Understanding and Predicting Monetary Policy Framework Choice in Developing Countries

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Abstract

We investigate which factors predict choice of monetary policy framework (MPF) among emerging and developing countries. We examine the role that characteristics such as financial market depth and trade networks play in predicting the MPF choice of 87 such countries from 1985-2017. We find that the probability of a medium-sized country picking inflation targeting is approximately 10pp greater than the probability of a large country doing so, after controls are applied. This suggests that large economies do not feel as much of a need to target inflation as smaller ones do. We improve upon previous work on MPF choice by testing the model's prediction accuracy on unseen data, and addressing endogeneity. We achieve an average prediction accuracy of 68% when using cross-validation methods. This paper enables policymakers to see which MPF countries similar to their own have chosen, and to decide if it is suitable for them, too.

JEL Codes: E42, E52, E58, F40

1 Introduction

The evolution of exchange rate regimes (ERRs), and how countries choose such regimes, has been researched [see, for example, Juhn and Mauro (2002) and Levy Yeyati et al. (2010)]. Due to the rise in popularity of inflation targeting, the preconditions required for a country to become an inflation targeter has been explored (Batini and

Laxton, 2006). However, determinants of monetary policy frameworks (MPFs), on the whole, have received little attention.[1]

There now exists a MPF classification which covers 186 countries to date.[2] This analysis uses the classification's definition for a MPF: "...[T]he objectives and the context that condition monetary policy decisions: primarily the objectives pursued by monetary authorities, but also the set of constraints and conventions within which their monetary policy decisions are taken" (Cobham, 2021, p. 1). There is one paper that explores the determinants of MPFs for advanced and emerging economies (Cobham and Song, 2020), using the aforementioned classification. However, developing countries have not so far been investigated from this perspective.

This analysis makes use of the relatively new MPF classification dataset, and applies the methodologies from Cobham and Song (2020) and Levy Yeyati et al. (2010) to emerging and developing countries. Levy Yeyati et al. (2010) investigates the determinants of ERRs and identifies three main approaches to account for how they are chosen (optimum currency areas (OCA), the financial view, and the political view). Their paper models these approaches separately before including all 3 approaches into one model.[3] Their results show that the signs on the estimated coefficients (for the full sample) in the full model do not differ by much from the signs on the estimated coefficients (for the full sample) in the separate models. They argue that the results of the full model are in-line with the findings they achieve in their separate models.[4] Furthermore, they use a Wald test to run three joint significance tests (on the variables within each theoretical model). The results show that the variables are jointly significant for each theoretical approach.

This paper also separates the determinants of MPF choice into 3 similar theories. By

[1]Prior to 2018 there did not exist such a detailed, multi-dimensional MPF classification

[2]Available on https://monetaryframeworks.org/classifications

[3]They mention the need for putting all three approaches into one model as correlations are likely to exist between the variables. Therefore, the results of their partial tests could be biased.

[4]This raises the following question: how different must the estimated coefficients be (in terms of both magnitude and statistical significance) before the results are no longer considered in-line with each other? Especially as bias is a bigger concern in logistical models. Unlike in a standard linear regression, the estimated coefficients in a logistic regression can be affected by bias even when the omitted variable is orthogonal to the independent variables (Mood (2010)).

using a multinomial logit model this paper analyses the importance of a range of different factors on which countries' choices might depend. Thus, this work looks into what may have guided countries' past choices of MPFs for emerging and developing countries.

The results show that, unlike Levy Yeyati et al. (2010), the sign on the estimated coefficients differs on two occasions from the signs achieved when the theoretical approaches were modelled separately. This provides evidence in favour of the full model being used when analysing how variables affect the probability of MPF choice. In line with Levy Yeyati et al. (2010), the likelihood ratio tests show that the variables within each theoretical approach are jointly statistically significant. Thus, we find that each theoretical approach has empirical relevance.

The paper highlights a couple of key findings: Firstly, it identifies the extent to which a country trades with all the countries that use or peg to a given anchor currency and shows that, as this amount (as a proportion of GDP) increases (from 0 to maximum), the probability of a country opting for an exchange rate MPF (pegged to that currency) increases by approximately 56pp. Secondly, it finds that medium-sized countries are more likely than larger ones to choose an inflation targeting MPF and opt for a higher degree of monetary control (DoMC).

Lastly, when assessing the model's predictive accuracy for MPF choices (aggregated by target variable) through two different cross-validation techniques, it achieves an average accuracy rate of 68%. This accuracy rate is better than a simple model that just picks the most common category, discretion. This performance suggests that the model presented in this paper possesses a good capacity for generalising to data not previously seen.

The rest of the paper is set out as follows: section 2 is on the theories (optimum currency areas, financial integration, and political/institutional strength), section 3 discusses the degree of monetary control, section 4 is data and methodology (data, descriptive statistics, and methodology), section 5 is results (by target variable aggregation, prediction accuracy for target variable aggregation, by degree of monetary control, and prediction accuracy for degree of monetary control), section 6 is endogeneity and robustness (reverse causality, omitted variable bias, and robustness checks), and, finally, section 7 is conclusion.

2 The Theories

There are three main approaches to the (normative) choice of ERR and MPF that are prominent in the macroeconomic literature - optimum currency areas (OCA), financial integration, and the political economy. Levy Yeyati et al. (2010) empirically test the relevance of each of these approaches to the choice of ERRs. By finding variables that closely measure the factors identified within the three approaches, they find empirical support in favour of all of them.

Countries differ in multiple ways but key distinctions have been highlighted to exist between emerging/developing economies and advanced economies (see, for example, Mishkin (2004), Frankel (2010) and Cobham (2011)). These differences give insight into why choice of regime (be it monetary policy or ERR) is likely to differ. This paper combines the work of Cobham and Song (2020) and Levy Yeyati et al. (2010) and applies it to the determinants of MPFs in emerging and developing countries. Throughout this section the acronyms D, ER and IT are used. D is for discretion based MPFs - a country is classified as having a discretion MPF in the years where there are no announced, or even unannounced but observable, quantitative targets. In tables 1,2 and 3, D is used as the default category because it is the MPF that is most prevalent over time. ER is for exchange rate based MPFs. Finally, IT is for inflation targeting based MPFs.[5]

2.1 Optimum Currency Areas

Seminal work from Mundell (1961) and McKinnon (1963) on OCAs highlights the importance of a country's size and trade in the determinants of regime choice. Breedon et al. (2012) focuses on small rich countries but states that the smaller an economy,

[5]These categories are explained in more depth in Section 4.

the more vulnerable they are to ER volatility - larger countries are less vulnerable and therefore have IT as a more available option. In addition to size, as is typical in developing/emerging countries, their trade may be heavily concentrated within a currency bloc, or their income may be reliant on the exportation of a certain good which is denominated in one currency (e.g. fuel).[6] Frankel (2010) states that emerging/developing countries are typically more susceptible to volatility due to primary products (e.g. agriculture, forestry, and fishing) making up a greater share of their GDP. Lastly, the literature on the effects of trade openness on regime choice is mixed but the literature agrees that it is an important factor. Furthermore, there is literature on the relationship between inflation and trade openness. Lane (1997) finds that trade openness and inflation are negatively correlated (once controlling for country size)[7]. There are a variety of reasons as to why this negative correlation may exist, for example, strong foreign competition helps to limit the extent to which firms pass-on any price increases to their consumers (Bowdler and Nunziata (2006)). However, it is possible to have low inflation but not be an IT. For example, the trade openness might be helping to keep inflation low without the need for IT to be their choice of MPF. Thus, the relationship between trade openness and MPF choice is not obvious *a priori*.

This paper uses the following variables to empirically test the OCA hypothesis: economic size, which is split up into small, medium and large categories; anchor network, which is defined as the largest ratio of country's trade with each of the main anchor currencies to GDP, as per Cobham and Song (2020) who draw in turn on Meissner and Oomes (2009); trade openness, the ratio of imports and exports to GDP; and fuel exports, which is measured as a percentage of merchandise exports.

[6]Although this is a common argument for pegging such countries' exchange rates, oil price volatility is typically higher than ER volatility. Thus, it is not obvious that pegging to the US Dollar significantly stabilises export proceeds.

[7]A seminal paper by Romer (1993) finds a robust negative correlation between openness and inflation

Table 1: Sign predictions for variables included in the *optimum currency area* hypothesis[b]

	Sign Expectation[c]	
VARIABLE	**(ER*)**	**(IT*)**
Large	-ve	+ve
Medium	-ve	+ve
Anchor Network	+ve	?
Trade Openness	?	?
Fuel Exports	+ve	-ve

*Where D is the comparison/base category

[a]Controls for region, year, and state dependence/inertia
[b]Controls for region, year, and state dependence/inertia
[c]This is the expectation relative to the default category of discretion

2.2 Financial Integration

Capital account openness is viewed as one way of measuring financial openness (Bekaert et al. (2006)). Chinn and Ito (2008) have created an index measuring capital account openness which has wide country coverage and offers a long time-series. Within macroeconomics, capital flows form part of the impossible trinity argument. This is the idea that countries get to choose only two out of the following three options: fixed ER, free capital flow, and sovereign monetary policy. For example, a country with an open capital account cannot also both have control over monetary policy and target their ER. Alexander et al. (1995) states that the opening of the capital account typically, but not always, accompanies the transition to indirect monetary policy instruments (typically interest rates). IT relies on the use of such indirect instruments - operating via interest rates gives greater flexibility (both in terms of speed and size of response) to monetary policy.[8] In addition to this, shallow capital markets, particularly in emerging/developing countries, can be a common cause of fiscal dominance (Debelle et al. (1998)). Thus, countries with such capital markets may be less able to opt for an IT MPF which is incompatible with fiscal dominance. Therefore, *a priori*, this paper predicts that capital account openness will have a negative effect on ER MPF being picked but a positive

[8]Please refer to Cobham (2023) for more information on what is meant by *effectiveness* of monetary instruments and how indirect instruments are more effective than direct instruments.

effect on an IT MPF being chosen. As well as capital account openness there is financial market depth. Financial market depth is an important aspect of a country's financial development. Cobham (2011) explains that a well developed financial system has a deep and active bond market which involves non-bank private sector agents. This helps to separate monetary policy from fiscal policy by protecting against fiscal dominance - the government can borrow from these agents rather than the banking system. This kind of financial depth is necessary for a country to be able to pursue IT because fiscal dominance is incompatible with an IT MPF. Countries that lack this kind of infrastructure, consequently, are more limited in their choice of MPF. However, Cobham (2011) states that it is costly to develop one and Alexander et al. (1995) states that it is a complex process as it requires substantial infrastructure (e.g. electronic systems, an advanced legal and regulatory framework, and skilled human capital to operate the markets). Therefore, it is common for emerging/developing countries to lack such a system. Furthermore, as emerging/developing countries typically tend to have weaker financial institutions than advanced countries, their banking and financial systems are more vulnerable to high inflation and currency crises (Mishkin (2004)). Some developing countries' financial institutions borrow large amounts of money in foreign currency but lend mainly in domestic currency. This is because international investors typically tend to charge a high ER risk premium on emerging market local currency debt, and this premium can be increased further when ER volatility is high. Thus, depreciation of their currency tends to be more dangerous to their financial systems. Levy Yeyati et al. (2010) states that they expect there to exist a positive correlation between capital account openness and more flexible ERRs when currency mismatches are not as high. However, when there are large currency mismatches, there tends to be inconsistencies with the impossible trinity argument and the opposite result tends to be found. Therefore, the result on capital account openness should help to inform us if currency mismatch is a problem.[9]

[9] The data Levy Yeyati et al. (2010) use to measure currency mismatch is currently only available from 2001 and it is not available for all countries. As this would reduce the number of observations significantly, and an adequate substitute cannot be found, a variable measuring currency imbalances is not included. However, as a robustness check, we control for the Asian financial crisis as these countries

This paper uses the following variables in order to empirically test the financial integration hypothesis: capital account openness and financial market depth.

Table 2: Sign predictions for variables included in the *financial integration* hypothesis[a]

	Sign Expectation[b]	
VARIABLE	**(ER*)**	**(IT*)**
Capital Account Openness	-ve	+ve
Financial Market Depth	-ve	+ve

*Where D is the comparison/base category

[a]Controls for regions, year, and state dependence/inertia

[b]This is the expectation relative to the default category of discretion

2.3 Political/Institutional Strength

Institutional credibility and accountability is regularly cited as a must for a country to become an inflation targeter. On average, emerging/developing countries' monetary institutions tend to have lower credibility than monetary institutions in advanced countries, which is needed for more modern policy frameworks (e.g. IT). There is also the 'policy crutch' argument, mentioned in Levy Yeyati et al. (2010), which says that countries with a poor institutional record may adopt an ER peg in an attempt to anchor inflation expectations. Furthermore, an independent central bank is useful for monetary policy, not just in harnessing credibility and accountability, but also because fiscal considerations will not then dictate monetary policy. Emerging/developing countries' central banks are often more susceptible to fiscal dominance as they tend to have weaker fiscal institutions than their advanced counterparts. However, there are different ways in which a central bank can be independent. For example, Mishkin (2004) states that it is important for a central bank to be independent in practice[10] - being just legally independent is not enough.[11]

had a high amount of dollarised liabilities.

[10]This is important for good monetary policy in general but particularly so for countries wishing to inflation target.

[11]The paper gives Argentina vs. Canada as an example. Argentina's central bank is legally independent but lacks the public and political support for independence. Canada's central bank, however, does

In addition to central bank independence (CBI), there is the degree of autocracy/democracy of a country. Previous work finds that, relative to democracies, autocracies are more likely to maintain fixed ERRs and sometimes even undervalue their currency as part of a mercantilist policy (Steinberg and Malhotra (2014)). Furthermore, countries that are democracies are more conducive to IT because it requires public (and political) support (Mishkin (2004)). Cobham (2022) states that autocratic countries are unlikely to have independent central banks because this takes power away from the autocrats. Furthermore, these countries are unlikely to have transparent central banks as autocrats do not like to be held accountable and accountability depends on central bank transparency. Finally, the paper states that, for countries in the middle east and north Africa, IT is the MPF that is associated with the most democratic political arrangements, followed by loosely structured D.

This paper uses the following variables in order to empirically test the political/institutional strength hypothesis: a measure for strength of democracy, which is measured on a scale from autocracy to democracy; and a measure for central bank independence.

Table 3: Sign predictions for variables included in the *political/institutional strength* hypothesis[b]

	Sign Expectation[c]	
VARIABLE	**(ER*)**	**(IT*)**
Strength of Democracy	-ve	+ve
Central Bank Independence	-ve	+ve

*Where D is the comparison/base category

[a]Controls for regions, year, and state dependence/inertia
[b]Controls for regions, year, and state dependence/inertia
[c]This is the expectation relative to the default category of discretion

not look independent from a legal standpoint but is in practice.

3 Degree of Monetary Control

The previous section is based on the MPF classification as aggregated by target variable. The classification also aggregates on degree of monetary control (DoMC). It uses the following categories: intermediate, substantial, and intensive. The DoMC increases as you move from left to right (e.g. intermediate-substantial-intensive).[12]

Therefore this paper also looks into how the above variables help determine the choice on DoMC. Table 4 below shows the expected sign on the estimated coefficients.

Table 4: Sign predictions when aggregated by degree of monetary control

	Sign Expectation	
VARIABLE	**(Subst*)**	**(Intens*)**
Large	+ve	-ve
Medium	+ve	-ve
Anchor Network	?	?
Trade Openness	?	?
Fuel Exports	?	?
Capital Account Openness	?	?
Financial Market Depth	+ve	+ve
Strength of Democracy	?	-ve
Central Bank Independence	+ve	+ve

*Where intermediate is the comparison/base category

Firstly, as larger countries are less vulnerable to shocks (e.g. ER shocks (Breedon et al. (2012)), shocks to the market price of a good or a decrease in the exports of certain goods (e.g. tropical cash crops)[13](Frankema et al. (2022))) they may feel less of a need to opt for an intensive degree of monetary control, however, it is likely they will still opt for a serious degree of monetary control. Therefore, it is expected that the sign on the estimated coefficient for the large and medium variables will be positive for substantial degree of monetary control but negative for intensive degree of monetary control. A similar argument can be applied to medium-sized countries, and, thus, their expected

[12]The classification has fourth category, rudimentary, but this category is not present within the dataset this paper is using.

[13]These examples are an issue in a country that is not very well diversified. Usman and Landry (2021) states that the continent, Africa, has 8 out of the 15 world's least economically diversified countries. It also stresses the importance of diversification for resilience.

signs are the same as the expected sign on the 'large' variable.

Secondly, as a country's trade increases with countries within a certain trade bloc, it is likely they will want more control over their ER with that bloc. However, control over an ER is possible within all 3 categories of DoMC; the difference between each category is what instruments they have available to use in order to meet their objective. Therefore, the expected sign on the estimated coefficients is not obvious *a priori.*

Thirdly, and for similar reasons provided in the target variable section, the expected sign on the trade openness variable is uncertain. Although trade openness seems to be negatively correlated with inflation (Romer (1993)) this does not give any insight into DoMC MPF choice.

Fourthly, as a country has a greater proportion of their GDP as fuel exports, they may want a greater degree of control over their ER. However, similar to the reasoning given for the anchor network variable, this makes the expected sign uncertain for both substantial and intensive DoMC, as control over an ER is possible within all 3 categories of DoMC.

According to Levy Yeyati et al. (2010), they argue that capital account openness is typically positively correlated with more flexible ERRs due to capital account openness reducing the effectiveness of pegs. However, as mentioned previously, Levy Yeyati et al. (2010) states that this relationship may be flipped if currency mismatch is large. Therefore, as it is possible to have intermediate, substantial, or intensive DoMC whilst having a flexible ERR (e.g. discretion or inflation targeting) the estimated signs on the coefficients are uncertain.

Sixthly, greater financial market development enables higher monetary control, so the sign is expected to be positive for both substantial and intensive DoMC.

Penultimately, it is expected that the more autocratic a country, the more likely they are to opt for control over their ER (Steinberg and Malhotra (2014)). Cobham (2022) states that autocrats do not like to cede power; it is highly possible that they would view autonomous markets as a lack of control. Thus, intensive DoMC may be considered as giving too much power away to autonomous market forces. Therefore, the expected sign on intensive is negative but the expected sign on substantial is uncertain.

Lastly, countries with greater central bank independence typically tend to have a greater degree of monetary control as they can use indirect instruments to influence the interest rate - as opposed to using direct, non-monetary instruments. Furthermore, certain MPFs (e.g. IT) that are included in substantial and intensive DoMC have central bank independence as a pre-condition. Therefore, the expected sign on CBI is positive for both substantial and intensive.

4 Data and Methodology

4.1 Data

A panel dataset, from 1985 to 2017,[14] has been constructed using the variables shown in Appendix A. The dataset includes the emerging and developing countries from the following regions: Africa; Asia; Latin America and the Caribbean; Other Europe, Caucasus and Central Asia; and the Middle East.[15] Once accounting for data availability, and the 2 currency unions within Africa,[16] this results in 87 countries/currency areas. Furthermore, as policymakers typically observe and respond to past conditions as indicators of future condition, the explanatory variables need to be reflecting information about their past values. Therefore, the explanatory variables take on the average value of the the preceding 4 years.[17] Having the explanatory variables being an average of preceding years also helps to overcome endogeneity concerns, particularly in regards to reverse causality.[18]

[14]The MPF dataset is from 1974-2017 but, once accounting for data availability across all datasets, the first observation is in 1985. The CBI dataset stops at 2012 but we have extended 2012's value to 2017 as CBI does not typically change from year to year. The 1985 starting year is also beneficial as it leaves enough time for the fall out post-Bretton Woods to have died down.

[15]Please see Appendix C for a list of the countries, by region, that is used in this paper

[16]Central African Economic and Monetary Community and West African Economic and Monetary Union

[17]The average value for the preceding 2 and 3 years was also tried. 4 years has been chosen as it performed best when looking at information criteria.

[18]This is discussed in a lot more detail in Section 6.

4.2 Descriptive Statistics

Table 5: Descriptive Statistics of Explanatory Variables

Variable	Obs[a]	Mean	Std. Dev.	Min	Max
Large	1393	.154	.361	0	1
Medium	1393	.168	.374	0	1
Small	1393	.678	.468	0	1
Anchor Network[b]	1393	.262	.176	.01	.996
Trade Openness	1393	.721	.359	.117	2.196
Financial Market Depth	1393	.163	.187	0	.818
Strength of Democracy	1393	2.661	6.342	-10	10
Capital Account Openness	1393	.064	1.42	-1.924	2.322
Central Bank Independence	1393	.532	.181	.132	.904
Fuel Exports	1393	20.632	29.715	0	138.571
Inertia	1393	.969	.173	0	1

[a]This is the total number of observations for both the aggregation by target variable dataset and the aggregation by degree of monetary control dataset. There are a few differences in the number of countries within each dataset. The former has 1,360 observations, covers 72 countries and it removes any country that has 5 or fewer observations. The latter has 1,249, covers 78 countries and it does not include any observations from OECCA region due to this region containing too little variation in the dependent variable to allow the multinomial logit model to converge.

[b]Please refer to Appendix B on how this is calculated.

4.3 Methodology

The decision-makers (DM)[19] – the group/body of people who have the monetary policy decision making power within each country – face a choice between J alternative monetary policy frameworks. Alternative j provides them with utility U_{njt} (where j = 0,1 .... J)[20]. U_{njt} is the utility of country n from picking alternative j at time t. For example, a decision-maker would choose option i over option j, if and only if, $U_{nit} > U_{njt}$. Unfortunately, we are not able to directly observe/quantify U_{njt} - it is a latent variable. Therefore, it is necessary for it to be broken down as being composed of the following:

$$U_{njt} = V_{njt} + \epsilon_{njt} \forall j \tag{1}$$

[19]In this case, there are 87 decision-makers (i.e. the person/group of people who choose the MPF)

[20]In terms of this dataset J=2 and the categories are the following for MPF by target: D, ER, and IT, where j=0 is the base category (D). For MPF by degree of monetary control: Intermediate, Substantial, and Intensive, where j=0 is the base category (Intermediate). t is in years from 1985 to 2017.

where V_{njt} are the factors, which are observable, that affect the DM's utility - sometimes referred to as 'representative utility'. These factors are the independent variables/determinants of MPFs. ϵ_{njt} are the factors that affect utility that are not observable and, thus, these are treated as random. The multinomial logit model assumes that the log-odds of each MPF is linear in parameters:

$$V_{njt} = log(\pi_{njt}/\pi_{n0t}) = \beta' x_{njt} \tag{2}$$

where β is a column vector of the coefficients on the explanatory variables (the determinants of MPFs) and x_{njt} is a column vector of explanatory variables from country n at time t. π_{njt} is the probability of choosing alternative j and π_{n0t} is the probability of choosing D MPF.

Similar to the approach taken in Levy Yeyati et al. (2010), the multinomial logit model is used on each of the 3 theoretical approaches separately before bringing it all together into one model.[21] The signs and coefficients will be compared and a likelihood ratio test will be used to jointly test the relative importance of each of the theoretical views.

Lastly, manipulating equation 2 enables us to achieve the individual probabilities rather than dealing in terms of log-odds.

$$\pi_{njt} = e^{\beta' x_{njt}} / \sum_{j=0}^{J} e^{\beta' x_{njt}} \tag{3}$$

Therefore, specifying values for variable x_1 - and keeping the other explanatory variables constant at their average value - results in the predictive probability of country n choosing choice j. The plots of these show the economic significance of each variable. [22]

[21] All models control for region and year but the regional results are only shown for the full model. They also control for inertia as it is expected that there exists some degree of path dependence when it comes to choosing a MPF. Thus, including a control for past choices is likely to help mitigate any issue of serial correlation.

[22] Please see Appendix D for why this is useful

This approach has been used in Cobham and Song (2020) and has been applied mutatis mutandis to this paper.

Multinomial logit has been chosen over multinomial probit for two reasons: Firstly, previous literature has used multinomial logit so this paper has followed their approach. Secondly, multinomial logit is computationally less burdensome than multinomial probit. However, the former does assume independence of irrelevant alternatives (IIA), whereas the latter does not. Multinomial probit will be used as a robustness check to make sure choice of model does not greatly affect the results.

5 Results

5.1 By Target Variable Aggregation

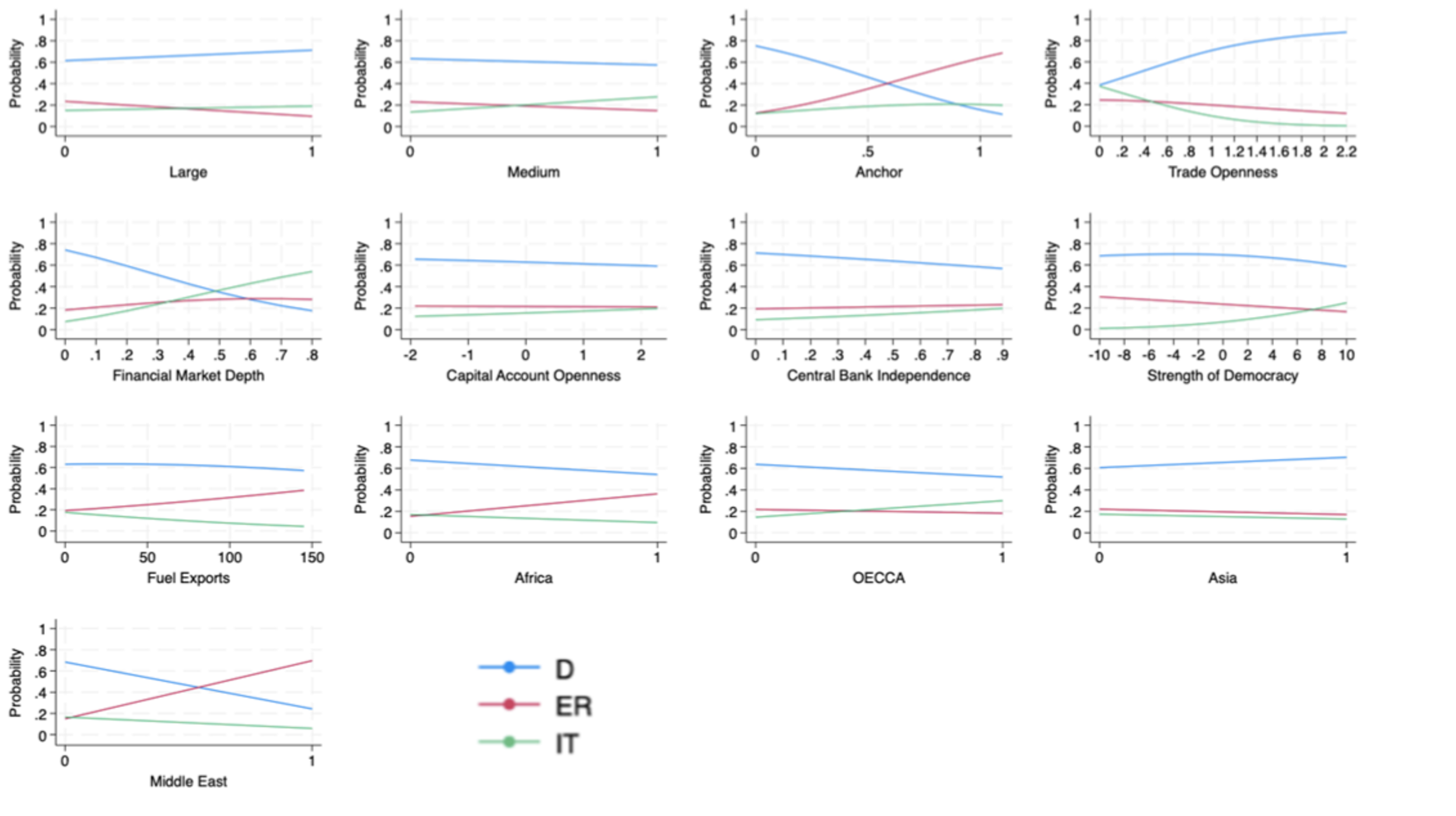
Table 6 shows the estimates of the coefficients for the three subset models (columns (1) to (6), inclusive) - assembled according to the relevant theories - and the full model (columns (7) and (8)). In every model in Table 6, D is the base category. As the magnitudes of the coefficients are difficult to interpret and rely on being compared to D, Figure 1 shows the predictive margin plots. These are not only a great visual aid but help to assess the economic significance of each variable.

Table 6: Multinomial Logit Results - Aggregation by Target Variable

	OCA		Financial		Political/Institutional		Full	
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
VARIABLES	**ER**	**IT**	**ER**	**IT**	**ER**	**IT**	**ER**	**IT**
Large	-1.956***	1.456***					-1.800***	0.452
	(0.709)	(0.380)					(0.637)	(0.514)
Medium	-0.555*	2.600***					-0.822**	1.774***
	(0.286)	(0.371)					(0.326)	(0.544)
Anchor Network	4.230***	-0.0845					5.066***	2.601*
	(0.869)	(1.123)					(0.898)	(1.387)
Trade Openness	-0.240	-0.958*					-1.022*	-3.939***
	(0.523)	(0.574)					(0.527)	(0.927)
Fuel Exports	0.013***	-0.033***					0.010***	-0.017**
	(0.003)	(0.005)					(0.003)	(0.008)
Financial Market Depth			2.941***	5.577***			2.789***	7.888***
			(0.628)	(0.604)			(0.616)	(0.973)
Capital Account Openness			0.146**	0.027			-0.004	0.271*
			(0.057)	(0.089)			(0.071)	(0.145)
Strength of Democracy					-0.090***	0.242***	-0.046**	0.247***
					(0.016)	(0.038)	(0.019)	(0.043)
Central Bank Independence					0.171	0.356	0.571	1.970**
					(0.682)	(0.583)	(1.007)	(0.810)
Africa	YES	YES	YES	YES	YES	YES	1.902***	-0.890*
							(0.373)	(0.553)
Asia	YES	YES	YES	YES	YES	YES	-0.604	-0.766
							(0.412)	(0.487)
OECCA	YES	YES	YES	YES	YES	YES	-0.200	2.110***
							(0.559)	(0.652)
Middle East	YES	YES	YES	YES	YES	YES	3.588***	-0.952
							(0.484)	(1.039)
Year Fixed Effects	YES	YES	YES	YES	YES	YES	YES	YES
Controls for State Dependence	YES	YES	YES	YES	YES	YES	YES	YES
Observations	1,360	1,360	1,360	1,360	1,360	1,360	1,360	1,360
Pseudo R2	0.356		0.300		0.306		0.434	
Log likelihood	-805.527		-874.222		-867.652		-708.197	
McFadden R2	0.38		0.33		0.33		0.46	

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Base Category = D
OCA: $\chi^2 = 129.41$***
Financial Integration: $\chi^2 = 88.83$***
Political/Institutional Strength: $\chi^2 = 39.99$***

Figure 1: Plots of Predictive Margins: Aggregated by Target Variable[a]



[a]Please see Appendix E for this figure with confidence intervals.

When comparing the individual approaches (columns (1) to (6)) to the full model (columns (8) and (9)), there are two differences in estimated signs (the anchor network variable under IT and capital account openness under ER). Furthermore, even though the statistical significance of the variables across all models is fairly consistent, it is not exactly the same and, thus, this paper will focus on interpreting the results of the variables from the full model only (columns (7) and (8)).[23] The pseudo R2 and log likelihood statistics also recommend the full model. The results from the likelihood ratio test, as shown by the chi-squared results, show that the variables within each theoretical approach to choice of MPF (OCA, financial integration, and political/institutional strength) are each jointly statistically significant. Therefore, each approach is shown to have empirical relevance.

In column (7), the coefficient on a country being large in economic size, compared to a small economy, is negative and statistically significant. Meaning that large economies are significantly less likely to opt for an ER MPF over D. However, the reverse is true for countries choosing between IT and D (as shown in column (8)) and the coefficient is not statistically significant. The results are similar when a medium sized economy is compared to a small economy, with the only difference being the coefficient is now statistically significant for IT. This result agrees with the *a priori* sign expectations. These results can be explained by the theory that small economies are more vulnerable to shocks, particularly shocks to their ER, and, thus, are more likely to target their ER. As larger economies are less susceptible to ER fluctuations, they can explore other MPFs, such as IT. From the predictive margins in Figure 1, we can see that the probability of a country picking IT increases by approximately 4pp when a country goes from being small to large country. However, it increases by more when country goes from being small to medium sized (increases by approximately 14pp). The probability of a medium sized country picking IT is approximately 28% whereas for large it is only 19%. As for countries picking ER, the probability falls by 14pp when a country goes from being small

[23]There are increased bias concerns when using a logistical model, compared to standard linear regression models, and, thus, it is more beneficial to analyse the determinants of MPFs using the whole model as this reduces the chance of bias.

to large. It falls by 8pp when a country goes from being small to medium sized. This is an interesting finding as it suggests that large economies do not feel as much of a need to target inflation in comparison to their smaller counterparts.

The parameter on the variable measuring anchor network is positive for both ER and IT (over D). This agrees with the *a priori* sign expectation for ER. Theoretically, countries that have a large value of trade, in proportion to their GDP, with countries that peg to one of the anchor currencies, are more likely to target their ER and join the anchor network. Whilst this does not explain the estimated coefficient on IT, it is useful to look at the predictive margin results. As can be seen, as the anchor starts increasing from 0 to the maximum value, the probability of a country picking IT increases a little before falling. Furthermore, the estimated coefficient is not statistically significant at the 5% significance level, whereas the probability of a country choosing ER is statistically significant.

As a country becomes more open to trade, they are significantly less likely to choose both ER and IT (over D). Figure 1 shows that the probability of choosing IT falls by a greater amount than it does for ER (25pp more).

The parameter on fuel exports is positive and statistically significant for ER and this agrees with the *a priori* sign expectations. As mentioned previously, countries that have a larger proportion of their exports being fuel based may think they can stabilise their revenue if they target their ER. For example, this is cited as the reason that middle eastern countries peg their ER to the US Dollar (Khan (2009)). As for IT, this coefficient is negative and statistically significant.

As a country increases their financial market depth, they are significantly more likely to opt for both ER and IT (over D). For IT, this is supported by the theory - a deep financial market is necessary condition for countries to be able to adopt indirect instrument to target inflation. As for ER, this result may seem counter-intuitive and does not agree with the *a priori* sign expectation. For example, it could be argued that an ER MPF does not require a well developed financial system and, thus, is the more common choice for countries without such a developed system. However, the coefficients in Table 6 are being compared to D. Therefore, it is imperative to also look at the relevant plot in Figure 1. From this we can see that as financial market depth increases, the probability of a country choosing ER increases slightly until about 0.6 when it starts to fall. IT, on the other hand, has approximately a 46 percentage point increase in the probability when financial depth goes from minimum to maximum.

For capital account openness, the parameter on ER is negative and not statistically significant. For IT, it is positive and statistically significant. This implies that, as capital account openness increases, emerging/developing countries are more likely to opt for independent monetary policy than targeting their ER. This is in-line with Levy Yeyati et al. (2010) as they expect a positive correlation between capital account openness and a flexible ERR (to become an inflation targeter it is necessary to have a flexible ERR) when currency mismatch is not as large.[24]

As a country's strength of democracy becomes more democratic, they are significantly less likely to opt for ER (over D). They are significantly more likely to choose IT (over D). Both findings concur with the *a priori* sign expectations. The results agree with the theory that more autocratic countries opt for targeting their ER. From the plot in Figure 1 we can see that the probability of choosing IT increases by approximately 23pp. The probabilities of choosing ER and D falls by approximately 13 and 10pp, respectively.

The parameter on central bank independence is positive for both ER and IT (over D), however, it is only significant for IT. Whilst it may be expected that the coefficient on ER would be negative, as per the *a priori* sign expectation, the predictive margins plot show a relatively flat line for ER, which is an indication of low economic significance. However, for IT, as central bank independence increases, the probability of a country picking IT increases by approximately 11pp.

As for the regions, we can see that the coefficient on countries within the Africa region, compared to Latin America and the Caribbean, is positive and statistically significant

[24] This result is reassuring as a variable measuring currency mismatch explicitly has not been included in the model.

for ER but negative and not significant for IT (at the 5% significance level). This result is not surprising. Multiple countries within Africa are not very well diversified and have high levels of debt which makes them highly susceptible to external shocks, particularly shocks to their ER. Furthermore, they may rely on their ER to help control inflation. The coefficient on IT is negative but not statistically significant. From Figure 1 we can see that the probability of a country choosing an ER MPF increases by approximately 21pp if they are a country within Africa. The line for IT is almost flat, suggesting low economic significance.

The countries within Asia are less likely to choose both ER and IT over D, compared to countries within Latin America and the Caribbean. This result is not statistically significant.

For countries part of OECCA, compared to those in Latin America and the Caribbean, they are less likely to opt for ER but statistically more likely to opt for IT. In the dataset, the data on these countries starts in the later years (2001-2017) when IT is more likely to appear as it had risen in popularity.

Lastly, countries within the Middle East are statistically more likely to opt for ER and less likely, but not significantly so, to opt for IT.

5.2 Prediction Accuracy for Target Variable Aggregation

Figure 2 shows the probability that each country's MPF (aggregated by target variable) is correctly chosen by the model. On average, the model has a prediction accuracy of 79%, which is 4pp higher than the prediction accuracy of the model used in Cobham and Song (2020). Figure 2 shows that there is 1 country (Albania) for which the model never predicts the correct MPF. This is not too different to Cobham and Song (2020) as their model predicts 2 countries completely incorrectly. Looking further into Albania, there is data from 2001-2017 and their MPF choice is IT for whole time period. There are two interesting things that stand out about Albania when compared to other IT countries.[25] Firstly, it has a strength of democracy that is more volatile over-time. Secondly, its financial market depth score lowers slightly as time progresses whereas for the other IT countries their financial market depth values either stays the same or increases as time progresses. Therefore, these two facts could possibly explain why the model fails to ever predict Albania's choice of MPF correctly.

Figure 2: The Model's Average Prediction Accuracy per Country

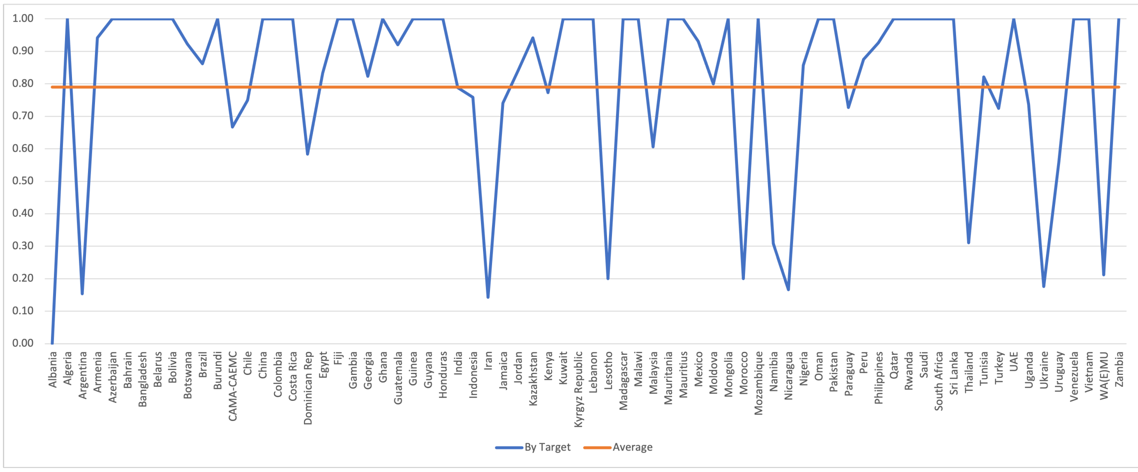
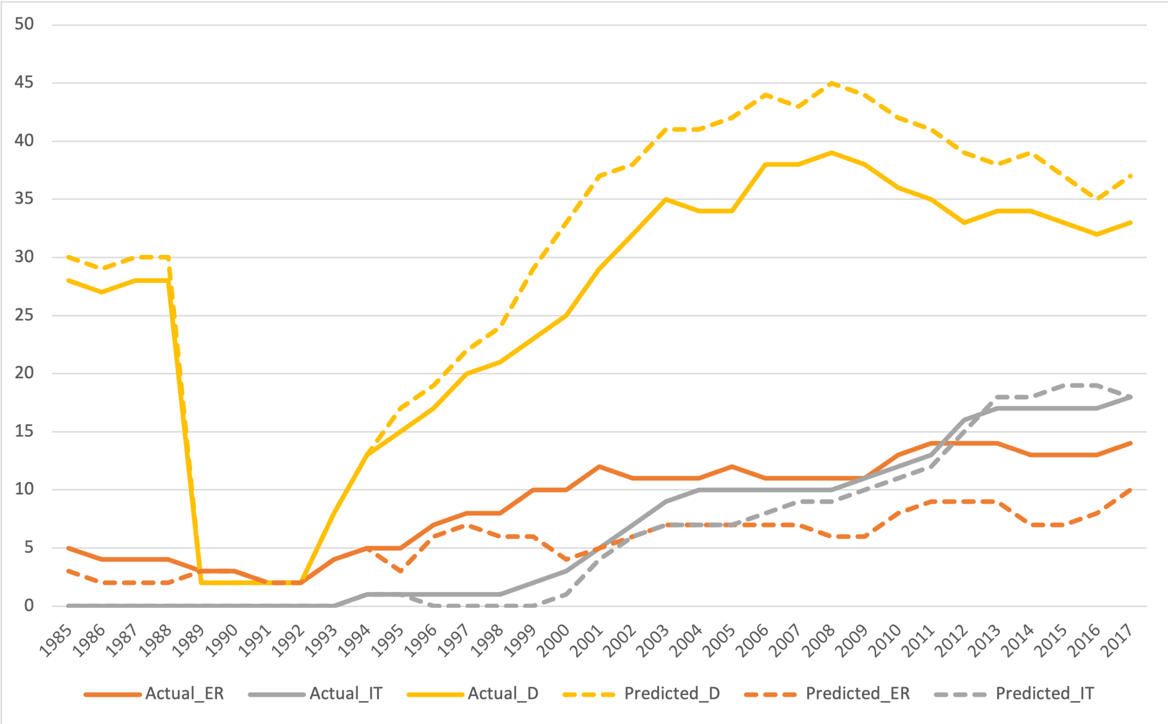


Figure 3 shows the frequency of each MPF for actual and predicted. It shows that the dotted lines (predicted MPF frequency) track the solid lines (actual MPF frequency) well and, in some places, are the same. The figure shows that the model tends to over-predict for D. This is likely because D contributes to the majority (approximately 62%) of the dataset. This model outperforms a 'simple' model - one which just predicts the most dominant category (i.e. D). It can also be seen that the total frequency of MPFs is not constant across the years. This is due to data availability and is particularly prominent in the early 1990s where the fuel export variable has missing data.

[25]It is important to note that the IT category has the smallest proportion of the dataset (15.72%).

Figure 3: Actual vs. Predicted frequency for each MPF: Aggregated by Target Variable



5.3 By Degree of Monetary Control

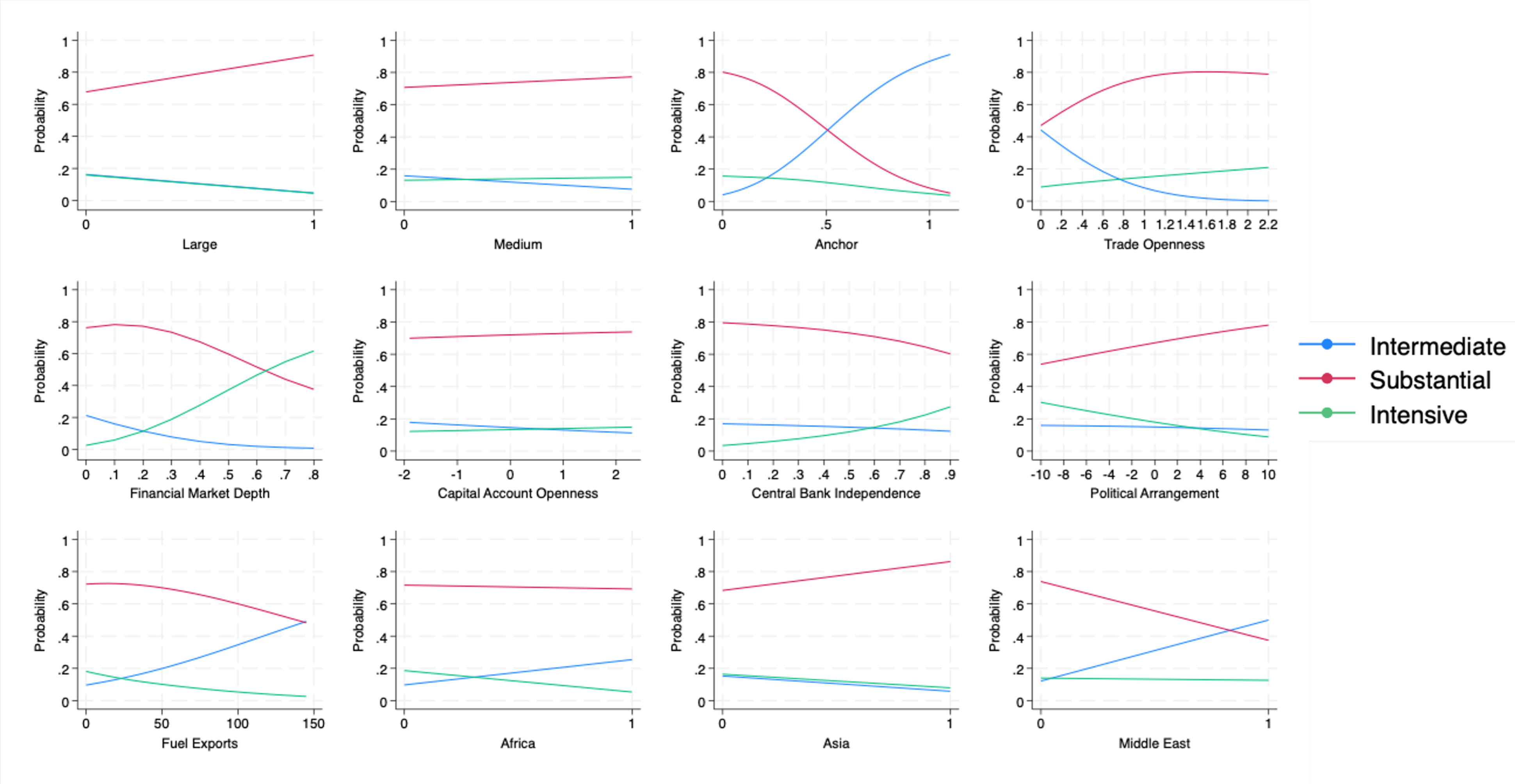
The above results are based on the MPF classification being aggregated on the target variable. The classification also aggregates on degree of monetary control and the estimation results are shown in Table 7. Furthermore, Figure 4 shows the predictive margin plots.

Table 7: Multinomial Logit Results - Aggregation by Degree of Monetary Control

	Full	
	(1)	**(2)**
VARIABLES	**Substantial**	**Intensive**
Large	2.181***	-1.602
	(0.643)	(1.883)
Medium	1.308***	1.590***
	(0.427)	(0.732)
Anchor Network	-10.790***	-11.640***
	(1.593)	(2.003)
Trade Openness	4.148***	4.969***
	(0.846)	(1.005)
Fuel Exports	-0.024***	-0.068***
	(0.004)	(0.017)
Financial Market Depth	5.374***	15.850***
	(1.632)	(2.275)
Capital Account Openness	0.198**	0.329**
	(0.093)	(0.162)
Strength of Democracy	0.035	-0.165**
	(0.025)	(0.066)
Central Bank Independence	0.331	7.787***
	(1.015)	(2.487)
Africa	-1.806***	-4.981***
	(0.385)	(0.794)
Asia	1.696***	-0.971
	(0.492)	(0.871)
Middle East	-3.693***	-3.495***
	(0.725)	(1.067)
Year Fixed Effects	YES	YES
Controls for State Dependence	YES	YES
Observations	1,249	
Pseudo R2	0.518	
Log likelihood	-476.815	

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Base Category = Intermediate

Figure 4: Plots of Predictive Margins: Aggregated by Degree of Monetary Control[a]



[a]Please see Appendix F for this figure with confidence intervals.

The estimated coefficient on the variable for both a large and medium sized economy is positive and statistically significant for substantial degree of control, which agrees with the *a priori* sign expectations. Therefore, both large and medium sized economies, when compared to small economies, are more likely to choose a substantial DoMC, relative to an intermediate DoMC. A large economy, compared to a small economy, however, is less likely to opt for an intensive DoMC. On the otherhand, as visually shown in Figure 4, a medium sized economy has an increased likelihood of choosing an intensive DoMC. However, the line is relatively flat which implies that small economies are nearly as likely to opt for an intensive DoMC too. This is an interesting result and suggests that large economies, compared to small economies, feel less of a need to opt for the highest form of monetary control but still like to have a substantial DoMC. As mentioned earlier, this is potentially due to larger economies being less vulnerable to external shocks.

The parameter on the variable measuring anchor network is negative and statistically significant for both substantial and intensive (over intermediate). This agrees with the *a priori* sign expectation for substantial. It can be argued that a country with a high anchor network would opt for either a full targeting or fixed ER MPF. Therefore, in terms of DoMC this places them into either the intermediate or intensive category. As it is unlikely to put them into the substantial category, it is not surprising that their probability of choosing substantial falls considerably as the anchor network value goes from minimum to maximum (falls by approximately 75pp). In comparison, the fall in the probability of picking intensive is much smaller (falls by approximately 15pp).

As a country becomes more open to trade, they are significantly more likely to opt for both substantial and intensive degrees of monetary control (over intermediate).

As a country increases their percentage of fuel exports, relative to GDP, they are significantly less likely to opt for both substantial and intensive. This agrees with the *a priori* sign expectation that was presented for substantial.

The coefficient on financial market depth is positive and statistically significant in both columns 1 and 2. Again, this agrees with the *a priori* sign expectation. Greater financial market depth is a necessary requirement to have higher DoMC. Figure 4 shows that as financial market depth increases, the probability of a country having intensive DoMC increases by approximately 59pp.

As a country's capital account becomes more open, they are statistically more likely to opt for both substantial and intensive (over intermediate). This agrees with the substantial *a priori* sign expectation. However, as can be seen from Figure 4, the lines are not very steep which suggests capital account openness has low economic significance in choice of MPF when aggregated by DoMC.

The more democratic a country becomes, the more likely they are to opt for a substantial DoMC when compared to an intermediate DoMC. The opposite is true for intensive DoMC. The latter disagrees with the *a priori* sign expectation. However, this could potentially be explained by the following argument: countries that are more democratic are less likely to need to have full or narrow monetary policy target as they do not need to rely on them as a 'policy crutch'. For example, it is likely they are already trusted by their citizens and are accountable therefore they manage to anchor inflation expectations without needing to have a higher DoMC. Finally, as can be see in Figure 4, there is a slight fall in the probability of picking an intermediate DoMC as a country becomes more democratic.

As a country's central bank becomes more independent, they are more likely to opt for both substantial and intensive DoMC, but it is only statistically significant for the latter. This agrees with the *a priori* sign expectation placed on substantial. The result shown in Figure 4 is interesting as it shows a fall in probability for both intermediate and substantial when central bank independence increases. This implies that a more independent central bank is more likely to favour IT.

A country that is within Africa, compared to being within Latin America & the Caribbean, is significantly less likely to have substantial and intensive DoMC (when compared to intermediate). It could be potentially argued that to possess a high DoMC requires training and ability (e.g. people with PhDs making the monetary policy decisions), both of which may be much less common in countries within Africa than in Latin America & the Caribbean.

A country that is within Asia, compared to being within Latin America & the Caribbean, is significantly more likely to have a substantial DoMC but less likely to have an intensive DoMC.

Finally, a country that is within the Middle East, compared to being within Latin America and the Caribbean, is significantly less likely to have both substantial and intensive DoMC. However, the flat green line as shown in Figure 4 implies that the probability of opting for intensive is similar between the two regions. Therefore, there may be some unobserved regional characteristics that both of these regions possess that impacts choice of MPF when aggregated by DoMC.[26]

5.4 Prediction Accuracy for Degree of Monetary Control

Figure 5 shows the probability that each country's MPF (by DoMC) is correctly chosen. On average, the model has a prediction accuracy of 84%. This is 5pp higher than the model's prediction accuracy for MPF when aggregated by target variable. However, there are 3 countries (Comoros, Ecuador, and Lebanon) that the model never manages to correctly predict. Cobham and Song (2020) find that their DoMC model, when compared to their target variable model, predicts fewer countries completely incorrectly. Unfortunately Albania is not included in the DoMC model, due to not being able to include the OECCA countries. It would have been interesting to see if this model also predicts Albania completely incorrectly. Comoros and Ecuador both have only 4 data points and were excluded from the target variable model. Ideally, they would have been excluded from this model too but having to exclude OECCA countries already lowered the observations and lowering the number of observations further raises the standard errors due to multinomial logit models working best when there are more observations. Lebanon,

[26] A fully comprehensive model would include variables that reflect the characteristics of these regions so that the regional fixed effects were not necessary. However, this is beyond the scope of this research.

however, was correctly predicted 20% of the time in the target variable MPF model. It has data from 2009-2017, inclusive, but has intensive DoMC for all of the years - this makes up the smallest proportion of dataset for DoMC (13.25%) whereas in the target variable dataset it goes into the ER MPF category which is the second biggest (21.82%). Therefore, it may be that this model struggles to predict Lebanon for DoMC as it does not have as many observations to build a pattern on.

Figure 5: The Model's Average Prediction Accuracy per Country

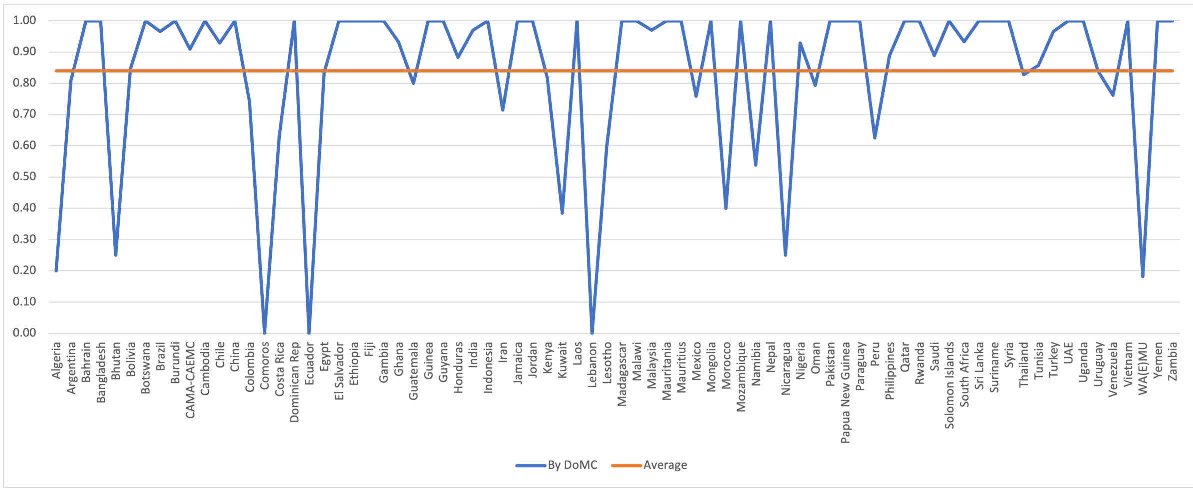
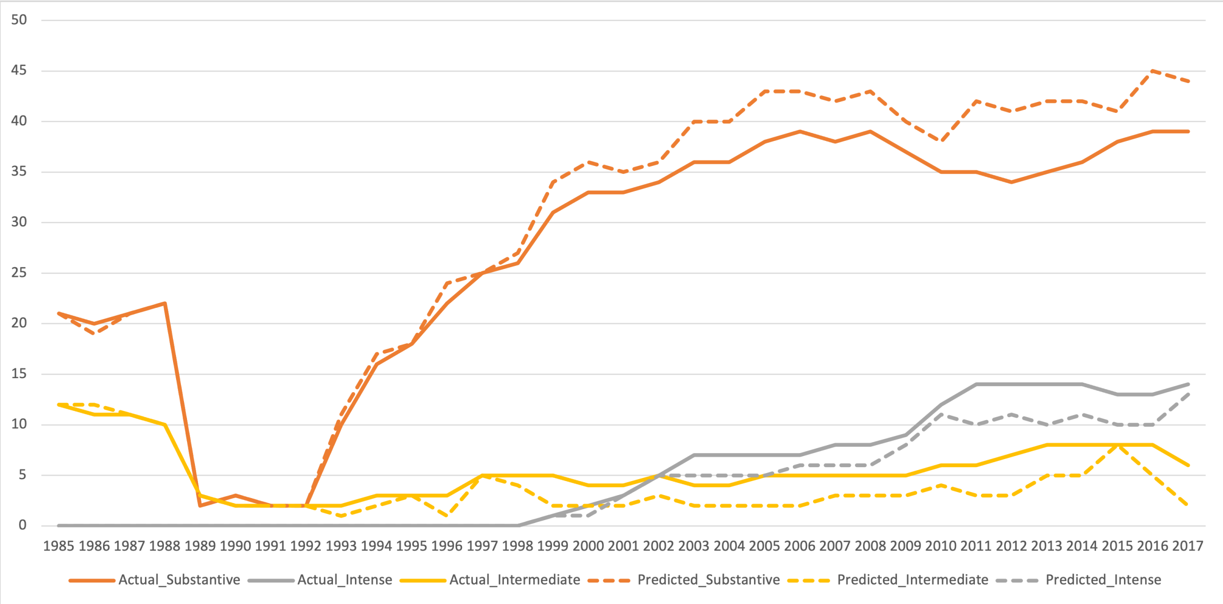


Figure 6 shows the frequency of each MPF (by DoMC) for actual and predicted. Similar to that for target variable, it shows that the dotted lines (predicted MPF frequency) track the solid lines (actual MPF frequency) well and, in some places, are the same. In this model, the only category it over-predicts is substantial. Similar to the target variable model where D was the main classification to be over-predicted, and had the majority in the dataset, the substantial category has the majority in the DoMC dataset (approximately 72%). Lastly, the same as before, if we were to assume a 'simple' model - which just always predicts the dominant category - this model would perform better.

Figure 6: Actual vs. Predicted frequency for each MPF: Aggregated by Degree of Monetary Control



6 Endogeneity & Robustness

This paper is primarily a predictive paper, rather than causal inference, however, this paper attempts to address any endogeneity concerns, too. The two channels that endogeneity could be present in this paper are via reverse causality and omitted variable bias.

6.1 Reverse Causality:

All explanatory variables, except region dummies and inertia, take the average value of the preceding 4 years. This has been done for two reasons: Firstly, it is unlikely that central banks/DM's make choices about their MPF as far as 4 years in advance, therefore helping to mitigate reverse causality concerns. Secondly, the previous literature argues that taking the average of the preceding 4 years helps to overcome reverse causality because MPF_t cannot be causing something in the past. However, despite this being used in previous literature, Bellemare et al. (2017) argue that lagging variables is not enough to overcome a reverse causality issue. They argue a reverse causality problem can simply be rewritten as an omitted variable problem. Therefore, Section 6.2 tries to address any omitted variable concerns.

There are two main concerns raised in regards to reverse causality. The first is to do with financial market depth: countries are not developing their financial markets due to choosing a MPF other than IT, so deep financial markets are not needed. We do not think this is a valid concern for the following reasons:

1. Countries do not 'pick' D as their MPF, per se. It is a category where there is a lack of an objective or there are multiple, conflicting objectives; this is part of the reason why Cobham (2023) refers to it as a 'residual' category. Therefore, as a country would not want/choose to be categorised as D, they would not not develop their financial markets just to be classified as D.

2. D is a rather broad category[27] thus, in this paper, D can (and does) contain examples of countries who have a D MPF due to having effective instruments but unclear objectives and trade-offs. Therefore, in instances where the instrument is the interest rate, for this to be an effective instrument there must exist a developed financial system.

3. D is typically a transition category.[28]

4. Countries with an ER MPF do not need deep financial markets to operate that MPF but Mishkin (1999) states that it is potentially dangerous to have an ER regime without deep and liquid financial markets; well developed financial systems can help to absorb shocks as well as reduce the impact of any speculative attacks.[29] Therefore, it is unlikely that a country would not not develop their financial system just because they have chosen an ER MPF.

[27]Especially in this paper since it is an aggregation of unstructured, loosely structured, and well structured discretion.

[28]Please refer to Cobham (2023) for more information.

[29]An example of this is *Black Wednesday* in 1992 when George Soros speculated against the British pound.

The second concern is the following: countries develop an independent central bank due to wanting to pick an IT MPF. Thus, the causal relationship between CBI and MPF is reversed. We do not think this is a valid concern for the following reasons:

1. The dependent variable is the MPF they *actually* have rather than the MPF they *wish* to have.[30]

2. CBI provides other benefits (e.g. enhanced credibility, lower and more stable inflation rates without targeting a specific inflation rate, and enables policymakers to make (policy) decisions that are free from political interference) and, thus, CBI is not just exclusive to an IT MPF. Therefore, even if a country wishes to have an IT MPF, they may be developing an independent central bank and have a D MPF.

3. If we look at the data, the average CBI value for D, ER, and IT is 0.51, 0.51, and 0.62, respectively. Whilst it is higher under IT, it is not significantly higher.

6.2 Omitted Variable Bias:

The results shown in Section 5 are for the specific model, however, other variables that theoretically seem important were included initially.

Firstly, Cobham and Song (2020) includes variables that measure past inflation. This is because countries that have suffered with high inflation in the past, may opt for an IT MPF as a way to keep inflation under control. Following this, this paper also tried including a measure for past inflation. Inflation data for emerging and developing countries is not as readily available as it is for developed countries; the inflation data series that are available are also prone to have a lot of missing values. This paper uses inflation data from the WDI series and creates a variable that is the average value of the preceding 5 years of inflation. Cobham and Song (2020) creates a past inflation variable that looks back further in time, however, due to poor data availability this would cause

[30]It is possible that the MPF they *wish* to have is an important variable that we are missing so we discuss this more in Section 6.2. More specifically, this particular issue is discussed on p34.

too few observations and questionable standard errors. As can be seen in Appendix G.1 past inflation in this model does not seem to play an important role in countries' MPF choice. When this is compared to Table 6, the signs are consistent except for two variables: Anchor under IT and Central Bank Independence under ER. Despite the change to a negative sign once an inflation measure is incorporated, the results continue to be statistically insignificant at the 5% level in both cases. Consequently, since the variable for past inflation does not achieve statistical signifiance and significantly decreases the number of observations, this analysis chooses not to include a variable that measure past inflation rates. However, it is crucial that we are able to theoretically justify the absence of the significance, as attributing it solely to inadequate data might indicate the exclusion of a relevant variable, thereby introducing bias into the model. Therefore, a potential explanation for this finding is that emerging/developing countries are more concerned about ER pass-through than inflation. Therefore, they focus on their ER, potentially in the hopes that this will lower/stabilise their inflation, rather than targeting inflation directly (see Frankel (2010),p.22, for more information). Furthermore, countries that have suffered from high past inflation (e.g. triple digits) and have managed to lower it (e.g. to double digits) may be content that their inflation is less severe, but also think that directly targeting inflation is too costly.

Secondly, the paper by Levy Yeyati et al. (2010) includes a variable to measure financial mismatch, suggesting the risk of endogeneity by its exclusion in this analysis. This concern is particularly relevant for developing countries, which are more prone to borrowing in foreign currency. As a proxy variable to account for currency mismatch, this analysis introduces a dummy variable aimed at identifying the countries and periods most impacted by the Asian financial crisis, reflecting the literature's indication of these nations having substantial dollar-denominated liabilities. The results, however, not only found this variable to statistically insignificant but the estimated coefficients on the capital account openness variable were -0.048 and 0.290, respectively. By comparing these to the estimated coefficients presented in columns (7) and (8) in Table 6, it can be seen that they hardly differ.

In addition to the above, when mentioning the key differences between developing/emerging countries and advanced countries, primary products making up a greater share of their GDP was mentioned. Therefore, it is possible that this information is needed to be included in the model as a variable. A variable that measures agriculture, forestry and fishing, value added, as a percentage of GDP, was included in the model. However, the variable was not statistically significant and the coefficients on the other variables were unchanged. Therefore, as this variable lowered the number of observations, it, too, was left out of the final model. It could also be argued that the effects of this are controlled for in the anchor network variable.

As mentioned above, it is possible that the MPF countries *wish* to have, rather than what they *actually* have, is an important variable that has been omitted from the model. Unfortunately, there is no way of measuring this. Therefore, year dummies were included to pick up any common global trends towards (or away from) a specific MPF. Given the global nature of monetary policy discussion and the influence of international organisations, the assumption that global trends can influence the adoption of particular MPFs seems justified. Whilst this does not pick up any country-specific factors that drive adoption of a particular MPF, the paper's inclusion of other variables, such as strength of democracy and CBI, should cover this.

Finally, even though this paper has heavily relied on the existing literature to ensure there are no important variables missing, there is always potential for omitted variables. Whilst country-level fixed effects cannot be included in this model due to the incidental parameters problem, this paper does include region-level fixed effects in the hopes that it controls for any remaining unobserved heterogeneity.

6.3 Robustness Checks:

In the analysis the two currency unions are included as two single units. Thus, as a robustness check, we include them as individual countries. The results are displayed in

Appendix G.2. As can be seen, the results are in-line with those shown in columns (7) and (8) in Table 6. However, to ensure the slight differences in magnitudes are not a concern, it is important to compare the predictive plots. As can be seen by comparing Figure 1 to Appendix G.2, they are almost identical.

Secondly, instead of using a multinomial logit model, a multinomial probit model has also been used. This is because the former model operates under the rather strong assumption of IIA whereas the latter does not. Both the estimated coefficients and the plots of predictive margins, as shown in Appendix G.3, are very similar to those produced when using a multinomial logit model. This suggests that any violations of the IIA, if there are any, are not significantly affecting the estimates.

Thirdly, the prediction accuracy results shown in Section 5.2 and Section 5.4 are more prone to suffer from over-fitting. For those predictions we did not use a separate training set and, instead, used the entire dataset to train the model. This means we have no way of knowing how well the model would generalise to new, unseen data because it has been influenced by every data point available. Therefore, it is highly possible that the model has not just learnt the underlying patterns in the data but also any noise or random fluctuations. It was done this way so that the prediction accuracy results could be compared to previous work which also did not use a training set (e.g. Cobham and Song (2020)). However, to improve on previous practices, and as a robustness check, this paper implements a simpler method of a cross-validation process called the 'holdout' method on the dataset for MPFs aggregated by target variable. The 'holdout' method is a way of assessing the model's predictive performance on unseen data. We use this method in two different ways. In the first instance, we split the data into a training set (approximately 70% of the data) and a test set (the remaining 30%). The model is then trained on the training data and validated on the test set. This is a single split and the test set (i.e. the 'holdout' set) is not included in the model training. We perform the holdout method fifty times, with different random splits each time.[31] We

[31] We ensure that all the observations for each country are kept together (i.e. if Country A is in the training data, no observations for Country A will be in the holdout data.)

then take an average of the prediction accuracy results. The average prediction accuracy from the holdout method is approximately 66%.[32] This is lower than the 79% prediction accuracy that was established when the model was fitted to the whole dataset, which suggests some element of overfitting. However, 66% still outperforms a simple model.[33] Additionally, a delve into the model's correct predictions reveals a balanced distribution across various MPF categories, showing that its accuracy is not limited to consistently predicting category D accurately while occasionally succeeding with other observations by chance. This observation reinforces our claim that this paper offers valuable perspectives on the factors influencing the choice of MPF in emerging and developing countries.

It is insightful to evaluate the model's performance on an individual country basis (when the MPF is aggregated by the target variable). Therefore, in the second instance, unlike in the 70/30 split, we train the model using data from all countries except one, which is then used as the test set. After testing, the omitted country is reintegrated into the training set, and a new country is excluded for the next round of training and testing. This cycle is repeated until every country has been excluded once. Detailed in Section G.5, is a table displaying the average prediction accuracy for each country when it is the one excluded, accompanied by comments that shed light on the MPF structure of each country's data and the model's accuracy in predicting various MPF categories. The overall prediction accuracy achieved through this method approximates 70%. Notably, the model does not consistently predict any single MPF regime correctly or incorrectly, underscoring our aim to delve into the specifics of each MPF regime. This pattern mirrors the observations from the 70/30 split approach, confirming the nuanced performance of our model across different MPF regimes. In addition to this, the model demonstrates the ability to accurately forecast outcomes even when there is a shift in the MPF regime within a country over time. We investigated this aspect because countries typically experience slow transitions in MPF regimes, indicating a presence of regime inertia. This

[32]Please see Section G.4 for a list of the results for each of the 50 splits, as well as some summary statistics.

[33]Where a simple model is just one that predicts D as that is category that has the majority of the observations.

slow change raised the possibility that the model's overall reasonable accuracy might be attributed to this inertia. However, examining the comments reveals situations in which a country operates under multiple MPF regimes, and the model's predictive performance is not limited to correctly predicting a single regime before inaccurately forecasting post-transition regimes.[34]

Therefore, as shown above, the model used in this paper is robust to a different treatment of the two currency unions, alternative model specifications, and cross-validation methods. Taking an average of the two different cross-validation procedures, we get an average prediction accuracy of 68%, which outperforms a simple model by 5pp.

7 Conclusion

This study has delved into the factors influencing MPFs in emerging and developing countries, aiming to enhance both comprehension and prediction. Beyond applying the work of Cobham and Song (2020) to developing countries, this research enhances existing approaches in several key areas: First, it leverages theory to probe the motivations behind MPF choice, in contrast to Cobham and Song (2020)'s emphasis on tracking MPF trends over time. Second, it addresses the challenge of endogeneity with greater rigor, detailing efforts to mitigate this issue. Third, and most notably, it employs cross-validation techniques to assess the model's proficiency in forecasting outcomes for new, previously unseen data, a step forward from the approach of using the entire dataset for both training and prediction used in Cobham and Song (2020).

By building upon previous methodologies, our study incorporates insights from the work of Levy Yeyati et al. (2010), and categorises the determinants of MPF into three main theoretical frameworks: optimal currency area (OCA), financial, and political theo-

[34]For a clearer understanding, please refer to Section G.6, where we have used colour coding to highlight comments related to countries experiencing regime changes. The coding is as follows: Red indicates a regime switch occurred, and the model failed to accurately predict any regime. Orange signifies a regime switch where the model incorrectly predicted all regimes. Green represents a regime switch, with the model successfully predicting some observations in each regime accurately.

ries. Echoing Levy Yeyati et al. (2010) approach, we construct three distinct models based on these theories and subsequently integrate all variables into a comprehensive, unified model. These theoretical frameworks were instrumental in guiding the selection of variables for our analysis, with variables within each theory demonstrating joint statistical significance. By comparing the individual theoretical models to the integrated model, we observe differences in the signs of two variables, while the comprehensive model exhibits improved log likelihood and pseudo R-squared values. Given these findings and the heightened awareness of omitted variable bias in multinomial logit models, our research prioritizes the comprehensive model in examining the determinants of MPFs.

This paper presents several key insights, with two findings standing out for their significance: First, the influence of the trade anchor network on MPF selection is crucial. This variable was adapted from the methodology us by Cobham and Song (2020) to better suit the emerging and developing countries analysed in this study. Specifically, countries with a large value of trade, in proportion to their GDP, with countries that peg to one of the anchor currencies, are more inclined to stabilise their ER and join the anchor network. Additionally, as the value of the anchor network increases, countries are increasingly likely to adopt an intermediate DoMC. Second, after adjusting for various factors, medium-sized countries are found to be approximately 9pp more likely than larger countries to adopt IT. This indicates that larger economies may not perceive as strong a need to focus on IT compared to their smaller counterparts. While previous research has explored the impact of country size on ERRs, the specific influence of size on the propensity to adopt IT has not been thoroughly examined.

In addition to the above, the comprehensive model demonstrates robustness against various tests, including adjustments for the treatment of the two currency unions, alterations in model specifications, and maintains considerable predictive accuracy under hold-out cross-validation methods. More specifically, when using the entire dataset for training and prediction, the model accurately predicts 79% of countries' MPF decisions (with MPF classifications aggregated by target variable). In contrast, employing holdout cross-validation in a 70/30 split, the model achieves an average prediction accuracy of 66% for countries' MPF choices (also aggregated by target variable). Furthermore, when employing hold-out cross-validation by excluding one country each time, the model achieves an average prediction accuracy of 70%. Thus, taking an average of the two, gives us a prediction accuracy of 68%. This level of accuracy surpasses that of a simple model, and the application of cross-validation techniques represents a novel contribution to the study of MPF in the existing literature. Thus, the model not only enhances our comprehension of MPF selection in emerging and developing countries but also exhibits a strong capacity for generalisation to new, unseen data for predictive purposes.

Finally, this paper, by theoretically guiding and empirically evaluating the factors which predict MPF choice in emerging and developing countries, offers valuable insights for policymakers. While it may seem apparent, the research underscores that policymakers in these countries have historically made diverse MPF choices, indicating that distinct differences have driven these decisions. Instead of solely relying on studies of economic performance to guide their MPF selection (such as those outlined in Cobham et al. (2022)), policymakers could also consider the findings of this paper to examine the MPF choices of countries with similar characteristics to their own. This comparison could inform their decision on whether a particular MPF choice observed in a similar context might be appropriate for their country as well.

A Variable List

Variable:	Description:	Source:
MPF	Monetary Policy Framework	Cobham (2021)
Economic Size	$\frac{1}{2}(\frac{GDP_i}{GDP_{all}}+\frac{Population_i}{Population_{all}})$ Where 'all' refers to the total of all countries in the dataset.	WDI Series
Large	$\frac{1}{2}(\frac{GDP_i}{GDP_{all}}+\frac{Population_i}{Population_{all}})>0.02$	
Medium	$0.02>\frac{1}{2}(\frac{GDP_i}{GDP_{all}}+\frac{Population_i}{Population_{all}})>0.01$	
Small	$0.01>\frac{1}{2}(\frac{GDP_i}{GDP_{all}}+\frac{Population_i}{Population_{all}})$	
Trade Openness	$\frac{import_{i,t}+export_{i,t}}{GDP_{i,t}}$	WDI Series
Anchor Network	Largest ratio of country's trade with each of the main anchor currencies to GDP.	-Direction of trade data (IMF) -Shambaugh Exchange Rate Regime Classification
Central Bank Independence	An index measure for central bank independence	Garriga (2016)
Financial Market Depth	An index measure of financial market depth.	Svirydzenka (2016)
Political Stance	An index measure, on a scale of -10 to 10, for autocracy/democracy.	Jaggers and Marshall (2009)
Capital Account Openness	An index measure for capital account openness	Chinn and Ito (2008)
Fuel Exports	Fuel exports as a % of merchandise exports	WDI Series
Africa Other Europe+Central Asia+Caucasus Latin America+Caribbean Middle East Asia	Region dummies	https://monetaryframeworks.org/countries/
State Dependence/Inertia	A dummy measuring inertia. 1 if $MPF_t=MPF_{t-1}$, 0 otherwise.	

B Anchor Network

Similar to that used in Cobham and Song (2020), the anchor network can be calculated using the following:

$$A_{k,i} = \Sigma_j[(import_{i,j,t} + export_{i,j,t}) \text{ x } (\text{D}(anchor_{j,t}\text{=k})/GDP_{i,t})]$$

Where,

$A_{k,i}$ is the anchor network of country i for anchor currency k.

$import_{i,j,t}$ is the trade value/number of imports, from country j to country i, at time t.

$export_{i,j,t}$ is the trade value/number of exports, from country i to country j, at time t.

Country j, are all the countries that anchor to the anchor currency, k.

Thus, D($anchor_{j,t}$=k), is a dummy variable that is 1 if they peg to the anchor currency and 0 otherwise[35].

Lastly, it is then all divided by the GDP of country i at time t and the highest value is used as shown below.

The difference between this and Cobham and Song (2020) is that here the anchor currencies, k, are the following: the US dollar, French franc, Indian rupee, and South African rand. The anchor network value is whichever one is biggest:

$$anchornetwork_{i,t} = max(A_{dollar,i}, A_{franc/euro,i}, A_{rupee,i}, A_{rand,i})$$

For example, when calculating a measure for anchor network effects for Botswana, it is the total of Botswana's imports and exports with all countries that peg to the South African Rand, including Botswana's trade with South Africa itself.

[35] This can be either a hard or a soft peg as shown in the Shambaugh Exchange Rate Regime classification https://iiep.gwu.edu/jay-c-shambaugh/data/

C Country List by Region

Africa	Asia	Middle East	Latin America + Caribbean	OECCA
Algeria	Bangladesh	Bahrain	Argentina	Albania
Botswana	Bhutan	Iran	Bolivia	Armenia
Burundi	Cambodia	Jordan	Brazil	Azerbaijan
CAMA-CAEMC	China	Kuwait	Chile	Belarus
Cape Verde	Fiji	Lebanon	Colombia	Georgia
Comoros	India	Oman	Costa Rica	Kazakhstan
Egypt	Indonesia	Qatar	Dominican Republic	Kyrgyz Republic
Ethiopia	Laos	Saudi	Ecuador	Moldova
Gambia	Malaysia	Syria	El Salvador	Ukraine
Ghana	Mongolia	Turkey	Guatemala	
Guinea	Nepal	UAE	Guyana	
Kenya	Pakistan	Yemen	Honduras	
Lesotho	Papua New Guinea		Jamaica	
Libya	Philippines		Mexico	
Madagascar	Solomon Islands		Nicaragua	
Malawi	Sri Lanka		Paraguay	
Mauritania	Thailand		Peru	
Mauritius	Vietnam		Suriname	
Morocco			Uruguay	
Mozambique			Venezuela	
Namibia				
Nigeria				
Rwanda				
South Africa				
Tunisia				
Uganda				
WAEMU				
Zambia				

D Point Estimates vs. Predictive Probabilities

Suppose there are 3 options to choose from: A, B and C.

You may only choose one of the available options.

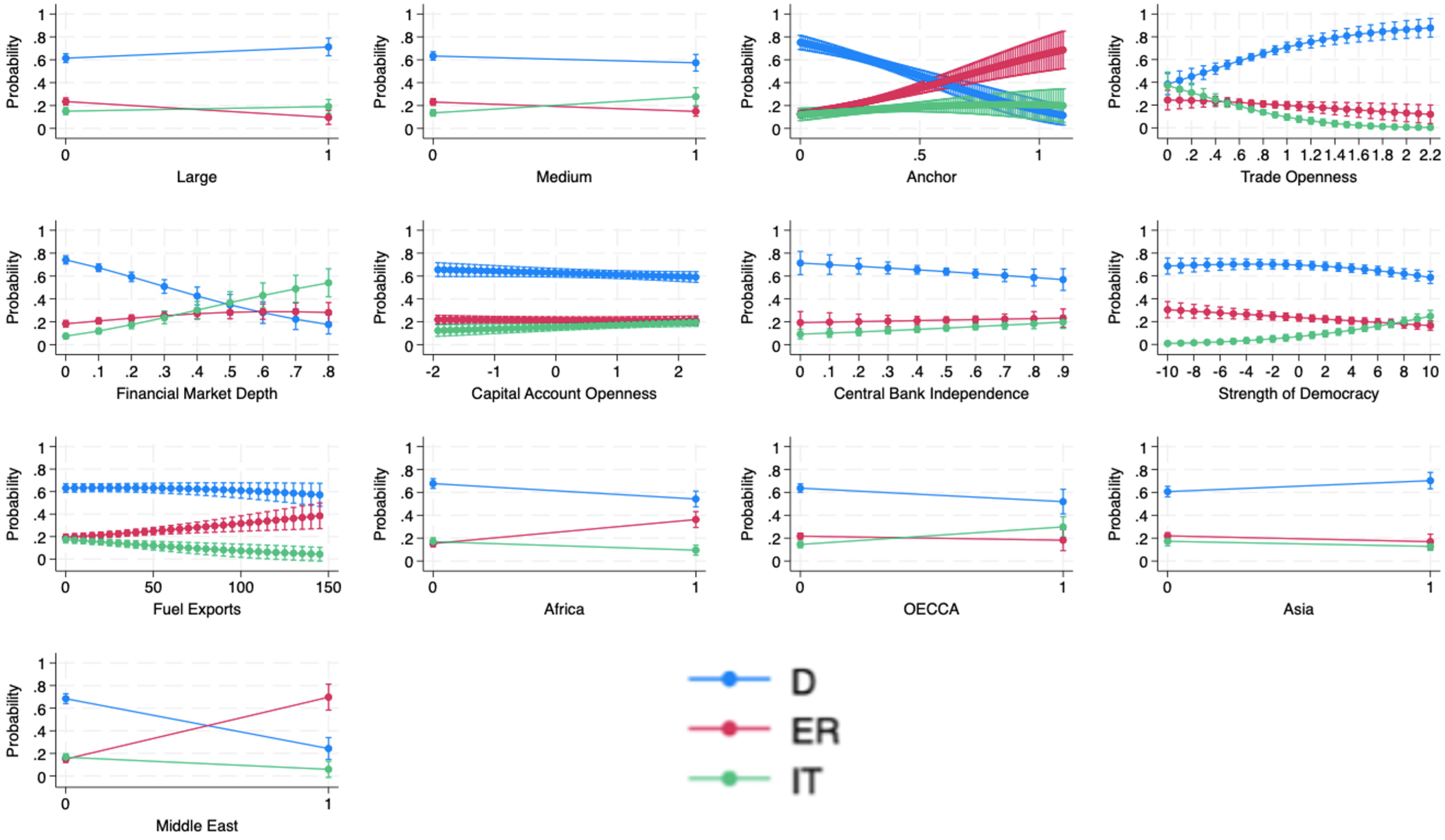
There is a variable, x, which is suspected to influence people's choice and, thus, this variable is included in the model. Multinomial logit model gets used and A is the base category. The estimation results show that the coefficient on x for option B is negative and the coefficient on x for option C is negative.

This tell us the following:

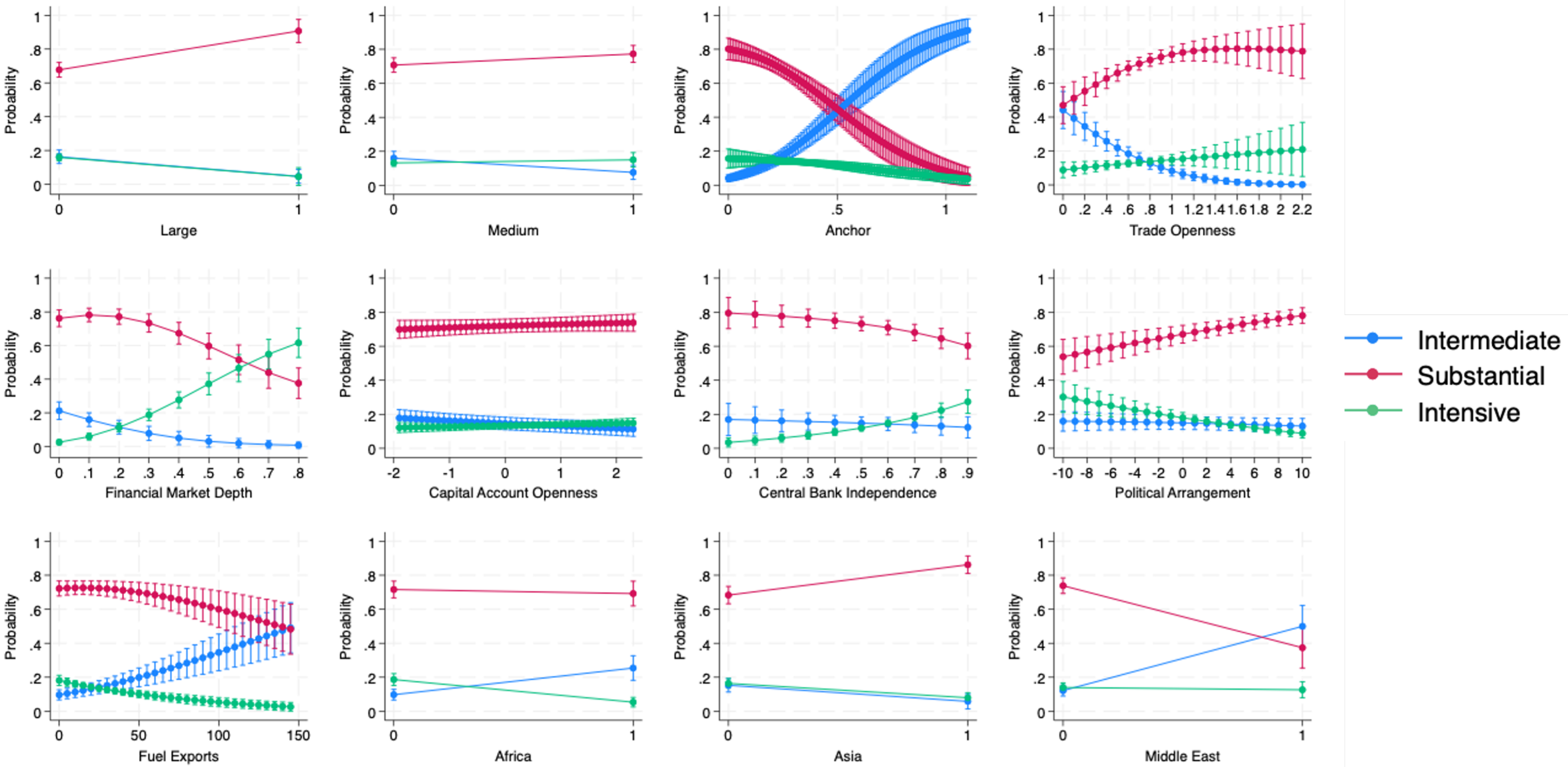
- As x increases, people are relatively more likely to choose A rather than B. They are also relatively more likely to choose A rather than C.

However, what the point estimates do not tell us is how people are likely to move between B and C as x increases. This movement could end up dominating and, as a result, it is possible for the predictive probability plot to go the opposite way to the sign displayed on the point estimate. Therefore, predictive probabilities are useful because they enable us to see how the probability of each outcome changes as x increases. As a result, the plot for predictive probabilities gives us a better insight into both the magnitude and economic significance of the impact of each variable.

E Plots of Predictive Margins with Confidence Intervals: by Target Variable



F Plots of Predictive Margins with Confidence Intervals: by Degree of Monetary Control



G Endogeneity & Robustness

G.1 Inclusion of an inflation variable

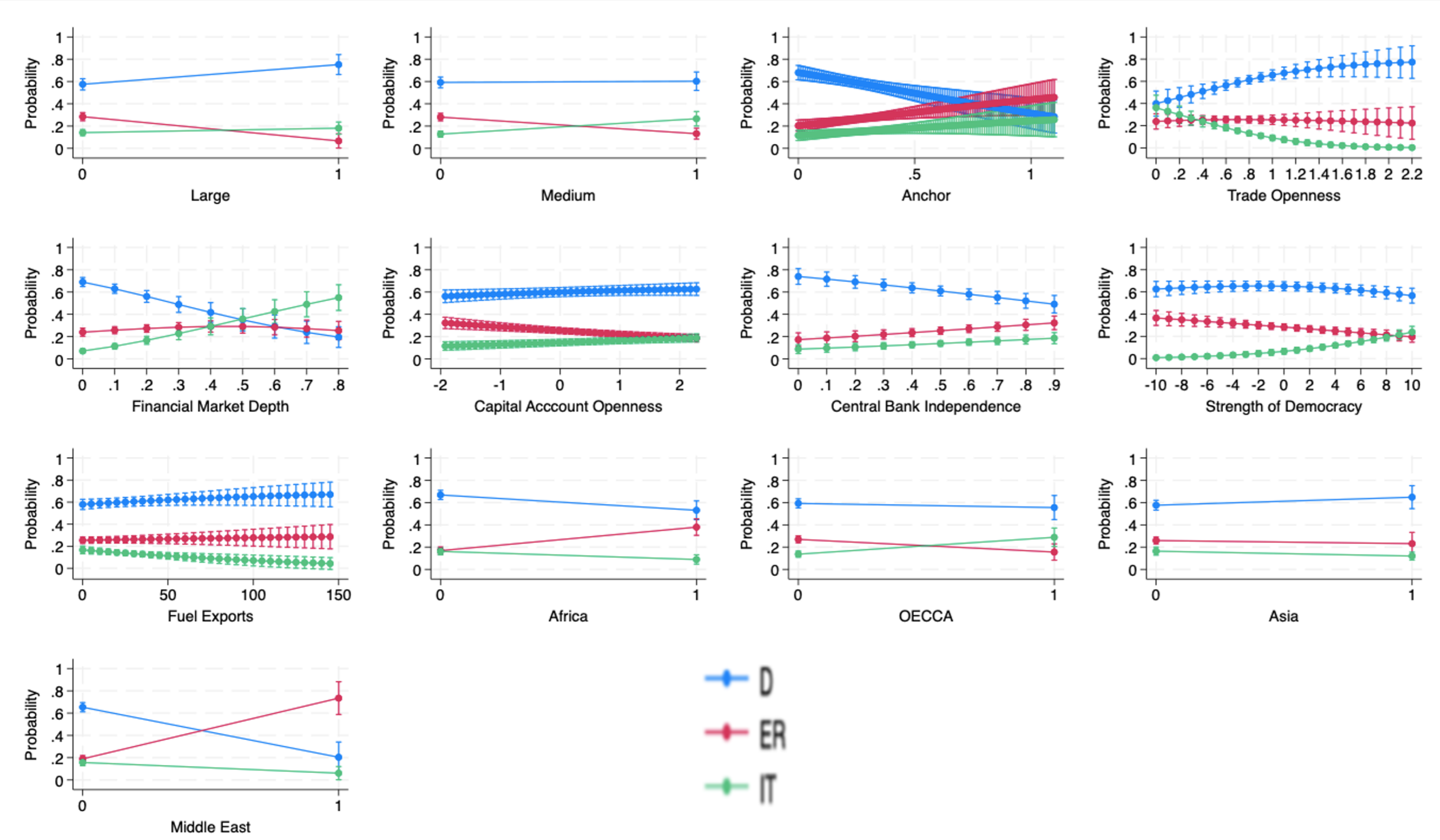
	(1)	(2)
VARIABLES	**ER**	**IT**
Large	-3.489***	2.097***
	(1.051)	(0.618)
Medium	-0.723*	4.446***
	(0.405)	(0.779)
Anchor	5.831***	-2.070
	(1.073)	(1.611)
Trade Openness	-1.223**	-1.586
	(0.570)	(1.076)
Financial Market Depth	3.300***	6.738***
	(0.689)	(1.115)
Strength of Democracy	-0.042	0.248***
	(0.028)	(0.056)
Capital Account Openness	-0.272**	0.085
	(0.111)	(0.135)
Central Bank Independence	-0.115	5.220***
	(0.926)	(1.192)
Fuel Exports	0.011***	-0.034**
	(0.003)	(0.015)
Past Inflation	-0.001	-0.001
	(0.008)	(0.061)
Region Fixed Effects	YES	YES
Year Fixed Effects	YES	YES
Controls for State Dependence	YES	YES
Observations	1,001	1,001

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Where D = Base Category

G.2 Unions included as single countries: by target variable

	(1)	(2)
VARIABLES	**ER**	**IT**
Large	-2.597***	0.327
	(0.783)	(0.407)
Medium	-1.446***	1.651***
	(0.375)	(0.428)
Anchor	2.367***	2.507**
	(0.817)	(1.249)
Trade Openness	-0.336	-4.048***
	(0.441)	(0.868)
Financial Market Depth	1.929***	8.012***
	(0.687)	(0.811)
Strength of Democracy	-0.050***	0.250***
	(0.019)	(0.045)
Capital Account Openness	-0.273***	0.245**
	(0.072)	(0.106)
Central Bank Independence	1.632***	2.058***
	(0.603)	(0.758)
Fuel Exports	0.001	-0.018**
	(0.003)	(0.008)
Region Controls	YES	YES
Year Fixed Effects	YES	YES
Controls for State Dependence	YES	YES
Observations	1,438	1,438

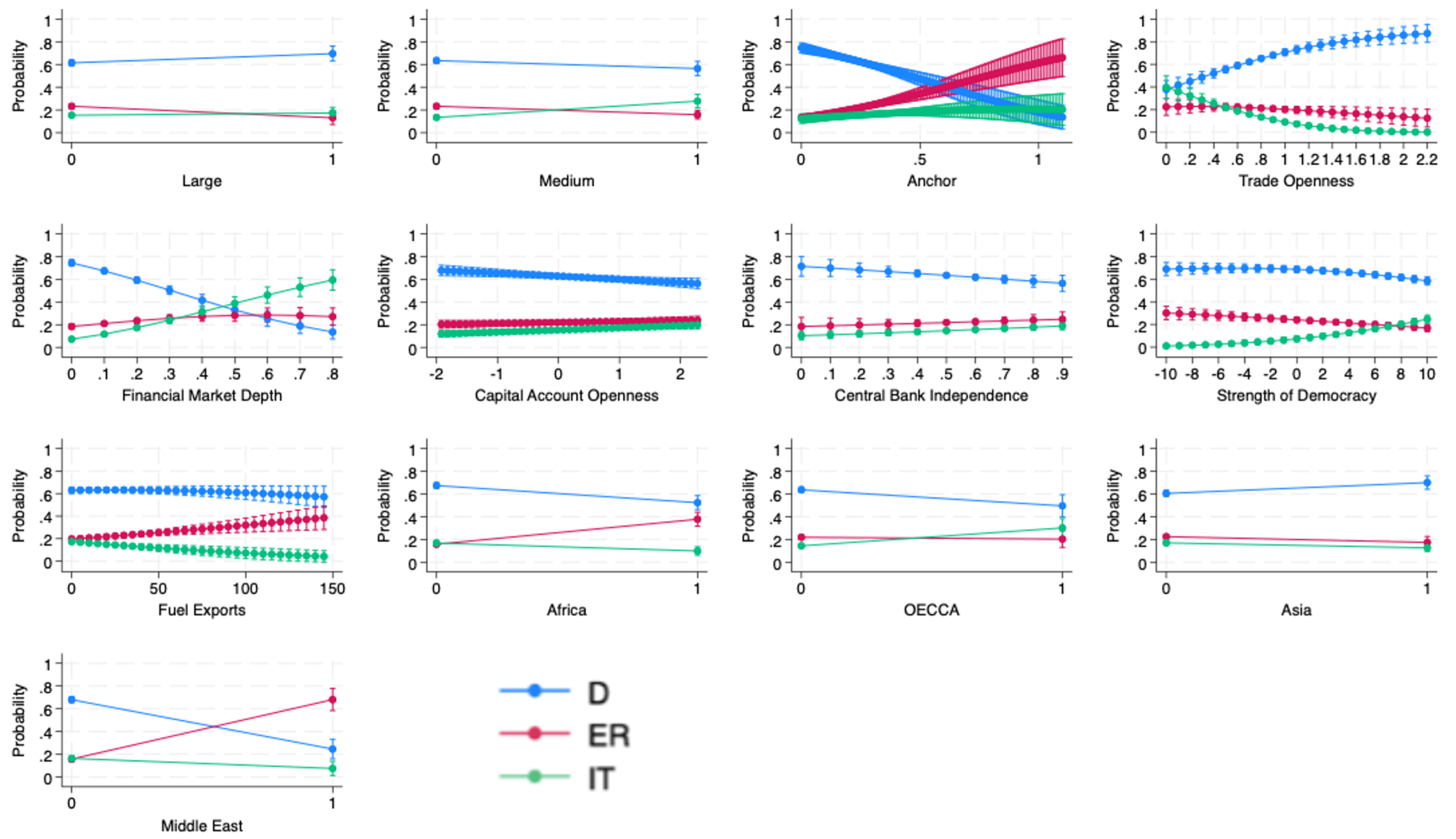
Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Base Category = D


Probability
Large
Medium
Anchor
Trade Openness
Financial Market Depth
Capital Acccount Openness
Central Bank Independence
Strength of Democracy
Fuel Exports
Africa
OECCA
Asia
Middle East
D
ER
IT

G.3 Results of Multinomial Probit

	(1)	(2)
VARIABLES	**ER**	**IT**
Large	-0.840**	0.120
	(0.341)	(0.308)
Medium	-0.432**	1.352***
	(0.220)	(0.306)
Anchor	3.410***	1.979**
	(0.591)	(0.890)
Trade Openness	-0.716**	-3.231***
	(0.339)	(0.576)
Financial Market Depth	2.282***	6.318***
	(0.445)	(0.640)
Strength of Democracy	-0.0261**	0.179***
	(0.0122)	(0.0286)
Capital Account Openness	0.0821*	0.235***
	(0.0497)	(0.0826)
Central Bank Independence	0.630	1.255**
	(0.603)	(0.502)
Fuel Exports	0.00657***	-0.0127**
	(0.00210)	(0.00513)
Africa	1.381***	-0.515
	(0.222)	(0.323)
OECCA	0.0907	1.618***
	(0.317)	(0.428)
Middle East	2.525***	-0.315
	(0.278)	(0.589)
Asia	-0.440*	-0.598**
	(0.234)	(0.298)
Controls for State Dependence	YES	YES
Observations	1,360	1,360

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Base Category = D


Probability
Large
Medium
Anchor
Trade Openness
Financial Market Depth
Capital Account Openness
Central Bank Independence
Strength of Democracy
Fuel Exports
Africa
OECCA
Asia
Middle East
D
ER
IT

G.4 Cross-Validation: 70/30 split

The list below shows prediction accuracy for each of the 50 splits, to 1 decimal place, in ascending order.

57.8	60.7	63.7	66.5	71.8
58.3	60.7	63.7	66.6	73.0
58.8	60.7	63.7	66.8	73.1
58.8	60.8	63.8	68.6	73.4
59.3	60.8	64.3	69.3	73.4
59.3	60.8	64.4	70.2	73.4
60.1	61.3	64.5	70.5	73.4
60.3	61.6	66.0	70.6	75.7
60.4	61.8	66.0	71.0	76.8
60.4	63.7	66.1	71.1	77.2

Average: 65.7

Median: 64.3

St. Dev.: 5.6

G.5 Cross-Validation: exclude 1 country

(Omitted) Country	Accuracy (%)	Comments
Albania	0.0	All wrong and all IT.
Algeria	100.0	10 obs, all D.
Argentina	15.3	26 obs, 20 D, 4 right. 6 ER, 0 right.
Armenia	82.4	17 obs. 10D, 7 IT. 3 wrong were D.
Azerbaijan	100.0	17 obs, all D.
Bahrain	100.0	7 obs, all ER.
Bangladesh	100.0	22 obs, all D.
Belarus	6.7	1/15 right. All were D.
Bolivia	100.0	26 D, all right.
Botswana	69.2	13 D, 9 right.
Brazil	79.3	29 obs. 16 IT, 11 right. 13 D, 12 right.
Burundi	100.0	10 obs. All D.
CAMA-CAEMC	15.2	33 obs, all ER. 5 right.
Chile	60.7	28 obs. 24 IT, 13 right. 4 D, all right.
China	90.9	22 obs, all D.
Colombia	88.9	27 obs, 17 IT, 14 right. 10 D, all right.
Costa Rica	100.0	19 obs. 3 IT, 16 D.
Dominican Rep	58.3	12 obs. All IT wrong and 1 D wrong.
Egypt	83.3	24 obs. 19 D, 17 right. 5 ER, 3 right.
Fiji	100.0	16 obs, all D.
Gambia	100.0	5 obs, all D.
Georgia	70.6	17 obs, all D. 12 right, 5 wrong.
Ghana	100.0	15 obs, all D.
Guatemala	80.0	25 obs. 8 IT, 3 right. 17 D, all right.
Guinea	100.0	7 obs, all D.
Guyana	40.0	5 obs, all D, 2 right.
Honduras	100.0	17 obs, all D.
India	57.6	33 obs. 29 D, 15 right. 4 IT, all right.
Indonesia	58.6	29 obs. 17 D, all right. 12 IT, all wrong.
Iran	0.0	7 obs, all D.
Jamaica	63.0	27 obs all D. 17 correct.
Jordan	84.0	25 obs. 4 D, all wrong. 21 ER, all right.
Kazakhstan	94.1	17 obs. 16 of D correct and the 1 IT wrong.
Kenya	72.7	22 obs, all D. 16 right.
Kuwait	100.0	13 obs, all ER.
Kyrgyz Republic	100.0	12 obs, all D.
Lebanon	0.0	8 obs, all ER.
Lesotho	0.0	5 obs, all ER.
Madagascar	100.0	19 obs, all D.
Malawi	100.0	19 obs, all D.
Malaysia	36.4	33 obvs. 26 D, 11 right. 7 IT, 1 right.
Mauritania	100.0	5 obs, all D.
Mauritius	100.0	9 obs, all D.
Mexico	65.5	19 obs. 12 D, all right. 17 IT, 7 right.
Moldova	80.0	It got 1 D wrong, 2 IT wrong. 15 obs
Mongolia	100.0	9 obs. All D.
Morocco	16.0	25 obs. 4D, all right. 21 ER, all wrong.
Mozambique	100.0	13 obs, all D.
Namibia	0.0	13 obs, all ER.
Nicaragua	12.5	24 obs. 3 D, all right. 21 ER, all wrong.
Nigeria	85.7	14 obs, all D, 12 right.
Oman	100.0	29 obs, all ER.
Pakistan	100.0	24 obs, all D.
Paraguay	72.7	22 obs. 16D, all right. 6 IT, all wrong.
Peru	70.8	24 obs. 8D, all right, 16 IT, 9 right.
Philippines	85.2	27 obs. 11 D, 7 right. 16 IT, all right.
Qatar	100.0	15 obs, all ER.
Rwanda	100.0	12 obs, all D.
Saudi	100.0	18 obs, all ER.
South Africa	100.0	15 obs, all IT.
Sri Lanka	100.0	21 obs, all D.
Thailand	10.3	29 obs. 3 D, all right. 8 ER, 18 IT.
Tunisia	71.4	28 obs, all D, 20 right.
Turkey	0.0	29 observations. 21 D, 8 IT.
UAE	100.0	12 obs all ER.
Uganda	73.7	19 obs. All 5 IT wrong, 14 D right.
Ukraine	0.0	17 obs. 13 ER, 4D.
Uruguay	48.0	25 obs. 20D, 12 right. All IT wrong.
Venezuela	61.9	21 obs, all D. 13 right.
Vietnam	100.0	All D.
WA(E)MU	0.0	33 obs, all ER.
Zambia	100.0	18 obs, all D.

G.6 Cross-Validation: exclude 1 country (inc. highlights)

(Omitted) Country	Accuracy (%)	Comments
Albania	0.0	All wrong and all IT.
Algeria	100.0	10 obs, all D.
Argentina	15.3	26 obs, 20 D, 4 right. 6 ER, 0 right.
Armenia	82.4	17 obs. 10D, 7 IT. 3 wrong were D.
Azerbaijan	100.0	17 obs, all D.
Bahrain	100.0	7 obs, all ER.
Bangladesh	100.0	22 obs, all D.
Belarus	6.7	1/15 right. All were D.
Bolivia	100.0	26 D, all right.
Botswana	69.2	13 D, 9 right.
Brazil	79.3	green29 obs. 16 IT, 11 right. 13 D, 12 right.
Burundi	100.0	10 obs. All D.
CAMA-CAEMC	15.2	33 obs, all ER. 5 right.
Chile	60.7	28 obs. 24 IT, 13 right. 4 D, all right.
China	90.9	22 obs, all D.
Colombia	88.9	27 obs, 17 IT, 14 right. 10 D, all right.
Costa Rica	100.0	19 obs. 3 IT, 16 D.
Dominican Rep	58.3	12 obs. All IT wrong and 1 D wrong.
Egypt	83.3	24 obs. 19 D, 17 right. 5 ER, 3 right.
Fiji	100.0	16 obs, all D.
Gambia	100.0	5 obs, all D.
Georgia	70.6	17 obs, all D. 12 right, 5 wrong.
Ghana	100.0	15 obs, all D.
Guatemala	80.0	25 obs. 8 IT, 3 right. 17 D, all right.
Guinea	100.0	7 obs, all D.
Guyana	40.0	5 obs, all D, 2 right.
Honduras	100.0	17 obs, all D.
India	57.6	33 obs. 29 D, 15 right. 4 IT, all right.
Indonesia	58.6	29 obs. 17 D, all right. 12 IT, all wrong.
Iran	0.0	7 obs, all D.
Jamaica	63.0	27 obs all D. 17 correct.
Jordan	84.0	25 obs. 4 D, all wrong. 21 ER, all right.
Kazakhstan	94.1	17 obs. 16 of D correct and the 1 IT wrong.
Kenya	72.7	22 obs, all D. 16 right.
Kuwait	100.0	13 obs, all ER.
Kyrgyz Republic	100.0	12 obs, all D.
Lebanon	0.0	8 obs, all ER.
Lesotho	0.0	5 obs, all ER.
Madagascar	100.0	19 obs, all D.
Malawi	100.0	19 obs, all D.
Malaysia	36.4	33 obvs. 26 D, 11 right. 7 IT, 1 right.
Mauritania	100.0	5 obs, all D.
Mauritius	100.0	9 obs, all D.
Mexico	65.5	19 obs. 12 D, all right. 17 IT, 7 right.
Moldova	80.0	It got 1 D wrong, 2 IT wrong. 15 obs
Mongolia	100.0	9 obs. All D.
Morocco	16.0	25 obs. 4D, all right. 21 ER, all wrong.
Mozambique	100.0	13 obs, all D.
Namibia	0.0	13 obs, all ER.
Nicaragua	12.5	24 obs. 3 D, all right. 21 ER, all wrong.
Nigeria	85.7	14 obs, all D, 12 right.
Oman	100.0	29 obs, all ER.
Pakistan	100.0	24 obs, all D.
Paraguay	72.7	22 obs. 16D, all right. 6 IT, all wrong.
Peru	70.8	24 obs. 8D, all right, 16 IT, 9 right.
Philippines	85.2	27 obs. 11 D, 7 right. 16 IT, all right.
Qatar	100.0	15 obs, all ER.
Rwanda	100.0	12 obs, all D.
Saudi	100.0	18 obs, all ER.
South Africa	100.0	15 obs, all IT.
Sri Lanka	100.0	21 obs, all D.
Thailand	10.3	29 obs. 3 D, all right. 8 ER, 18 IT.
Tunisia	71.4	28 obs, all D, 20 right.
Turkey	0.0	29 observations. 21 D, 8 IT.
UAE	100.0	12 obs all ER.
Uganda	73.7	19 obs. All 5 IT wrong, 14 D right.
Ukraine	0.0	17 obs. 13 ER, 4D.
Uruguay	48.0	25 obs. 20D, 12 right. All IT wrong.
Venezuela	61.9	21 obs, all D. 13 right.
Vietnam	100.0	All D.
WA(E)MU	0.0	33 obs, all ER.
Zambia	100.0	18 obs, all D.

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