Amnesty International's Torture Allegations
Introducing the Ill-Treatment and Torture (ITT) Country-Year Data*

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The Ill-Treatment and Torture (ITT) Data Collection Project uses content analysis to measure Amnesty International's (AI) *allegations* of government ill-treatment and torture from 1995 to 2005. ITT's country-year (CY) data uses a modified version of the ordinal scale proposed by Hathaway (2002) and quantifies not only AI's allegations about the incidence of ill-treatment and torture at the country-year unit of observation, but further across different responsible government agents and across different econo-socio-political groups of alleged victims. This paper describes quantitative patterns found in the Beta release of ITT's country-year (CY) data and proposes several research questions for future research using the new data.

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1 Introduction

A primary mission of international non-governmental organizations (INGOs) like Amnesty International (AI) and Human Rights Watch (HRW) is to monitor the human rights records of governments, calling attention to state transgressions and pressuring governments for reform. As part of their activities, human rights INGOs periodically allege that a government is responsible for ill-treatment or torture; other times, they accuse a government of demonstrating a pattern of abusive behavior. This type of INGO activity is often called "information politics," the defining characteristics of which include unbiased research, grassroots mobilization and fund raising, and the distribution of information to make people aware of transgressions (e.g., Keck and Sikkink 1998, Cmiel 1999, Clark 2001, Ron, Ramos and Rodgers 2005). Several well known data collection efforts have utilized these reports to create ordinal data about governments' abuse of human rights (Hathaway 2002, Gibney, Cornett and Wood 2009, Cingranelli and Richards 2010*a*). These projects have been invaluable, supporting a wide variety of statistical analyses that have helped researchers better understand the covariates of human rights performance (e.g., Poe and Tate 1994, Cingranelli and Richards 1999*a*, Apodaca 2001, Keith 2002, Davenport and Armstrong 2004, Bueno de Mesquita et al. 2005, Hafner-Burton 2005, Neumayer 2005, Abouharb and Cingranelli 2007, Hathaway 2007, Richards and Gelleny 2007, Vreeland 2008, Keith, Tate and Poe 2009, Powell and Staton 2009, Simmons 2009*b*, Cingranelli and Filippov 2010, Conrad and Moore 2010*b*).

Although existing data has paved the way for large-N, cross-national research on human rights, the Ill-Treatment and Torture (ITT) Data Collection Project makes it possible to pursue at least two opportunities that existing data do not permit. First, rather than conceptualize INGO reports about human rights as evocative of the performance of states vis-à-vis their international obligations, as previous data collection projects have done, ITT codes these reports to quantify allegations advanced by AI. ITT's conceptual focus does not concern the behavior of states in so much as it concerns the behavior of a particular INGO: Amnesty International. This is of theoretical, as well as empirical, import as the impact of the activity of INGOs is of considerable interest to a broad research community within the international relations and international law subfields. Second, in addition to producing an ordinal measure of AI's allegations of the incidence of torture in all countries with populations over one million, ITT also codes a number of additional characteristics of the allegations advanced in AI publications. Specifically, the ITT project codes information to help researchers answer four questions about state torture: How many victims?; Which government agencies torture?; What types of torture are used?; and What is the state response to torture? To answer these questions, the ITT project has generated data at two different units of analysis: the torture event or allegation, and the country-year. By performing content analysis of AI publications (specifically, AI's annual reports, press releases, and action alerts) the ITT project measures *allegations* of *state torture* leveled by AI from 1995-2005.

For our purposes, state torture occurs only when the perpetrator is an agent of the state, the victim is a person detained under the state's control, and the alleged abuse meets the definition of torture in the United Nations Convention Against Torture (CAT) (Conrad and Moore 2010*a*, pp. 9-11). ITT defines a torture as a unique experience occurring to each (group of) persons(s).[1] The CAT defines torture as follows:

> torture means any act by which severe pain or suffering, whether physical or mental, is intentionally inflicted on a person for such purposes as obtaining from him or a third person information or a confession, punishing him for an act he or a third person has committed or is suspected of having committed, or intimidating or coercing him or a third person, or for any reason based on discrimination of any kind, when such pain or suffering is inflicted by or at the instigation of or with the consent or acquiescence of a public official or other person acting in an official capacity. It does not include pain or suffering arising only from, inherent in or incidental to lawful sanctions.

Turning to ITT's focus on state ill treatment and torture, the project only codes AI allegations when a state is functioning: during periods of state collapse or foreign

[1]By unique experience, we refer to the torture experience: the type of torture, the agency responsible, the type of victim, etc.

occupation, ITT does not code allegations.[2] More specifically, like the CIRI project, ITT does not produce codes for country-years that the Polity project codes as not having a functioning state.[3]

Unlike existing efforts, the ITT project distinguishes between two units of observation: specific allegations (SA) and country-year (CY) allegations. The distinction between these two units of observation involves the breadth of their spatial-temporal domain. Country-year allegations are allegations about the general use of torture across a given country throughout a given year by a given government agency (if specified). They are more general in nature than specific allegations, and they apply only to reports that describe torture occurring across an entire country over an entire year. Reports that refer to torture occurring within a limited time (i.e., less than a year) or space (e.g., a region, a specific prison) are SA allegations (Conrad and Moore 2010*a*, pp. 11-13). This study reports information on the ITT CY data.[4] The CY data code information on three characteristics not available in other cross-national data on state torture: the government agency alleged to have committed the abuse, the econo-socio-political group of which the alleged victim is a member, and whether or not AI claims the government obstructed NGO/INGO access to victims. In what follows, we discuss the key measures included in the CY data and how the relate to the extant cross-national data on state torture.

2 Nuts and Bolts of the ITT Country-Year Data

The ITT country-year (CY) data use a modified version of the ordinal scale proposed by Hathaway (2002) to code the level of torture (LoT) alleged by AI to have occurred *throughout a country over the course of an entire year*, as described in

[2]To be clear, AI makes allegations about both state and non-state actors and does so without regard to the definitions of state collapse employed by ITT. ITT coders coded all allegations against state actors, but we exclude from our CY data those allegations made during years when the Polity project codes the state as failed or occupied. In mid to late 2012 all of the files needed to replicate the ITT data collection will be made available on the project website; interested researchers will be able to use those files to obtain the data on failed or occupied states.

[3]Please see Conrad and Moore (2011, pp. 8-9). The Polity project's website is: `http://www.systemicpeace.org/polity/polity4.htm`.

[4]We plan to release ITT SA data in late 2011 and early 2012.

Conrad and Moore (2011). Let us unpack that statement. First, note that existing efforts to collect cross-national data on the extent to which governments engage in the ill-treatment and torture endeavor to measure government behavior (e.g., Hathaway 2002, Cingranelli and Richards 2010*a*). The ITT project expressly does not code government behavior. Instead, it codes AI *allegations* about government ill-treatment and torture, taking into consideration that (1) it is not possible to know, much less report, the "true" level of ill-treatment and torture occurring in any one country (e.g., Rejali 2007, p. ?), and (2) AI is a strategic actor with limited resources that issues reports only when it is highly confident about the accusation, and further where it believes it is most likely to influence governments (e.g., Cmiel 1999, Clark 2001).

Turning to ITT's CY data in particular, these data code only those allegations that make claims about abuse occuring throughout a country over the course of an entire year. To illustrate, if AI alleges that people held in a specific prison are frequently beaten, that allegation would not be recorded for the CY data because it is limited in its spatial domain. Similarly, allegations of torture during an election would not be recorded for the CY data because they are limited in their temporal domain. Instead, these allegations would be coded using ITT's specific allegation (SA) coding rules,[5] the data for which have not yet been released. In order to code CY data on government torture incidence, ITT adopts the Hathaway (2002) six point ordinal scale to measure the intensity of government ill-treatment and torture reported in AI's allegations.[6] We instructed our coders to code only country-wide allegations occurring throughout the year that used one of the following key words:[7]

- 1 = Infrequent
- 2 = Some(times)

[5]This difference suggests that the ITT data may not correlate strongly with the Hathaway (2002) data or the Cingranelli and Richards (1999*a*) data. Those projects code AI allegations about people held in a specific prison being frequently beaten, as well as allegations of abuse surrounding elections. We should note, however, that those projects code only Annual Reports; in its Annual Reports, AI by and large limits itself to broad allegations about abuses that occur throughout the country.

[6]We identified a number of synonyms for these terms. Please refer to Conrad and Moore (2011) for more information.

[7]In country–years for which AI did not make any allegations that met these criteria ITT's CY data record a value of 0: No Allegation.

- 3 = Frequent
- 4 = Widespread
- 5 = Systematic

It is important to emphasize that these words describe the frequency with which an alleged violation of the CAT occurs, but do not comment on the type of violation. Interested observers and scholars alike have a strong tendency to want to distinguish among types of torture, often implicitly identifying some types as worse than others. For example, ill treatment is often implicitly considered a less "intense" form of abuse than torture, and so on. Human rights activists, however, rarely make such distinctions, and this is consistent with the idea of a bright line distinction in law. With respect to the CAT, a given act is either in violation or it is not. AI publishes allegations about violations of the CAT, and the ITT project uses the LoT scale to code the frequency with which these allegations occur. As such, the LoT variables in the ITT CY data *do not* make such any sort of "intensity" of violation distinction, and should not be used to measure such a concept. The CY LoT variables instead measure AI's allegation of the frequency with which a state violates the CAT throughout the country during a particular year.

ITT's CY data is further distinct from previous data collection efforts on torture and ill-treatment in that it codes not only the incidence of torture alleged in AI's reports, but also (1) the government agency AI alleges to be responsible for the abuse, and (2) the type of victim that AI alleges was abused by the state. ITT distinguishes among five government agencies, which we label Agency of Control (AoC): Police, Prison, Military, Intelligence, Immigration Detention, and Paramilitary (Conrad and Moore 2010*a*, pp. 7-8). AI's allegations do not always identify a government agency, so the data including a sixth category: Unnamed/Not Stated. Because ITT codes AI's allegations, not the "true" state of the world, coders were instruted to code what AI alleged: they were not to use the AI report as a cue to divine what government agency was responsible for any given allegation of abuse.

Turning to Victim Type (VT), ITT coders distinguished between four groups of victims: Criminal, Political Dissident, Member of a Marginalized Group, and State Agent (Conrad and Moore 2010*a*, p. 8). As with the AoC variable, VT contains an

Unnamed/Not Stated value. The Political Dissident category includes prisoners of conscience, human rights activists, and protestors. Members of marginalized religious and ethnic groups, the elderly and youths, and immigrants are all coded as Members of a Marginalized Group. If AI alleges that a victim is an illegal immigrant the coders recorded both Criminal and Member of a Marginalized Group.[8]

The ITT Country–Year (CY) data are available in four distinct structures, all of which report the level of torture (LoT) for the relevant units:

- Country-Year (CY)
- Country-Year, Agency of Control (CYAoC)
- Country-Year, Victim Type (CYVT)
- Country-Year, Agency of Control Victim Type (CYAVT)

In what follows, we discuss in more detail the validity and reliability of our LoT measure. We also explore a variety of univariate and bivariate patterns that emerge from the Beta version of the first three of the datasets described above,[9] and we discuss in more detail several ideas for future research on human rights that can be conducted using the ITT CY data.

2.1 Validity

Although ITT CY data on government torture allegations permits the disaggregation of rights violations by state agency and victim type, it is not the first cross-national data on state torture practices. We use two other cross-national measures of torture, one from Cingranelli and Richards (2010*a*) and one from Hathaway (2002), to establish the convergent validity of the ITT CY LoT measures. Convergent validity describes the extent to which concepts or measures that should be related to one another in theory are actually related to one another in practice. Accordingly, Table 1 shows the correlation between ITT CY LoT measures and the CIRI (Cingranelli

[8]Neither values on AoC and nor values on VT are mutually exclusive.

[9]We have yet to investigate Beta version of the Country–Year, Agency of Control Victim Type (CYAVT) data.

and Richards 2010*a*) freedom from torture measure (in the second column) and the Hathaway (2002) torture measure (in the third column). The ITT LoT variables presented in Column 1 include measures of torture allegations across all state agencies (CY LoT), within the individual agencies described above (CYAoC), and against the individual victim types described above (CYVT). CIRI's measure of freedom from torture ranges from zero to two, with higher values indicating a greater respect for the right to freedom from torture. Accordingly, we expect each of our ITT CY LoT measures to be *negatively* correlated with the Cingranelli and Richards (2010*a*) freedom from torture measure. The Hathaway (2002) measure of torture, on the other hand, ranges from zero to five; higher values indicate higher levels of torture. We expect each of our LoT measures to be *positively* correlated with the Hathaway (2002) measure of torture. Table 1 reports these correlations.

As expected, each of the ITT CY LoT measures shown in Column 1 is negatively correlated with CIRI's *freedom from torture* measure, and positively correlated with data from Hathaway, which measures *violations*. They range in absolute value from 0.04 to 0.48, thus exhibiting almost no correlation through moderate levels. Not surprisingly given the different scales used by CIRI (three values) and Hathaway (the source for the ITT scale), the absolute value of the correlations are higher for Hathaway in all but one case. We take two primary points from this exercise: the absence of correlations with the wrong sign provides convergent validity, and the low to moderate size of the correlations demonstrates that the ITT contain rather different information than that provided in either CIRI or Hathaway.

What best explains the low to moderate correlations? To be sure, ITT was created to code AI's allegations, whereas Hathaway and the CIRI project use those allegations to code state behavior. Yet despite this conceptual distinction, given that all three projects perform content analysis on documents that allege violations one might anticipate higher associations. The difference in scales is one issue, but there is certainly more to it than that as the ITT and Hathaway correlations do not rise above 0.48.

Consider that the CIRI project assigns its torture variable values based on the coder's judgment about all of the torture allegations against a particular state in a particular country-year Cingranelli and Richards (2010*a*,*b*). The Hathaway data

Table 1: Correlation of ITT CY LoT Measures with CIRI Freedom from Torture and Hathaway Torture

	CIRI Freedom From Torture	**Hathaway Torture**
CY LoT	-0.43	0.48
CYAoC LoTUnnamed	-0.41	0.48
CYAoC LoTPolice	-0.25	0.40
CYAoC LoTPrison	-0.25	0.43
CYAoC LoTMilitary	-0.32	0.43
CYAoC LoTIntelligence	-0.04	0.09
CYAoC LoTImmigration	-0.07	0.04
CYAoC LoTParamilitary	-0.12	0.10
CYVT LoTUnnamed	-0.42	0.48
CYVT LoTCriminal	-0.29	0.44
CYVT LoTDissident	-0.30	0.41
CYVT LoTMarginalized	-0.18	0.35
CYVT LoTStateAgent	-0.08	0.18

were collected using the same approach. By comparison, ITT only codes allegations in our country-year data when AI claims that abuse occurs throughout the country over the course of the year.[10] Neither the CIRI nor the Hathaway data distinguish between allegations with a broad spatial–temporal domain matching the country–year and those with a limited spatial and/or temporal domain, but the ITT project does. Which data is more useful for a given project, then, depends upon that project's goals.

With that broad background, we briefly examine some of the specific correlations in table 1. Consider first the ITT CY LoT measure, which reports the highest value of alleged country-wide torture over all agencies and victim types in a year. Since this is the ITT CY variable most similar to the CIRI and Hathaway variables it is not surprising that it produces the largest (negative) correlation with the CIRI freedom from torture measure (-0.43), and the highest (positive) correlation with the Hathaway measure of torture (0.48). Among the various ITT CYAoC variables, Unnamed is more highly corrected with both the Cingranelli and Richards (2010*a*) measure (-0.41) and the Hathaway (2002) measure (0.48). In contrast, the CYAoC measure least correlated with the CIRI measure is Intelligence (-0.04), while the CYAoC measure least correlated with the Hathaway measure is ITT Immigration (0.04). These low values suggest to us that there is potentially interesting variation to be explored, and we show below that when one moves from global to regional (and even country) comparisons, one continues to find differences that at first glance suggest that work with the ITT data may well yield useful insights.

Similar patterns exist when the ITT data is divided into AI allegations of torture against different groups of victims. The CYVT Unnamed LoT measure exhibits the largest absolute value more correlation with both the CIRI (-0.41) and Hathaway (0.44) variables. ITT LoT data on torture allegations against Criminals and Dissidents are more correlated with the country-year measures generated by Cingranelli and Richards (2010*a*) (-0.29, -0.30) and Hathaway (2002) (0.44, 0.41), respectively. The CYVT StateAgent is the least correlated disaggregated ITT measure of torture against specific types of victims across both the CIRI freedom from torture (-0.08)

[10]ITT also codes AI's allegations of ill treatement and torture that are limited temporally or spatially, but does so as event data. Those data will be released in late 2011 and early 2012.

and Hathaway torture measures (0.18).

2.2 Reliability

To evaluate the reliability of the ITT coding rules we conducted a series of inter-coder reliability checks during the year in which the content analysis was performed. Conrad and Moore (2011, p. 15) provide a brief discussion of the ITT coder recruitment and training process, as well as the analysis of inter-coder reliability. We plan to later release a detailed study of the results of our inter-coder reliability checks across all CY and SA measures. To assess reliability of the measures contributing to the CY data (i.e., Level of Torture, Agency of Control, Victim Type, and Restricted Access), we adopted the proportion of overall agreement measure described by Ubersax (2009):

$$P_{OA} = \frac{\sum_{j=1}^{C}\sum_{k=1}^{K} n_{jk}n_{jk-1}}{\sum_{k=1}^{K} n_{jk}n_{jk-1}}$$

Table 2 shows that the four variables contributing to the CY data had inter-coder reliability scores ranging from 0.739 (Victim Type) to 0.919 (Agency of Control):

Table 2: Proportion of Overall Agreement Across Coders

Variable	P_{OA} Score
Level of Torture (LoT)	0.761
Agency of Control (AoC)	0.918
Victim Type (VT)	0.739
Restricted Access	0.919

3 Univariate Patterns of AI's CY Allegations

3.1 Frequencies

Table 3 displays frequencies of the LoT measure in the Beta release of the CY, CYAoC, and CYVT data sets described above.[11] Although there are 2,002 country-

[11] We ask any readers interested in these data to refrain from citing figures from the project until the final release of the ITT CY data in summer 2011 without explicitly reference to the fact that they

years covered by each of these data sets, the values in the Total column of table 3 are all less than 2,002. Two types of missing values produce this outcome. First, as noted above, ITT codes only AI allegations of *state* ill-treatment and torture. Thus, when states collapse or are occupied by foreign powers, those country-years are assigned a missing value code (Conrad and Moore 2011, pp. 8-9).

Second, the Beta release of the data include negative values for several phrases that AI uses with some frequency to identify a state's practice as improving, worsening, or staying the same.[12] When allegations that use these phrases do not include additional information that made it possible for coders to assign a value on the LoT scale coders assigned a value of "better," "worse," or "status quo." In many cases coders had been able to assign a value in the preceding year; for those cases we wrote a batch cleaning file that added one to, subtracted one from, or simpy used the preceding year's value, accordingly.[13] Although this procedure assigned LoT values to many cases, there nevertheless remain a number of cases for which we are unable to assign a value. We are very interested to obtain feedback from the research community about ideas for assigning values in these instances.[14] The final release of the ITT CY data will contain a specific solution for this issue,[15] but the data reported in Table 3 treat these as missing values.

The first row of Table 3 records the distribution of LoT aggregated at the country-year: this is the highest level of country–wide annual torture alleged by AI for all AoCs and VTs in a particular country during a given year. In only 32% (445) of country-years did AI not issue at least one allegation of country-wide violation of the UN Convention Against Torture (CAT). Note that this is not a single alleged act of abuse: the ITT CY data do not record AI's allegations of a single act of abuse.[16] The ITT CY data only code allegations of abuse that occur throughout

are referencing the Beta release. We further ask that readers performing analyses with the Beta data re-do their analyses using the final release of the data once those become available.

[12]Please see Conrad and Moore (2011, pp. 5-7).

[13]The Cleaning Manuals which describe the process by which we created the CY data from the spreadsheets coded during the content analysis are not presently available online, but will be posted on the project website when the final CY data are released in summer, 2011.

[14]We have some of our own, but hope to "crowd source" the best solution.

[15]Researchers will also be able to download a version of the data that have no solution imposed so that they might employ a different one.

[16]As noted above, those allegations are coded in a distinct set of data that will be released beginning

Table 3: Level of Torture (LoT), AI Allegation Frequency by Measure

	None	Infrequent	Several	Routinely	Widespread	Systematic	Total
CY:							
LoT	445	24	184	179	200	354	1,386
CYAoC LoT:							
Unnamed	825	12	119	96	146	210	1,399
Police	877	15	158	160	127	123	1,460
Prison	1,127	10	111	62	69	106	1,485
Military	1,194	4	53	67	77	122	1,517
Intelligence	1,588	1	6	5	1	17	1,618
Immigration	1,570	2	16	11	4	5	1,608
Paramilitary	1,572	2	6	8	2	16	1,606
CYVT LoT:							
Unnamed	664	19	143	125	180	224	1,355
Criminal	929	22	124	117	124	135	1,451
Dissident	1,192	11	99	77	47	94	1,520
Marginalized	1,073	17	112	102	64	106	1,474
StateAgent	1,578	3	4	8	4	11	1,608

NOTES: Negative values (e.g., -999) omitted from reported frequencies. Total may differ across measures as a result.

the country over the course of an entire year. In 39% of country-years, AI alleged either Widespread or Systematic abuse of the rights enshrined in the CAT (200 and 354, respectively). AI alleged either Several or Routine use of ill-treatment and torture in another 26% of country-years (184 and 179, respectively), and Infrequent abuse in only 2% (24) country-years. These figures are broadly consistent with the global pattern described in Cingranelli and Richards (1999*b*, p. 522), who reported that the rights outlined in the CAT are the most widely contravened rights in the world.[17]

What emerges when one turns attention to the government agency AI claims is responsible for victimization? Below we delve into regional and national patterns, but here we consider only the global level. It is immediately apparent that Unnamed and Police are the government agencies that AI most commonly names and shames: there are 574 country-years for which AI issued an allegation without identifying the state (41%) and 583 country-years in which AI called out the Police for violations (40%). Prisons are named and shamed in 24% of the allegations (358) and the Military in 21% of the country-years (323).[18] By comparison, Intelligence agencies, agencies responsible for detaining Immigrants, and Paramilitary organizations are named and shamed by AI in only 2% each of the country-years (30, 38, and 34 country-years respectively). Lastly, Police exhibits a fairly uniform spread across the levels: Several through Systematic all have between 123 and 158, while Immigration displays a cluster at Several and Routinely. For the other AoCs the spread across the values other than No Allegation are roughly similar to those we saw in the country-year LoT variable.

In addition to observing the frequencies shown in Table 3, it is interesting to consider graphical displays of the spread of LoT values for each of the the three data sets described above. Box and whisker plots visually depict the central tendency and dispersion of the values of a variable. In the plots below the median value

in late 2011.

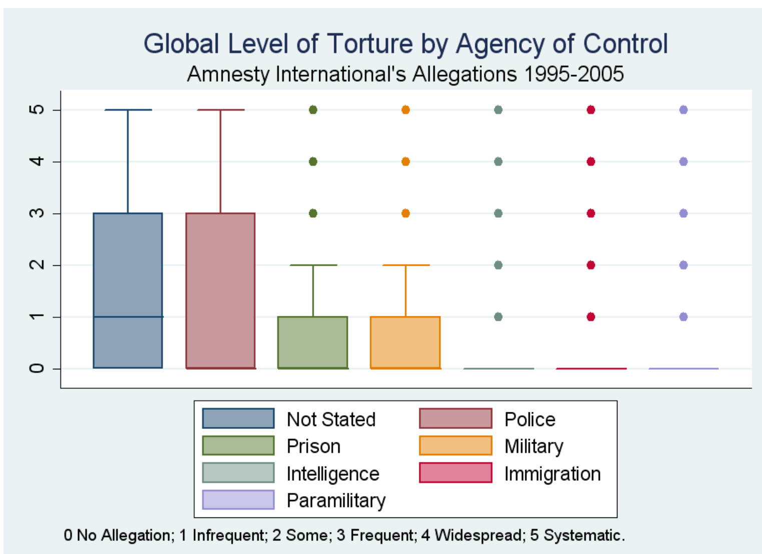
[17]Over the years 1980-2008, the CIRI data record that 79 percent of the country–years exhibit either little or only some respect for the right to freedom from torture.

[18]Please observe that when AI alleges that more than one government agency engages in a country-wide pattern of abuse the ITT CY data records each agency. Thus, one should not expect the AoC cell entries across rows to sum to the total number of country-years, 2,002.

is depicted as a solid horizontal line, and a colored rectangle covers the range of the 25th through the 75th percentiles of the variables' values. A thin vertical line stretches from the edge of the rectangle to encompass what are known as the upper and lower adjacent values. Technically, these values are the 75th (25th) percentile plus (minus) 1.5 times the mean value (Stata 2003, p. 159). Dots are used to depict any values that lie outside of the range of the lower and upper adjacent values.

Figure 1 further amplifies what we observed in Table 3: both Unnamed and Prison have the largest spreads with the zero to 75th percentile ranging from zero to three.[19] The mean of Unnamed is one, but the mean of all of the named AoCs is zero. Both Prison and Military reach the 75th percentile at one and have an upper adjacent value of two.

Figure 1



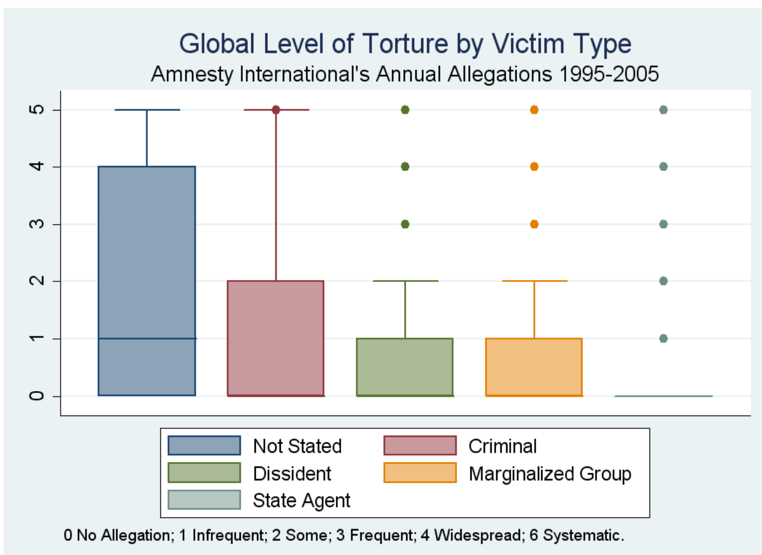
How should one best interpret these data? More specifically, should one claim that AI focuses its resources on abuses committed in prisons and by police and

[19] As discussed above, in tables 1, 3, and 4 we dropped the cases that were assigned values of "better," "worse," or "status quo" as these values were treated there as "missing." For all of the box and whisker figures in this paper, however, we implemented a specific solution (not described here, as it is rather involved) to the missing values issue: i.e., assigned non-missing values to thethe cases where the relevant LoT variable was coded as having a "better," "worse," or "status quo" value.

military, or is it better to argue that these data are representative of the “true” distribution of state torture (effectively assuming that AI invests its monitoring, investigative, and reporting resources equally wherever abuse occurs)? We recommend the former approach and argue that scholars should research the extent to which AI (and other INGOs) invest their monitoring, investigative, and reporting resources in proportion to violations. We have no particular reason to believe that AI does not do so, but it strikes us as prudent to study that issue rather than assume it to be so.[20]

Returning to Table 3, the type of victim (VT) LoT variables exhibit a similar emphasis on a few types: the Unnamed and Criminal categories are more common than the Dissident and Marginalized victim groups. The State Agent group is quite rare. Figure 2 displays the same information graphically, showing that 51% of Unnamed country-years involved an allegation (691), 36% of the Criminal country-years contain an allegation (522), and 22, 27, and 2% of Dissidents, Marginalized Populations, and State Agents involved allegations, respectively (328, 401, and 30, respectively).

Figure 2

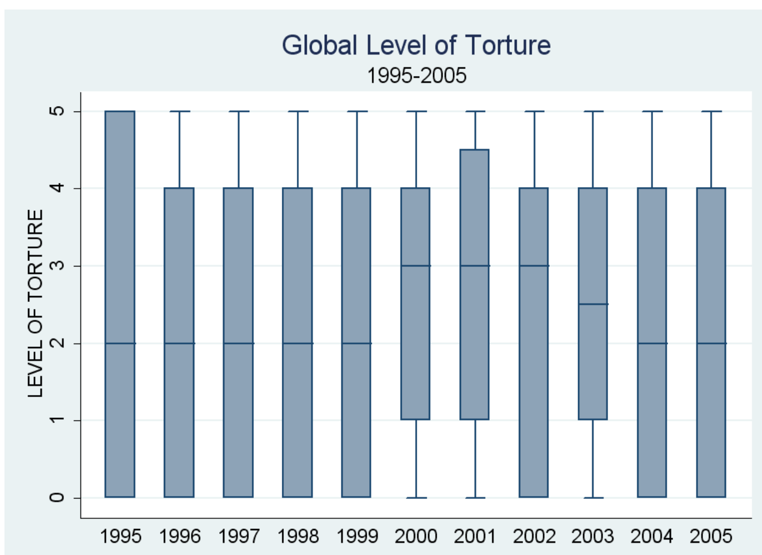


[20]Please refer to the discussions in Hill, Moore and Mukherjee (2010), Gourevitch and Lake (2011).

3.2 Temporal Patterns

We now consider the amount of variance in LoT at the country-year level over the 1995-2005 period. Simmons (2009*a*) has conjectured that INGOs like AI have an incentive to change their standards over time as states increase their respect for rights. She argues that because INGOs mobilize both labor and donations by informing people of dire circumstances, INGOs have an organizational incentive to consistently report bad news. If states' respect for the CAT improves, INGOs like AI will consequently turn their attention to other violations they would have ignored in the past. Figure 3 depicts the global distribution of CY LoT over the period 1995-2005. Although hardly definitive, these data fail to support Simmons' conjecture: the value of both the global mean and the 25th percentile rise in 2000, but both then fall in 2004 and 2005. With the exception of that movement, however, the distribution over the six point LoT ordinal scale is effectively stable.

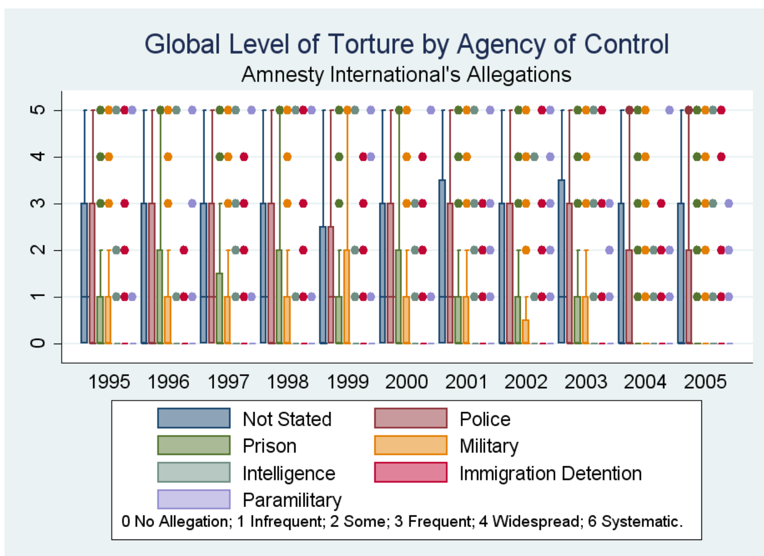
Figure 3



When we break the data down by AoC in Figure 4 we see a similar stability in Unnamed, a small decline in abuse by Police, and more marked declines in allegations of abuse against both Prisons and Military. The temporal trend in AI's allegations against Military AoCs is particularly intriguing: It spikes in 1999, not in

2002-2003 as one might have anticipated given state responses to the 9/11, London, and Spain terror attacks, then drops thereafter such that No allegation encompasses the distribution through the upper adjacent value.[21] Without conducting careful research, however, we cannot speculate as to whether this pattern is due to a shift in monitoring, investigative and reporting resources away from the Military (and Prisons) by AI, or whether this drop in allegations reflects improvement in Military agencies' respect for the CAT. Asking such questions is not possible using CIRI data or the Hathaway data, but the ITT CY data make it possible for scholars to develop innovative research designs that will permit them to study these questions.

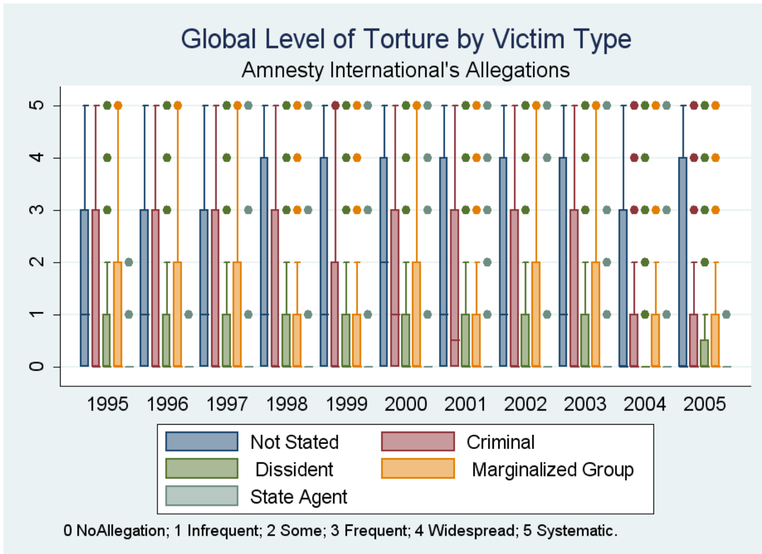
Figure 4



Turning our attention to temporal trends across VT, consider Figure 5. These data strike us as basically stable across all victim type groups: there is minor temporal variation in some of the groups, but it appears that these changes are unlikely to exhibit statistically significant differences across different types of victims.

[21]In 2004-2005 allegations of Infrequent through Systematic abuse by Military agencies are outliers.

Figure 5



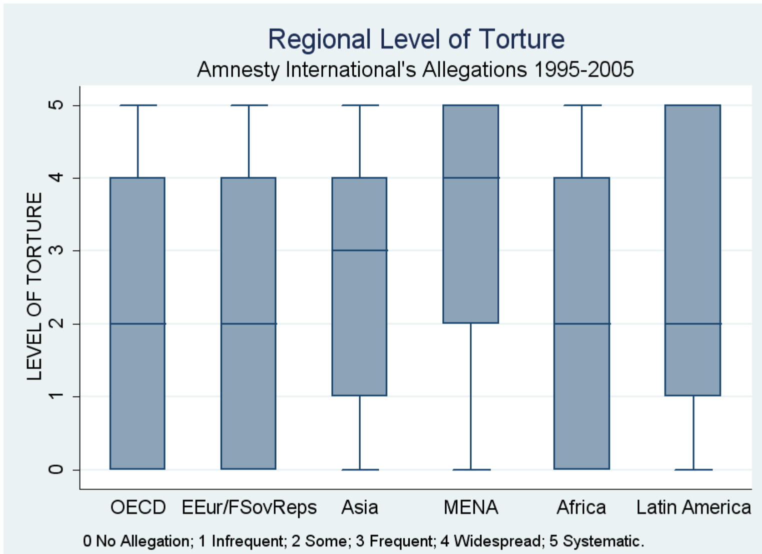
3.3 Regional Patterns

In addition examining global patterns we explore whether there are interesting regional patterns in AI's allegations about the level/incidence of torture. Figure 6 depicts variation in the CY LoT across six regions of the world: OECD countries (aka advanced industrial democracies), Eastern Europe and the Former Soviet Union, Asia, the Middle East and North Africa (MENA), Sub-Saharan Africa, and Latin America & the Caribbean.[22]

The MENA region jumps out: AI alleges that 75% of the MENA country-years engaged in Some through Systematic abuse, with an average of Widespread abuse. For Asia, AI alleged that 50% of the country-years (from the 25th through the 75th percentile) exhibited from Some to Widespread abuse, with an average Frequent abuse. In the other four regions, AI alleged an average level of Some abuse, though Latin America & the Caribbean attracted a larger spread of alleged abuse than the OECD, Eastern Europe and the Former Soviet Union, and Sub-Saharan Africa. As already noted, whether these different patterns more strongly reflect differences in

[22]We assigned countries to regions using the coding decisions used by the Minorities at Risk project: `http://www.cidcm.umd.edu/mar/`.

Figure 6



AI's commitment of monitoring, investigative and reporting resources or differences in the respect for the CAT in these regions is a topic for further research. But it is interesting to break these down further by both AoC and VT; we suspect that readers will find the patterns in Figure 7 plausibly consistent with what they believe about ill-treatment and torture across the globe during the 1995-2005 period. Similarly, Figure 8 displays the regional box and whisker plots for the types of victims identified in AI's allegations. As with the regional AoC plots we suspect that this also has considerable face validity.

In both Figures 7 and 8, the MENA region attracts both the most broad and the highest allegations of LoT from AI, followed by Asia, Latin America & the Caribbean, Sub-Saharan Africa, Eastern Europe and the Former Soviet Union, and then the OECD countries. These patterns suggest that the ITT CY data provide interesting grist for exploring not only global trends (McCann and Gibney 1996, Cingranelli and Richards 1999*b*), but for regional patterns as well.

Figure 7

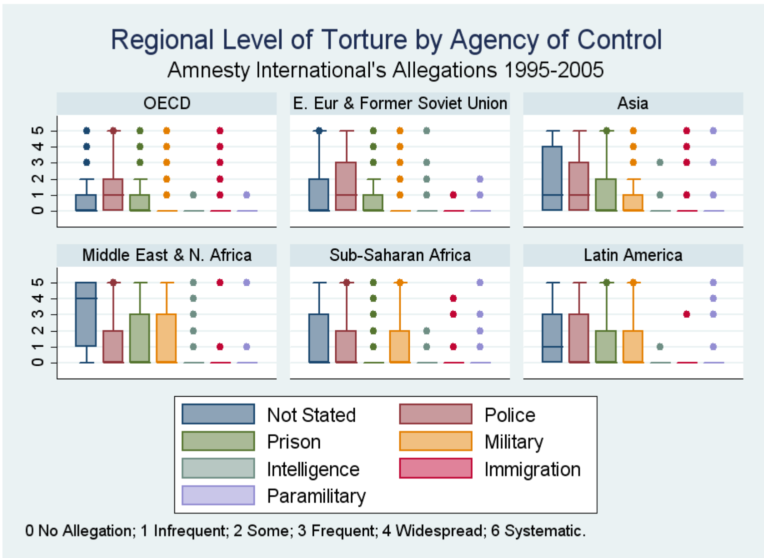
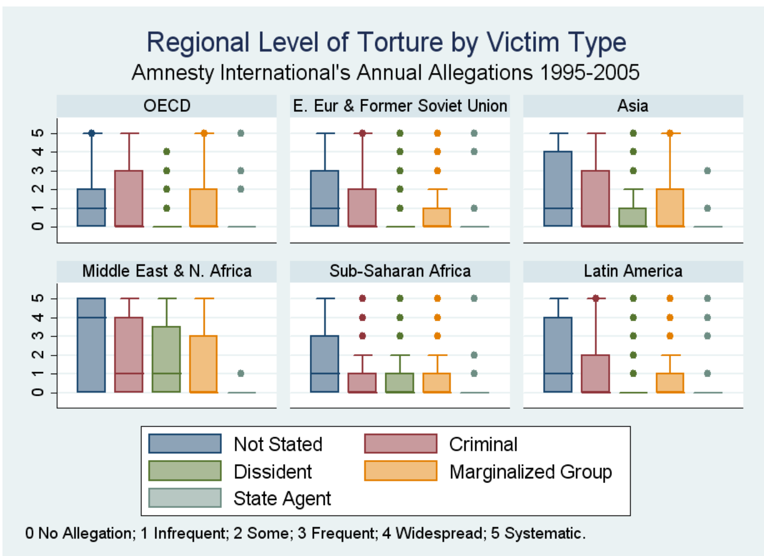


Figure 8



3.4 Illustrative Country Patterns

The ITT CY data should also be of interest to researchers interested in specific countries' respect for rights (Conrad and Moore 2010*b*) or in patterns of AI's allegations for specific countries. For illustrative purposes, we select Indonesia, Japan, Kenya, Mexico and the United States as interesting cases and plot the AoC LoT and VT LoT for each country in the Appendix to this paper. In the interests of space we leave the evaluation of these plots to the reader and merely note that there is considerable variation across these countries and within each country over time.

4 Bivariate Patterns of AI's CY Allegations

New cross-national data is always welcomed in the social sciences. At a minimum, new data permits scholars to assess the robustness of their empirical results across different measures of a concept. We look forward to seeing the ITT data used in such a way; especially in the area of human rights, where states have an incentive to hide their behavior, assessment of results across measures is of the utmost importance. Given the emphasis above on the distinction between ITT and existing data—due to ITT's focus on AI's allegations rather than states' behavior—this might appear an odd claim. However, we believe that ITT can be usefully employed to study not only AI's "naming and shaming" activity (which is the most obvious, and direct use of the data), but also to study states' behavior. The vast majority of large-N statistical research has examined states' behavior, and to put ITT to such a use researchers will need to develop a model of the process that links AI's allegations to the unobservable (i.e., latent) variable: states' abuse of (or respect for) the CAT. To use ITT's CY LoT variables as a measure of state behavior in a statistical analysis will require, at a minimum, the specification of control variables that influence the likelihood that AI would "name and shame" a state *if it did violate the CAT*. Put more concretely, researchers will need to include measures that capture the likelihood that AI would observe a violation when it takes place, and then report it. The ITT variable Restricted Access is one candidate, as is data on the number of offices AI has in each country in the world (Krüger 2008). Ron, Ramos and Rodgers's (2005) data on media attention is also a plausible control variable: AI's need to raise labor and donations gives it an incentive to name and shame violators who are in the news (Finnemore and Sikkink 1998, p. 899; Simon 2006, Brown and Minty 2008; Wong 2008, p. 135; Kelley 2009, p. 767; Lake and Wong 2009, pp. 140, 144). These are merely some first plausible candidates: the research community will surely develop useful models.[23]

That said, the ITT CY LoT data are useful as more than an instrument for testing the empirical robustness of current theory. It is the first cross-national human rights data that allows researchers to disaggregate allegations of torture by state agency and victim type. As such, we hope that the availability of the ITT CY data encourages human rights scholars to refine theories about the mechanisms that influence domestic respect for human rights across state agencies and across victim types. For example, recent work using the ITT CYAoC data finds that transnational terrorism attacks are associated with substantially increased torture by the military—but not by police or prison officials (Conrad et al. 2011). We can imagine a variety of additional questions for which the ITT CY data would also be appropriate: For example, does commitment to international human rights law affect state torture in the same manner across agencies? And what types of victims are most protected from human rights violations by effective domestic courts? In what follows, we discuss bivariate relationships that suggest potential avenues for future research on human rights using the ITT CY data.

First, research on the effect of international human rights treaties has attracted considerable attention among international organization (IO) scholars in recent years (e.g. Hathaway 2002, Hafner-Burton and Tsutsui 2005, Goodliffe and Hawkins 2006, Simmons 2009*b*). These studies have largely found that international human rights treaties are associated with little change in—and sometimes associated with worse—human rights practices than would have been anticipated absent treaty commitment (Hathaway 2002, Hill 2010). The ITT CY data make it possible to explore whether patterns found at the aggregate level using CIRI or Hathaway's data hold broadly across agencies and victim types. We expect that the effect of international (and domestic) institutions varies across state agencies and victim types.

[23] In a future iteration of this study the authors plan to examine the usefulness of such a model.

In the face of international human rights treaty commitment, executives sometimes lack the ability to unilaterally limit human rights violations (Conrad and Moore 2010*b*). But executive (lack of) control may not be the same across agencies or across different types of victims. Further, there is anecdotal evidence which suggests that INGO campaigns to influence states are more successful when they are more targeted. It is not difficult to imagine, for example, that executives may be better able to control torture within executive agencies than across prison systems. The ITT country-year data provides researchers with the ability to look at the effect of international human rights law across domestic agencies and across heterogeneous victim types.

Table 4 reports the coefficient estimates from bivariate ordered probit models that use ITT CY LoT measures as the relevant dependent variables. The dependent variables are listed in the first column of the table (thus forming the rows), while the four independent variables—CAT Signature, CAT Ratification, CIM, and Restricted Access—are shown across the first row of the table, and define the columns. Each of the cells of the table shows the coefficient estimate from an ordered probit model, where the dependent variables is the relevant ITT CY LoT measure and the independent variable is listed across the top of Row 1. As noted above, the impact of CAT signature/ratification has been of interest to a number of scholars. CIM is the acronym for contract intensive money, and has been used as a measure of judicial power. Lastly, we examined the Restricted Access variable because as an information political INGO, AI relies upon access to sources for its reporting. Note that there are no control variables included in the models to generate these estimates; the reported coefficients demonstrate bivariate relationships only and are intended purely for suggestive value.

Columns 2 and 3 of Table 4 show the coefficients from ordered probit models where the independent variables are whether not a state has signed and ratified the United Nations Convention on Torture (CAT), respectively. The results show that CAT commitment has a significant (bivariate) effect on the majority of ITT CY torture variables. With regard to agency of control, the notable exceptions are CYAoCImmigration and CYAoCParamilitary; neither CAT signing nor CAT ratification has a significant effect on these two dependent variables. Although

Table 4: Ordered Probit Coefficient Results (Bivariate Relationships)

	CAT Signature	**CAT Ratification**	**CIM**	**Restrict Access**
CY:				
LoT	0.19***	0.24***	0.27	0.82***
CYAoC LoT:				
Unnamed	0.25***	0.26***	-0.26	1.14***
Police	0.39***	0.42***	1.17***	0.53***
Prison	0.09	0.18**	0.17	0.97***
Military	0.21***	0.13*	0.25	0.55***
Intelligence	0.49*	0.59**	1.01	0.01
Immigration	0.13	0.19	3.27***	0.51***
Paramilitary	0.11	0.04	0.02	0.14
CYVT LoT:				
Unnamed	0.23***	0.27***	0.41*	0.97***
Criminal	0.33***	0.36***	0.03	0.76***
Dissident	0.12*	0.12*	-0.14	0.78***
Marginalized	0.21***	0.23***	1.14***	0.70***
StateAgent	0.22	0.26*	-0.28	0.31

NOTES: * $p < 0.10$ ** $p < 0.05$; *** $p < 0.01$; (two-tailed). Independent variables shown across the columns. Dependent variables shown down the rows.

both CAT signing and ratification positively affect CYVT LoTUnnamed, CYVT LoTCriminal, and CYVT LoTMarginalized, international commitment appears to have a lesser effect on allegations of state torture directed at dissidents and agents of the state. Although we do not speculate on the causal mechanisms at work here, the variance is interesting and perhaps deserves additional consideration.

Second, because there are arguably few international costs associated with ratifying an international human rights treaty and failing to abide by its stipulations (Hathaway 2002, Von Stein 2005), recent literature focuses on the costs and benefits of signing human rights agreements that are associated with domestic political institutions (Vreeland 2008, Powell and Staton 2009). Domestic courts, in particular, have been found to have a dramatic effect on human rights outcomes. On average, effective domestic courts tend to limit human rights violations, including state torture (e.g., Blasi and Cingranelli 1996, Cross 1999, Apodaca 2004, Howard and Carey 2004, Hathaway 2007). But does domestic judicial effectiveness have a greater depressing effect on human rights violations by all government agencies, or only some of them? Do effective domestic courts protect some victims more than others? Column 4 of Table 4 reports coefficient estimates from ordered probit models where the dependent variables are each of the ITT CY LoT measures and the independent variable is contract intensive money (CIM), a measure of domestic judicial effectiveness.[24] In our bivariate results, CIM does not have a significant effect on CY LoT. When torture allegations are disaggregated by agency, however, CIM has a significant positive effect on the number of torture allegations against the police and immigration detention centers, but little effect on torture allegations made against the prisons, the military, intelligence forces, or paramilitary groups supported by the state. Similarly, CIM has no effect on torture allegations against

[24]CIM ranges from 0 to 1 and reports the "ratio of non-currency money to the total money supply (Clague et al. 1999, 188)." Clague et al. (1999) argue that citizens with low confidence in domestic political institutions do not expect contracts to be honored and so prefer currency for monetary transactions, whereas people with more trust in contract enforcement will be more willing to invest their money in banks. CIM was created as a measure of how much people expect economic contracts to be enforced by government institutions, but recent literature argues that it is also appropriate as a measure of judicial effectiveness more generally (Rìos-Figueroa and Staton 2008, Powell and Staton 2009). Unlike other measures of judicial independence or rule of law, CIM provides information on the behavioral consequences of judicial effectiveness.

the majority of victim type categories. The exception is marginalized groups, for whom CIM is positively and significantly related to increased allegations of torture. We hasten to observe: having just explained the importance of modeling AI's likelihood of making allegations if one wishes to use ITT's LoT variables as measures of state behavior, we have just failed to do so. We recognize this, and trust that readers will not take these bi-variate results as more than suggestive for more serious analysis.

Finally, and in that spirit, the ITT CY data include a dichotomous variable as "1" for every country-year in which AI comments that it faced difficulties in accessing a particular country. In the extreme case, AI would have no opportunity to generate allegations against a particular country if that country was able to successfully prevent all AI access. In reality, however, AI *does* generate allegations against most every country in the world, although the organization takes note of situations in which it is unhappy with the lack of access to a particular country. Accordingly, we can imagine two hypotheses. First, countries in which AI comments on lack of access may be more likely to generate torture allegations than their more transparent counterparts. This could be because the countries that actually have bad human rights records face higher incentives to limit access by international non-governmental organizations (INGOs) like AI. Alternatively, countries in which AI comments on lack of access may be *less* likely to torture allegations than their more transparent counterparts. This could be the case if AI's lack of access is so bad—no matter how bad the "real" level of torture in the country—that the organization is unable to generate allegations.

The fifth column of Table 4 provides some initial evidence in favor of the first hypothesis presented above. In almost every case, lack of AI access is positively and significantly related to increased allegations of torture. This initial evidence suggests either that (1) states are not very effective in their attempts to limit AI access, or (2) states that limit AI access violate rights so consistently that it shows up even with the undercount. Future research into these topics—as well as how the effect of restricted access varies across agencies and victims—is necessary to adjudicate between these claims.

5 Conclusion

The ITT project was created to permit researchers to systematically explore the "naming and shaming" activity of arguably the most important of the information politics INGOs, Amnesty International. We set out to use content analysis to reliably code valid measures of AI's allegations, and have expressly sought to do so not at the national level, but instead to construct data across several units of observation from data coded at the level of the allegation. The CY datasets introduced in this study are but a part of that effort.

When we first explored the possibility of launching ITT we read through a number of AI reports to learn how detailed they were. We were pleasantly surprised to learn that AI regularly comments on government agencies and victims, and when the state investigates allegations, AI reports on this as well. In February of 2011 we posted on the project's website a Beta release of the CY datasets. We plan to leave that up until the summer and hope that users will download the data, put it to use, and provide us feedback about errors we have made, augmentations we might offer, and any other comments or suggestions that might help us enhance the value of the project. Please participate: we hope to hear from you.

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6 Appendix

Figure 9

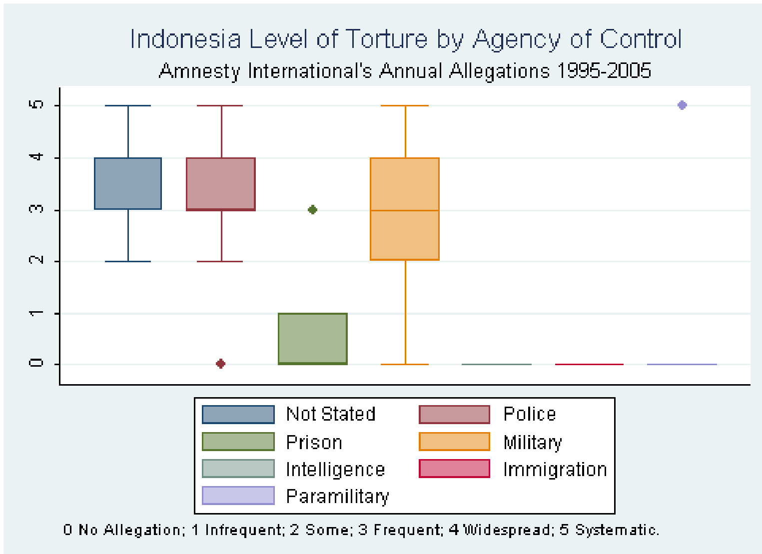


Figure 10

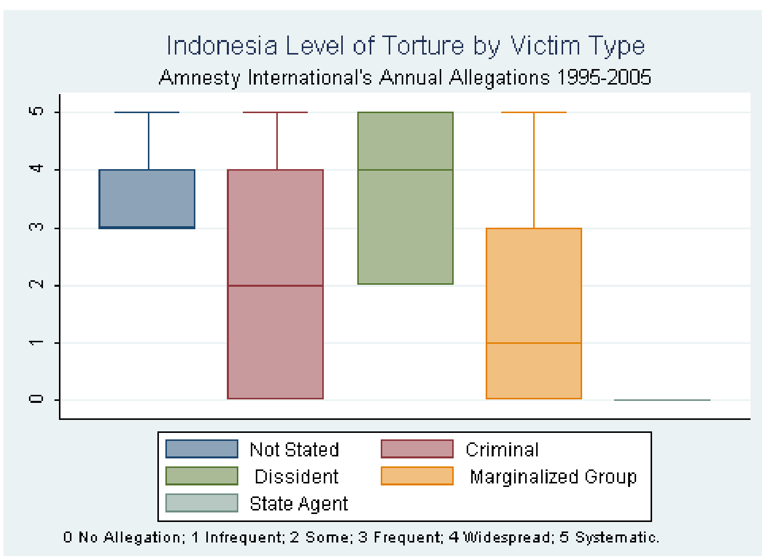


Figure 11

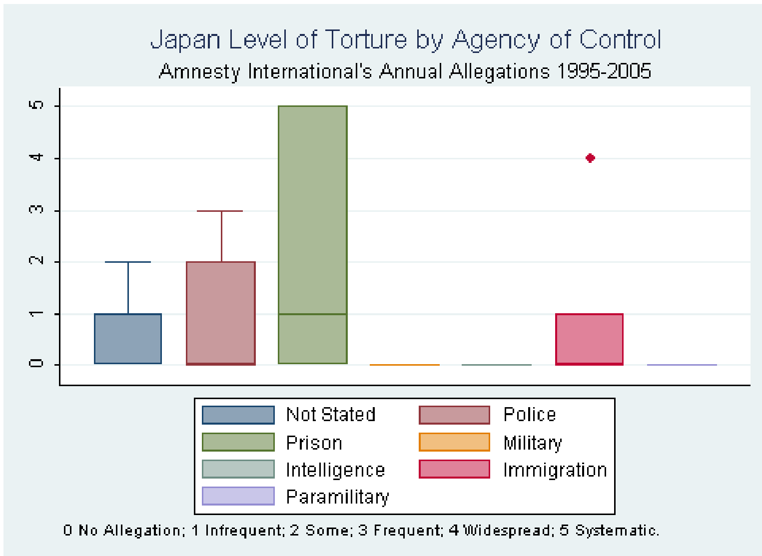


Figure 12

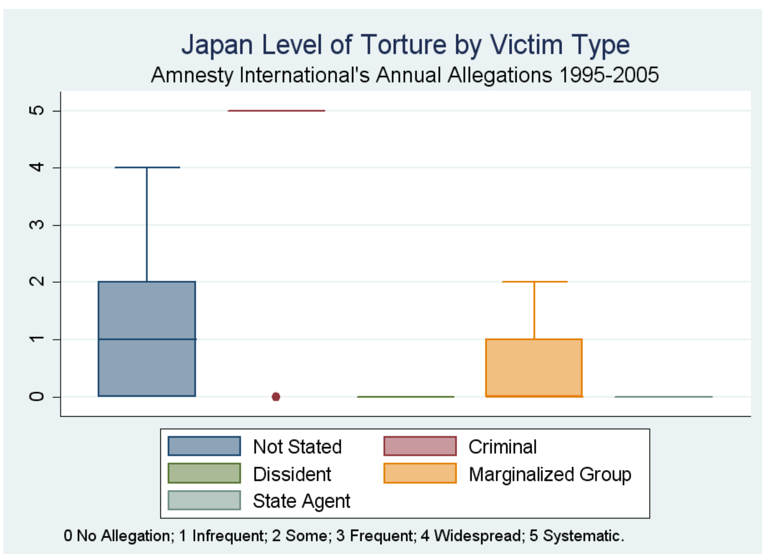
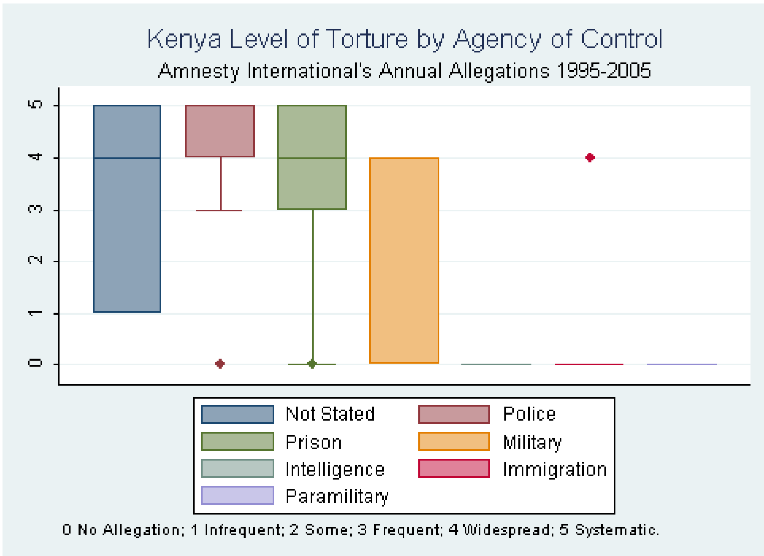


Figure 13



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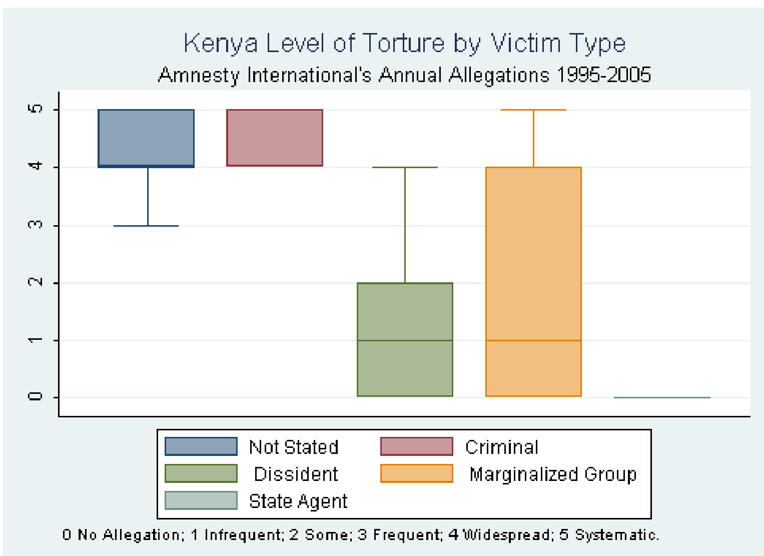

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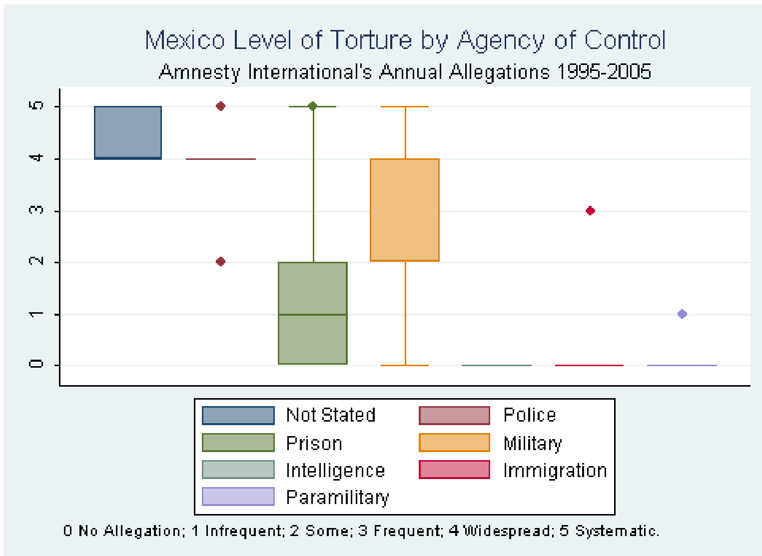

Figure 16

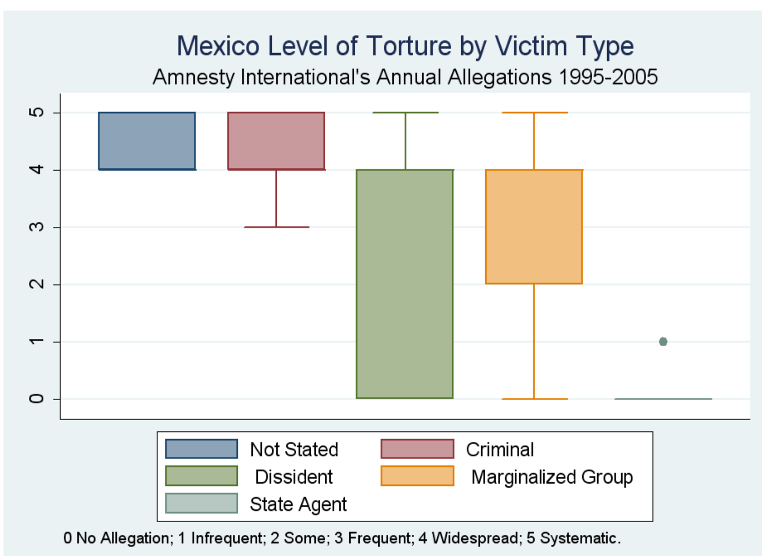

Figure 17

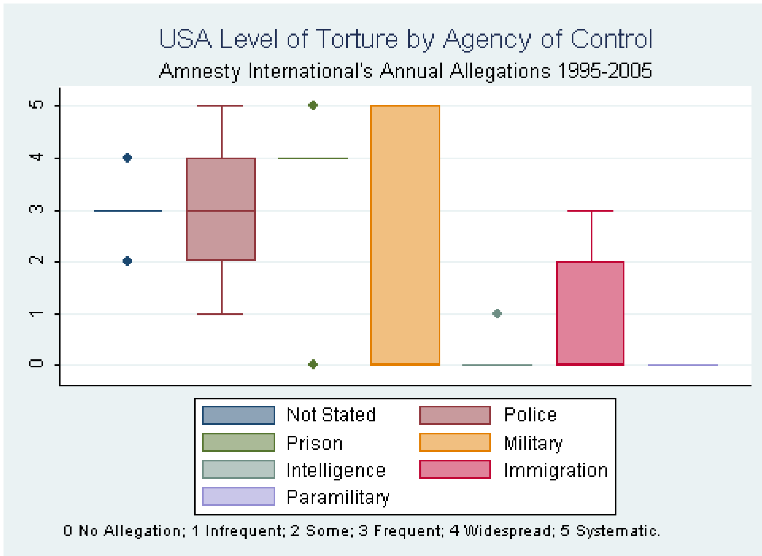

Figure 18