**Appendix A**

**Codebook for the State-level Compliance with IMF Programs (SCIPI) Datasets**

Data on compliance with International Monetary Fund lending agreements is scarce. Most studies that explicitly examine compliance use either a very limited set of cases, or a limited set of policies. Most of what we know about compliance with IMF loans is anecdotal. Part of this stems from the lack of data on IMF lending. Most researchers have used dichotomous measures of being under an IMF program (1/0) or dichotomous measures of compliance (1/0). This has resulted in ever more complex models and assumptions to test theories concerning IMF lending.

Recent work has begun to unpack loans into more fine-grained data that examines the existence of a specific type of policy in a loan or the number of conditions in a loan (see for example Rickard and Caraway 2018; Chapman et al. 2017; Stubbs et al. 2016; Beazaer and Woo 2016). However, to date there is no systematic cross-national data on IMF compliance. While we know a lot more about how many conditions are attached to loans and why type of conditions we are missing systematic information about whether these conditions are met.

This dataset hopes to fill this gap in our knowledge about IMF lending in the 21st century. This codebook outlines the State-level Compliance with IMF Programs (SCIP) dataset. I will outline the procedure used to produce the data as well as comment on the limitations of this dataset and areas where researchers should be more careful in their reading of the data and the assumptions they must make in order to use this data. This codebook is meant to make users aware of the limitations of the data as well as the assumptions I have made in the creation of this data. All of the files and code used to create this dataset are available upon request for any researcher who would like to re-code the data using different assumptions.

The SCIP dataset provides a wealth of information on IMF lending compliance as well as the timing of lending agreements. The data is provided in three user friendly formats for the universe of IMF loans between 2002 and 2019. Compliance is given in the aggregate, but is also provided by loan type (9 types of loans), policy type (prior actions, structural performance criteria, structural benchmarks, structural assessment criteria), as well as policy area (along 18 different policy areas). Compliance is also sorted into five categories, since compliance occurs along a continuum, and these categories account for conditions which are canceled, partially met, or modified as well as whether the condition was met or not met. The goals of IMF loans are provided for loans taken out between 2007 and 2019. The data also include the size of loans, the date that tranches were disbursed, the date a loan starts, the time between board reviews, whether loans were cancelled or precautionary, and accounts for the timing of policy reforms enacted before the official start date of a loan (prior actions).

This SCIP data is provided in three different formats (datasets) each of which uses a different unit of analysis. The SCIP-P dataset uses the loan condition as the unit of analysis. Each loan conditions have a unique id which can allow researchers to model leader decisions about compliance with specific policies. The SCIP-R dataset sets the IMF executive board review as the unit of analysis. It aggregates policies from the SCIP-P dataset into different categories (policy type, policy area) and provides compliance information along each of these categories. Finally, the SCIP-Y dataset sets the unit of analysis at the country-year which is the most common format of data analysis in political science.

The SCIP-P dataset was coded first, this information was collapsed by executive board review and arrangement into the SCIP-R dataset, and data in the SCIP-R dataset was collapsed by year arrangement. Thus, if you are searching for information on how policies were sorted into different categories this will be under the SCIP-P sections, timing will come under the SCIP-R section, etc. I do not repeat this information in each section, though I do try to include references to the correct section, so please search through this codebook for the information on each variable before assuming it does not exist. For those interested solely in the country year dataset you will have to read the sections on SCIP-P and SCIP-R to find descriptions of the variables in the dataset. I understand this may be inconvenient, but I had to weigh that against the fact that this is already 15 pages long. I have included important information in each section and encourage all users to read this thoroughly before using. I have tried to include as much information about this coding process as possible. However, if I have missed something or you find an error I have made please contact me with questions and comments at (XXXXX@XXX.edu) I am more than happy to share the data and .do files used to create this dataset as well as to discuss the data.

1. **Limitations, Assumptions, and Operationalization of Compliance**

The information used to create the SCIP datasets are taken from the IMF’s MONA database for IMF lending arrangements between 2002 and 2019. The data were downloaded in July of 2019. I used four of the datasets in the MONA database: description, program, purchases, and combined SPC PA SB. This data corresponds to structural conditions included in IMF lending. This means this dataset does *not* incorporate quantitative performance criteria and indicative targets. This was a purposeful choice as structural conditions are more easily attributable to leader behavior and non structural conditions almost never result in loan termination. The MONA database does not present information on IMF loans in any way that can be systematically analyzed by researchers. There are spelling errors in the same condition that makes it hard to compare to subsequent reviews, the same condition is duplicated up to 19 times in a single program review, there is no clear glossary to define the shorthand used in the dataset, in some descriptions a condition uses the acronym of an instition while in other reviews it spells it out. The choice to present data in different units of analysis, in seven different dataset, as string variables, with a large number of errors results in information that required years of work to make into a useable format. As it presently stands the MONA dataset cannot be used in any meaningful way by scholars. This project used a combination of content analysis, data transformation, and scaling analysis to create this dataset.

The source of this information is one limitation of the data. The assumption a user of this data needs to make is that IMF compliance evaluations are fair and unbiased. Any bias in how the IMF evaluates lending agreements will be transferred to the data. Unlike the now archived version of the MONA database the version of the dataset used here does not suffer from many of the past limitations that Willet and Bird (2004) point out. The newer MONA dataset has the universe of IMF loans and a compliance code for conditions that were not met at the time a loan was cancelled or interrupted. It does not however allow us to evaluate conditions that were not reviewed by the Executive Board. So, if a loan is cancelled prior to an Executive Board review, any condition that was underway cannot be coded as met or partially met. The conditions are coded as not met by the dataset and so likely underestimate the level of compliance. Given the consensus that compliance is notoriously low, I opt for a conservative estimate of compliance.

One important limitation that users should be aware of is the tendency for the IMF to alter the way it codes the MONA dataset. This means that even with the replication file, any attempt to update the dataset will likely need to alter the replication to incorporate new errors or record keeping irregulates in the MONA dataset. A previous version of SCIP was created using MONA data from 2015. When attempting to update the data I noticed several major changes to the coding scheme and no notes about when these changes had occurred or why. First, the variable “Economic Descriptor” which is used to sort policies into policy areas had changed from 71 categories in the 2015 version to only 33 categories in the 2019 versions. These changes were somewhat random as entire categories were missing and there was no documentation on where these new categories came from and whether they could be made to fit the old categories. A second change occurred in the coding of the compliance variable `PCStatus’. The short-hand descriptors of the compliance indicators changed between the two versions. The “Labels and Description” documentation that the IMF provides did not list more than half of the shorthand used within this variable. While this project was able to identify what the short hand stands for, new versions of the data with different short hand will require changes to the coding scheme. Attempts to contact the IMF for clarification were not responded to.

The SCIP-P dataset codes each policy into a unique case. However, policies are not uniquely identified in the MONA combined dataset that is used to create this data. I therefore use a variety of Stata 15 tools to identify unique policies. This was particularly tricky as the IMF does not spell the same loan condition the same in each review, and where a loan condition is altered it may appear up to 19 times in the same executive review board period. This means there are both a large number of duplicate conditions that need to be removed, and non-standardized data entry by the IMF making it significantly harder to find these duplicates. I use the following coding strategy to identify unique policies.

First, I use the strtrim stritrim and strlower string function in Stata 15 to remove extra spaces and create lower case data on the “Description” variable from the Combined dataset. Next, I use the substr commands to identify the first 80 characters of a loan condition. This removes descriptions that are spelled slightly different at the end between review periods. Finally, I use the group command to create a unique id for each of these string variables. I then go through manually and find cases where this has worked imperfectly and correct the coding. This occurs when the IMF spells things differently between reviews, uses short hand in one review but long hand in another. There remain some errors here in that some loan conditions which are longer than 80 characters have slightly different conditions. I also look for cases in which conditions in the same review period which look identical have different compliance statuses which suggests these are unique conditions. For example, a condition may have three parts and each loan condition corresponds to one part. I code these as three unique conditions where I can find them.

This data removes policies that have been met. Once the Executive Board evaluates a policy as met it is dropped from the dataset so that it does not show up in the next time period. Policies that are unmet in time T show up again in time T+1 and continue showing up in further reviews until they are met. This assumes a few things. First, that when a condition is evaluated by the Executive Board it is possible for the county to have met this condition. I assume the Executive Board would not be reviewing a policy that could not have been met. It also assumes that if a policy is not met in period T then it is equivalent to a new policy in time T+1. For country-year data this policy can show up more than once in a year. Unmet policies therefore increase the number of conditions in the next review. Over time the number of conditions evaluated in a review grows as a result of both the Executive Board evaluating new conditions, and non-compliance with old conditions.

This coding process leaves 21,281 conditions out of 41,488 original observations. The policies removed are those that are duplicates and policies that were met in period T but show up in period T+1, T+2 etc. Given the more than 41,000 cases, is it entirely possible that I have made an error somewhere along the way. If I have made an error this will likely result in the underestimation of the number of conditions where unique conditions are combined into a single condition (this only occurs where each condition has the same compliance status in each review), and an overestimation of conditions where spelling errors between the same condition in different review periods was so severe that nearest text matching algorithms and manual checking did not allow me to identify that two conditions were in fact the same. Given this coding strategy I believe the number of errors made is very small and within the scope of error that high quality data are subject to.

I include unmet policies in the next period for a few reasons. First, an unmet condition in time T is evaluated again at time T+1 and few conditions are met in their first review. I assume that if a policy has not been met in time T it requires the same amount of effort to meet it in time T+1 as it would have required to meet in time T. If a policy is partially met, then it will be coded as such since this dataset coded compliance along a spectrum. Second, I refrain from making assumptions about the timing of leader decisions regarding compliance. There may be a mismatch between what the IMF believes a country can accomplish in a specific time frame, and what they can actually accomplish. Leaders are also strategic in their decisions about which policies to implement and when.

There are a number of observations from 2001 and 2000 for loans that were taken out prior to 2002 but which continued to be evaluated in 2002. This dataset does not include loans which were ended prior to 2002. Users are free to drop these observations or use them to draw inferences on the early part of loans which might be useful given their question of interest.

There a small number of conditions that have the same unique id but different arrangement numbers. These are policies that were worded exactly the same from a previous IMF loan and carried over into a new loan. I do not treat these as new policies but rather a continuation of the old policy.

**Operationalizing Compliance**

This dataset offers two possible ways to explore compliance with IMF lending. The first, is whether in any Executive Board review a country has implemented the conditions it was asked to implement. The second is how many conditions were met at the end of a loan. This first measure is lower than the second measure for all loans. The following example illustrates why this is the case. Imagine a loan with 3 executive board reviews and 10 unique conditions attached to the loan, all of which are evaluated in period 1. For simplicity let’s assume all conditions are evaluated as met or not-met and at the end of the loan the country has met 7 out of 10 conditions, 2 in period 1, 2 in period 2, and 3 in period 3. Compliance for the country looks thus:

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Country A conditions | Review period | Met | Not-met | compliance |
| 10 | 1 | 2 | 8 | 20% |
| 8 | 2 | 2 | 6 | 25% |
| 6 | 3 | 3 | 3 | 50% |
| Total conditions |  |  | Average: | **~32%** |
| 10 | . | 7 | 3 | **70%** |

If we evaluate compliance in any single review this country shows low compliance. In period 1 the country complied with 20% of conditions. Even in period 3 the country complied with only 50% of what was asked. However, if we look at overall compliance, this country met 7 out of 10 conditions. 70% compliance is a very high number in the IMF compliance literature. This dataset finds that these two numbers are significantly different. If compliance is measured in the second metric, then IMF compliance is quite high (~67%) while the first metric shows compliance as quite low (26%). Researchers should therefore be quite careful which measure of compliance they use. There are strategic reasons why a leader may choose to implement policies when they do. This is further complicated by the other 3 categories of compliance which are likely the result of leaders and the IMF updating their beliefs as well as bargaining between a variety of political actors. It is also likely that leaders evaluate very early on that they will not implement a condition. The choice of compliance measure therefore should be tailored to the theory being tested.

1. **Dealing with Time**

Time is a particularly tricky aspect of IMF lending to deal with. The first area in which time becomes a problem is the disbursement of loans. IMF data for disbursement does not match the dates of executive board reviews. I use the user written *nearmrg* command in STATA version 15 written and maintained by Eric A. Booth. This command allows me to tie the time of loan disbursement to the date for executive board reviews. This obviously introduces some bias as the date of disbursement is not the same as the date of review. Disbursement is sorted to the nearest board action date.

A second time issue surrounds the implementation of *Prior Actions* that were evaluated at the start of an IMF loan. The IMF often requires countries to implement reforms before a loan is given to screen out countries which are not serious about reform. However, this introduces problems for the evaluation of IMF lending. If IMF reforms are carried out prior to the start of an IMF loan then our measures of IMF lending to date have been biased. If a loan is taken out in January of 2018, but the country had already implemented reforms in the months prior to this (let’s say from October-December of 2017) then researchers will have a harder time seeing a change in their outcome of interest between 2017 and 2018 since reforms took place during both periods.

This dataset codes reforms met under review period 0 (coded as R0 - evaluated at the start of a loan) as having occurred prior to the official start date. In order to evaluate how far back in time to code these reforms I look at the time between the start of a loan and the first executive board review. I take the time between the start of a loan and the first review and subtract that from the start of a review. This assumes that executive board reviews occur at normal intervals in each loan. So the start of IMF reforms occurs at time T-1, a loan starts at time T, and a loan is evaluated for the first time at time T+1. The gap between T and T+1 is assumed to be the same as the gap between time T-1 and time T. This assumes borrower countries implement reforms at the same speed during the application phase compared to the borrower phase. The IMF’s bargaining power shifts from the time it is reviewing applications compared to once it has given out a loan, and a government’s reform incentives shift from the time it is facing an economic crisis without funds compared to its incentive after it has already received a loan.

The final timing issue occurs when I need to sort reforms into a fixed time period. Because reforms take place over the course of several months (a spell), any attempt to fit the time period used to evaluate policies to a fixed time period (say country-year) must make assumptions about when reforms take place. However, executive board reviews sometimes occur every quarter, sometimes every three months, sometimes only twice a year, and sometimes only once a year. Exactly when a review occurs is heterogenous within loans and between loans. The time period in which reviews are evaluated is not constant within a loan, and can sometimes be pushed back. I also find that executive board reviews often combine multiple review periods. When a loan is given the IMF and country agree to a set number of reviews (let’s say 6). At each review the IMF reviews which of the policies that should have been met, and which have been met. However, often two or more reviews are combined such that the second review includes review 2 and review 3.

This heterogeneity causes problems when trying to create a country-year dataset. I assume that the year in which a review takes place is the year in which reforms were evaluated. This assumption makes sense when reviews take place in the latter half of a year. However, if a review takes place on January 2nd, 2018 it is likely that reforms were actually made in the previous year. I assume that researchers using this data will likely lag the country-year measures. Thus, I keep reforms in early parts of the year as occurring in that year. Any other coding decision must make assumptions about when, within a spell, reforms take place (equally over time? In the beginning? Right at the end?). It must also set an arbitrary cut point upon which to lag reforms to the previous year (is it January, February, March…June?) Any researcher interested in altering this choice can use the SCIP-R dataset, alter the timing, and collapse the data themselves.

1. **State-level Compliance with IMF Program, Policies (SCIP-P) – policy level**

This SCIP-P dataset evaluates compliance at the policy level. This section will be the most detailed as all the data used in other versions of the dataset originate from here. The MONA dataset “Combined SPC PA SB” serves as the base for the rest of the data. All of the compliance data in the final SCIP datasets come from this base dataset. The other 3 MONA datasets provide auxiliary information. I will start with variables in the SCIP-P dataset that comes entirely from the “Combined SPC PA SB” dataset. Information from the 3 additional datasets are only included in the SCIP-R and SCIP-Y datasets. This information can be merged into the SCIP-P dataset using the ArrangementNumber and BoardActionDate as unique identifiers. My work currently has no use for the policy level data and so this is included for others to use. As such I have not spent as much time ensuring this has every piece of information it could.

1. This dataset has a number of loan specific identifiers:
2. ArrangementNumber – the IMF loan number
3. CountryName – country
4. CountryCode – Correlated of War unique country identifier
5. ApprovalDate – date the loan was officially approved
6. ApprovalYear – year the loan was officially approved
7. InitialEndDate – original scheduled end date of loan
8. InitialEndYear – original scheduled end year of loan
9. RevisedEndDate – revised end date
10. BoardActionDate – date of Executive Board review
11. *Loan Type*

I begin by identifying unique IMF loan types. Some of these loans have been discontinued over time (for example the PRGF and the ESF). Where loans are coded as falling into more than one-category they are coded as falling into both categories. These category variables are coded as dichotomous variables in which an arrangement either falls under one (or two) of these loan types or it does not. Loan types are coded out of the variable “ArrangementType”. The abbreviation is the variable name in the dataset. The unique loan types in this dataset are:

1. ECF – Extended Credit Facility
2. EFF – Extended Fund Facility
3. ESF – Exogenous Shocks Facility
4. PCI – Policy Coordination Instrument
5. PCL – Precautionary Credit Line
6. PRGF – Poverty Reduction and Growth Facility
7. PSI – Policy Support Instrument
8. SBA – Stand By Agreement
9. SCF – Standby Credit Facility
10. This dataset codes variables into four policy types:
11. PA – Prior Actions
12. SAC – Structural Assessment Criteria
13. SB – Structural Benchmarks
14. SPC – Structural Performance Criteria
15. Compliance is coded into five categories:
16. met – conditions met or met with delay
17. notmet – conditions coded as not met or which were not met at the end of a review period
18. cancelled – conditions that had been cancelled or waived
19. partiallymet – conditions partially met
20. modified – conditions that had been modified
21. *Compliance by Policy Type*

Each of the policy types are evaluated under each compliance category. Each conditions is sorted into a single one of these variables. The policy type represents the first part of the variable and the compliance indicator occurs after the underscore ( \_ ). The following variables are included in the dataset.

|  |  |  |  |
| --- | --- | --- | --- |
| SB | PA | SPC | SAC |
| SB\_cancelled | PA\_cancelled | SPC\_cancelled | SAC\_cancelled |
| SB\_met | PA\_met | SPC\_met | SAC\_met |
| SB\_notmet | PA\_notmet | SPC\_notmet | SAC\_notmet |
| SB\_partial | PA\_partial | SPC\_partial | SAC\_partial |
| SB\_modified | PA\_modified | SPC\_modified | SPC\_modified |

1. *Policy Area*

The table below identifies the coding scheme used to create 18 unique policy areas. I have opted for a broader set of policy areas to allow researchers to combine these into smaller categories to suit their purposes. Users can go back and recode these if they prefer different combinations. Some of these are readily combinable, for example civil service and public employment will most likely by combined with labor market policies which exclude the public sector. Each unique policy is included in only one category.

I use the MONA variable “Area” to combine like categories into a smaller set of policy areas. Please note that earlier versions of the MONA data uses different values for Area. Such that the 2015 version of the data had 71 categories while the 2019 version had only 33.

|  |  |
| --- | --- |
| Area (MONA variable)[[1]](#footnote-1) | SCIP Policy Area |
| 1.3. Expenditure measures, inc | budget |
| 1.4. Combined expenditure and | budget |
| 1.8. Budget preparation (e.g., | budget |
| 1.6. Expenditure auditing, acc | budget |
| 2. Central Bank | central Bank |
| 2.1. Central bank operations a | central Bank |
| 2.2. Central bank auditing, tr | central Bank |
| 3. Civil service and public em | civil service |
| 11.4. Anti-corruption legislat | corruption |
| 1.5. Debt Management | debt |
| 6. Financial sector | finance |
| 6.1. Financial sector legal re | finance |
| 1. General government | general |
| 1.9. Inter-governmental relati | institutional |
| 9. Labor markets, excluding pu | labor |
| 11.2. Natural resource and agr | land |
| 11.1. Private sector legal and | legal |
| 11. Other structural measures | other |
| 11.3. PRSP development and imp | poverty |
| 5. Public enterprise reform an | privatization |
| 5.1. Public enterprise pricing | privatization |
| 5.2. Privatization, public ent | privatization |
| 5.3. Price controls and market | privatization |
| 6.2. Restructuring and privati | privatization |
| 1.1. Revenue measures, excludi | revenue |
| 1.2. Revenue administration, i | revenue |
| 4. Pension and other social se | social |
| 4.1. Pension reforms | social |
| 4.2. Other social sector refor | social |
| 7. Exchange systems and restri | trade |
| 8. International trade policy, | trade |
| 1.7. Fiscal transparency (publ | transparency |
| 10. Economic statistics (exclu | transparency |

1. *Compliance by Policy Area*

All of the policies that fall under a category are separated further split into how the executive board evaluated compliance with that policy. This results in 5 categories for each of the 18 policy areas or 90 unique variables that evaluate compliance in each policy area. The format these variables take is the same as compliance by policy type (section 4 E). The name of the policy area is followed by an underscore ( \_ ) and the name of the compliance measure. For example conditions met in the budget category are under the variable budget\_met

1. *Unique policy identifier* new\_mini\_id

The coding procedure for how I identify unique conditions is discussed above (section 2). *new\_mini\_id* is a numeric variable in which each number corresponds to a unique IMF condition. There are 8,454 unique conditions in the dataset, and 21,281 conditions evaluated by the Executive Board.

1. *Unique conditions by policy area*

Each of the 18 policy areas as well as the overall loan have a variable associated with the unique number of conditions in each loan. Variables are coded as unique\_\* where the star is replaced by the name of the policy area. So unique trade conditions in a loan is unique\_trade. There are 18 variables which are a single integer for the unique number of conditions in that policy area for a loan.

1. *Review\_period*

This variable is an integer coding sequential review periods for the loan. For each loan this provides a sequential time indicator for the number of Executive Board reviews. This variable ranges from 1 to 13.

**5.) State-level Compliance with IMF Programs, Arrangement (SCIP-R) – Review level**

All of the variables listed above are included in the SCIP-R dataset. See above for variables covering: loan identifiers (A), loan type (B), policy type (C), compliance (D), compliance by policy type (E), policy area (F), compliance by policy area (G), unique conditions (I). These variables have been collapsed to the Arrangement - Executive Board review unit.

This sections outlines unique variables included in the SCIP-R dataset that do not appear in the SCIP-P dataset.

1. The SCIP-R dataset includes a number of timing variables that may be of use to researchers.
2. Review\_time – sticks close to the above variable. When two are combined they are coded as the average of the two periods. So R2R3 is coded as 2.5. When three review periods are combined it is coded as the first review period plus 0.75. So R2R3R4 is coded as 2.75. This allows researchers to identify reviews which were combined.
3. Review\_period – sequential indicator of Executive Board reviews. This ignores reviews that were combined
4. R0 – a dichotomous indicator of Executive Board reviews of policies implemented prior to the start of an IMF loan (see section 3 on time for a discussion of this variable).
5. Start\_time – Board Action Date plus one day. If the first executive board review is R0 (see above) then the start date is coded as the loan start date minus the time to the next Executive Board review. See section 3 above for discussion
6. End\_time – Executive Board review date. This is the end of the current review period.
7. Time\_gap – number of days between executive board reviews
8. See additional time variables in section 4A
9. Size of loan and disbursements

The size of the loan is taken from the “Description” dataset, the disbursement data is taken from the “Purchases” dataset. Please note that the value of figures is in IMF SDRs. The following variables have been included

1. Totalaccess – total size of the loan
2. ActualAmount – actual amount disbursed in this review period
3. OriginalScheduledAmount – amount that was originally scheduled to be disbursed
4. Cancelled and Precautionary Loans is taken from the “Description” dataset.
5. Cancelled\_loan – the review period in which a loan was cancelled. Be careful not to confuse with the compliance indicator cancelled.
6. Precautionary – dichotomous indicator of whether a loan was precautionary
7. IMF Program goals

Taken from the “Program” dataset. This included the goals attached to IMF loans. This data covers the period 2007-2019 and is not available for earlier loans. These goals are dichotomous for the entire period of the loan. These goals include:

|  |  |  |
| --- | --- | --- |
| MacroEconomic | Monetary | ProGrowth |
| ExternalStability | Inflation | Social |
| EconomicGrowth | ExchangeRate | Enterprise |
| PovertyReduction | Central Bank | Governance |
| FiscalRevenue | FinancialSector | Other |
| PublicExpenditure | Trade |  |

1. Overall compliance measures for the loan.
2. Total\_met – total number of conditions met in a loan. This variable does not change over the course of the loan. For a variable that does change from review period to review period see “met” in section 4.
3. Compliance\_review – number of conditions met divided by conditions possible to meet in a review period. This number changes from review period to review period. See section 2 for a discussion of this variable
4. Compliance\_final – final compliance metric. At the end of a loan how many conditions were met out of the unique conditions that could have been met. This is a single number that does not change over the course of the loan. See section 2 for a discussion of this measure.
5. Total\_conditions\_review – number of conditions evaluated in a review period
6. Total\_conditions\_evaluated – number of conditions evaluated in a loan to date. This is a cumulative number of the variable above it and is strictly increasing over the course of a loan.
7. **State-level Compliance with IMF Program, Year (SCIP-Y SCIP-M) – year & month**

All variables in the SCIP-R dataset come from collapsed data in the SCIP-P dataset. Data in the year dataset were collapsed by Arrangement number and Executive Board review year. All data in the SCIP-R dataset are expanded from the arrangement spell data into month data.

1. MONA categories were not cut off by the author. This is how the categories are presented in the dataset. [↑](#footnote-ref-1)