.16	-0.32	-0.06	1.00	0.79
UDS	-0.21	-0.43	0.49	-0.35	0.05	0.10	-0.14	-0.23	0.04	0.79	1.00

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